TRANSFORMING U.S. WORKFORCE DEVELOPMENT POLICIES FOR THE 21st CENTURY

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Toward a More Intelligent Workforce Development System

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To meet the challenges of developing a high-quality workforce for the twenty-first century, the next generation of workforce development programs will need to be smarter in providing information to customers. Job matching is an information-intensive process. For the workforce development system to maintain and even improve its effectiveness in assisting job seekers to find work and businesses to find qualified workers, the system will need to transform itself into a more intelligent one. An intelligent system, as envisaged in this chapter, not only provides customers with data essential to make informed decisions but also places this information in the proper context, personalized to the characteristics and circumstances of specific customers and made easily accessible at the time decisions are being made.[1]

When the Workforce Investment Act (WIA)—the major national workforce development system in place at the writing of this chapter—was enacted in 1998, it called for more integrated service delivery through One-Stop Service Centers, and subsequently more integrated data systems. While making some progress toward that end, information provided by WIA remains fragmented, and the administrative data generated by the WIA program are used more for accountability than for informing customers.

In July 2014, Congress passed the Workforce Innovation and Opportunity Act (WIOA), which replaces WIA to become the first major workforce development system of the twenty-first century. In drafting WIOA, Congress recognized the need for a more intelligent system by directing local boards to "develop strategies for using technology to maximize the accessibility and effectiveness of the workforce development system for employers and workers and job seekers" (H.R.

803, sec. 107, subsec. d [7]). More specifically, the bill requires the development of "strategies for aligning technology and data systems across One-Stop partner programs to enhance service delivery . . . and to improve coordination" (H.R. 803, sec. 101, subsec. d[8]). The bill leaves considerable latitude for designing such a system. This chapter offers insight into what information is needed and describes a few pilots and demonstrations funded by the U.S. Department of Labor (USDOL) in recent years that could serve as a basis for a more integrated and comprehensive information system. While it is difficult to pinpoint a precise estimate of the benefits of such a system, several of the previous initiatives, which could serve as components of an integrated information system, have been rigorously evaluated and show positive and statistically significant net impacts for customers and society.

INFORMATION CUSTOMERS NEED

The purpose of the public workforce development system is twofold: 1) to help people find jobs through job search assistance, counseling, and training; and 2) to help employers find qualified workers through referrals, training, and assessment. Both groups of customers face complex decisions in finding the right job match. Job seekers must choose from among different job prospects and career paths as well as reemployment services and training and education options, typically without sufficient information about the benefits and costs of the various options. Employers must identify the skill sets of job prospects and match them to their perceived workforce needs. Furthermore, both job seekers and businesses must deal with future uncertainties and incomplete information in making these decisions.

Job seekers and employers can benefit from an intelligent information system that provides them with access to personalized data at critical decision points as they navigate the labyrinth of complex decisions within the job search and talent search processes. Such a system requires more than simply placing information on the shelf in a One-Stop Service Center or on a Web site link, which customers must not only locate at the time they need the information but must also recognize its relevance for their specific circumstances. Instead, it requires the information to be readily accessible, personalized, and easily understood in the proper context at each key decision point.

In a recent article on the nexus of behavioral economics and labor market policy, Babcock et al. (2012) assert that "research has found that a large number of complex choices hinders decision-making and that interventions providing personalized and transparent information on the most 'relevant' choices can improve decision-making outcomes" (p. 12). The authors go on to say that not only is information essential in navigating the sequence of decisions involved in finding work but that behavioral economics suggests the context in which information is presented can matter in how individuals respond to choices. Furthermore, they suggest that "a successful workforce investment system is likely to be one that reduces complexity and the need for willpower from the perspective of workers, and relies less heavily on well-informed, patient participants for its smooth operation and success" (p. 10).

ELEMENTS OF AN INTELLIGENT WORKFORCE SYSTEM

Based on the needs of customers to make more informed decisions and to navigate the complex process of job matching and the lessons derived from behavioral economics, an intelligent workforce development system requires five basic elements. First, the system is data-driven. Longitudinal files are constructed for each workforce program participant in order to relate personal demographic information, educational and skill attainment, and past work history with postprogram employment outcomes. Second, information is customized for each participant so he or she can see the relevance of the information and can easily access the information at each critical decision point. Third, the system is evidence-based. The returns to training and the effectiveness of reemployment services are estimated for different groups of individuals facing different circumstances. Fourth, reemployment services and training are targeted to individuals with specific needs to ensure that provision of these services is cost-effective. Fifth, performance management of the workforce development system is based on measures that reflect the value-added of the system and not simply gross outcomes.

Many of these elements are either already embedded in the current workforce system or have been tried over the past years as pilots, demonstrations, or new initiatives. These elements must be closely intertwined to be effective. For instance, the construction of longitudinal data files is necessary in order to customize information for each participant and to compute the returns to training investment; in turn, the estimated effectiveness of services is needed to target resources to participants and to develop a value-added performance system.

However, these elements have yet to be brought together in an integrated and comprehensive fashion, which requires more than the integration of new technology; it requires, also, an inculcation of an evidence-based, data-driven culture. Fostering and sustaining such a culture requires more than simply presenting data; rather, it requires an analysis of the data and the capacity of the system to present the higher-level analytics to customers in meaningful formats on a timely basis.

CURRENT WORKFORCE DEVELOPMENT SYSTEM

Two workforce development programs—WIA and the Wagner-Peyser Employment Service (ES)—serve the vast majority of participants and set the guiding principles for the way reemployment and training services are delivered in the United States.[2] The three WIA programs—Adult, Dislocated Worker, and Youth—provide job search assistance, counseling, and training to the three groups targeted by these programs; the ES program provides job search assistance to job seekers, including dislocated workers receiving Unemployment Insurance (UI) benefits. Both programs provide recruitment services to businesses seeking to fill job openings. Local Workforce Investment Boards (LWIBs), which number nearly 600 across the nation, administer the WIA programs and contract with private providers to deliver most of the services. In many states, the reemployment assistance services provided by both WIA and ES are colocated within One-Stop Centers. Training services are typically provided at the facilities of the training provider, such as on the campus of a community college. The WIA and ES programs share similar employment assistance services, even to the extent that many states coenroll participants in both programs. Therefore, to simplify the discussion without limiting the generalizations that one can draw from the concepts presented in the chapter, much of the discussion will focus on the three WIA programs.

Several components of an intelligent workforce development system already exist within WIA, although they need to be improved in order to provide the information in the form and context necessary to better inform customers and program administrators. First, WIA has produced the elements of a data-driven system by compiling longitudinal data of its participants. Second, performance management is based on labor market and educational outcomes. Third, the basic elements of a resource-targeting system exist within ES programs under the Worker Profiling and Reemployment Services (WPRS) system. Although WPRS is not tied directly to WIA programs, it offers an example of the effectiveness of targeting resources within the workforce system. Current initiatives are under way or have been attempted through pilots that can help enhance and improve the existing components.

DATA-DRIVEN SYSTEM

The WIA legislation requires the construction of performance measures of employment and educational outcomes for each program at the national, state, and local levels. The measures are constructed by merging administrative records from the three programs with UI wage record data to form a longitudinal file for each program participant. The administrative records contain information about each participant's demographic characteristics, educational attainment, some skill-related certifications, barriers to entry, occupation and industry of the participant's most recent employment, and services received during enrollment in a program, among other data fields. Merging quarterly UI wage records with these files adds several quarters of employment history of each participant immediately prior to that participant's registering with a program and several quarters of employment outcomes immediately after his or her exiting from a program. The administrative data are obtained from state management information systems and are compiled in the Workforce Investment Act Standardized Record Data (WIASRD) database, which is updated quarterly. The availability of longitudinal data provides a data platform that can become the foundation for an intelligent workforce system.

In addition to administrative data generated by the workforce development programs and the UI system, customers typically have access to labor market information compiled by state labor market information agencies and the U.S. Bureau of Labor Statistics (BLS). One-Stop Service Centers also provide assessment tools (which are typically self-administered), forecasts of demand for occupations, and a partial listing of job openings in the local labor market. In most if not all cases, none of this information is customized to the personal needs, attributes, or circumstances of each customer. Furthermore, most occupation-demand forecasts look at long-run trends and are not tied to near-term business demand, and job postings cover only a portion of the actual jobs available.

Workforce Data Quality Initiative

States, with encouragement from the federal government, have started to develop data systems that augment the administrative data compiled in WIASRD by expanding the longitudinal files of each participant to include a person's K–16 education outcomes and linking that series to an expanded series of quarterly employment outcomes. The Workforce Data Quality Initiative (WDQI), a federally funded collaboration between the U.S. Departments of Education and Labor, is a competitively bid national program that provides funds for states to pull together educational records, workforce administrative data, and UI wage records in order to construct a longitudinal history of each worker's education and employment.

The information can be used in a variety of ways to inform the decisions of workforce program customers. For example, WDQI can track the educational and employment outcomes of each student by the individual training provider with which each is enrolled. This information on "success" rates is useful for prospective students in choosing training providers and educational institutions and for program administrators in holding service providers accountable for student outcomes. It also provides the basis for estimating the economic returns to education and employment services.[3] Furthermore, the WDQI expands the cover-age of WIASRD to include all employees who are covered under the UI system, not only those who are enrolled in the WIA programs.

WDQI is still in the development stage, with 26 states participating in rounds one and two. Under contractual agreement, participating states are expected to use their data analysis to create materials on state workforce performance to share with workforce system stakeholders and the public. According to USDOL, high-quality and consistent data about services offered and the benefits received as they enter or reenter the labor market are integral to informed consumer choices (USDOL 2013). Colorado, for example, has merged K–12 longitudinal data with UI wage records of college graduates from all public colleges and universities and three private colleges in the state to provide prospective students with information about the earnings potential of various academic majors at each educational institution. This information helps students make informed decisions in choosing career paths and shows the value of various levels of educational attainment. The Workforce Data Quality Campaign tracks the progress of states in using longitudinal data for informing workforce- and education-related decisions.

Timely Labor Demand Information

The growing use of the Internet to post job openings offers another source of data that can be useful to customers, particularly with respect to the demand for skills by businesses. While not a statistically valid survey, the use of "spiders" to search and compile Web-based information on job postings has the advantage over surveys of being timely and including all jobs posted on the Internet and not simply a sample of postings. Several states and LWIBs have contracted with vendors to gain access to this information on job openings posted on the Internet. The more sophisticated approaches use algorithms to reduce duplication of job postings and to aggregate them by industry and occupation classifications.

Web-based information can be broken out into highly detailed occupational categories and even reported by individual businesses. These services can be customized for specific locations and can glean from the job postings requirements related to educational attainment, certifications, experience, and other qualifications. However, a current difficulty with relying on job postings found on the Internet, or from other sources, is that no more than half the job postings list education requirements or other skill requirements sought by the employer. Without such information, it is difficult for job seekers to determine what skills they may need to qualify for a job opening and what training they may need to qualify in the future. Perhaps as the use of Web-based data increases and employers recognize the value of this data source for projecting skill needs, employers will be more willing to include skill and education requirements in their postings.[4]

VALUE-ADDED PERFORMANCE MANAGEMENT

To hold program administrators accountable for the outcomes of WIA programs and to foster continuous improvement, USDOL has established a performance-management system based on the longitudinal files of individual participants, described in the previous section (USDOL 2010).[5] Accountability of the programs is established by setting targets at each level of government and monitoring whether or not local workforce investment areas (LWIAs) and states meet or exceed their targets. When performance measures exceed their targets, the program is considered effective; when performance measures fail to meet their targets, the program is considered ineffective. Financial incentives are tied to these performance targets.

However, there is no clear relationship between a program meeting or exceeding its targets and its effectiveness in helping someone find or keep a job. Therefore, under the current performance system, program administrators have little if any information generated on a regular basis about the effectiveness of their programs, and thus little guidance in how to improve the system. Furthermore, it is unclear whether these performance measures provide administrators with the proper incentives to operate programs effectively. This section describes the performance measures currently in use by WIA programs, states their shortcomings, describes research findings of their incentive effects, and outlines methods USDOL has adopted to adjust the measures for confounding factors.

Common Performance Measures

For the two WIA adult programs, the performance measures focus on employment outcomes—the entered employment rate, employment retention rate, and earnings levels.[6] For the Youth program, the measures relate to educational attainment—placement in employment or education, attainment of a degree or certificate, and literacy and numeracy gains. WIA is a partnership among federal, state, and local governments and their nongovernmental intermediaries, and these performance measures are common across all three levels. Each year, USDOL sets national targets for each program; it then negotiates targets with each state, and the states in turn set targets for each of their LWIBs. Performance measures may vary from year to year and across states and LWIBs, depending on local economic conditions and characteristics of program participants. WIA requires that negotiations take into account these factors when setting targets, but it is unclear to what extent these factors are actually embedded in the targets, since negotiations are subjective and not transparent. Even more rigorous methods of adjusting targets for these factors, such as regression analysis, cannot purge the performance measures of these factors completely, although such an approach is more objective and transparent than negotiations.

The problem with interpreting performance measures as a reflection of the effectiveness of the workforce programs is that the common measures are not designed to be used in that way. The common measures focus, as they should, on whether or not a participant finds and keeps a job, but the measures cannot distinguish the contribution of the workforce programs from other factors that affect a person's employment. Other factors include a person's innate abilities, signaled by his or her educational attainment and work experience, and local labor market conditions. Evidence shows that these two sets of factors generally influence employment more than the reemployment and training services offered by the workforce system (Eberts and Huang 2011). Therefore, a program administrator may conclude that the services provided are effectively contributing to the employment outcomes of participants when the performance of the administrator's program exceeds its predetermined target, whereas it could simply be the case that the participants are more capable than was expected when the targets were set, or that labor market conditions are more favorable. Unless the performance measures are adjusted for these factors in a rigorous way, they provide administrators with little information as to the effectiveness of their programs and what they may need to do to improve the delivery of services. Typically, rigorous evaluations, using comparison groups, are conducted to estimate the net effect of a program.[7] Because of the expense in conducting such an evaluation, they are done infrequently, and thus their relevance may diminish over time.

Possible Adverse Incentives

In addition to concerns that the performance system implemented under WIA provides little guidance to administrators to improve their services, policymakers and researchers have for some time been concerned about the possible adverse behavioral responses to performance measurement systems. Questions have arisen as to whether the performance system may lead local administrators to "game" the system by admitting more qualified individuals in order to improve the performance of their programs, without actually improving the effectiveness of the services provided. Concerns have also surfaced as to whether financial incentives were sufficient to influence positive behavior.

James Heckman and a group of his graduate students conducted a series of studies on how performance standards and incentives influence the behavior of program administrators and staff and contribute to program outcomes or unintended consequences (Heckman et al. 2011). While the studies focused on the Job Training Partnership Act (JTPA), the predecessor to WIA, sufficient similarities exist between the two programs for their findings to be relevant to the current system.

The body of research drew two key lessons: First, agencies respond to incentives, even seemingly small ones, and second, the concern about "cream-skimming" is overstated. With respect to incentives, the researchers found that "low-powered cash incentives may, in fact, be high-powered because of the value of the budgetary awards in establishing the reputation of bureaucrats and the recognition that comes with them" (Heckman et al. 2011, p. 306). However, they cautioned that bureaucrats may learn over time the weaknesses of the system and how the weaknesses can be exploited to their advantage. They recommended that the incentive system and performance measures be reviewed regularly and redesigned when deemed necessary to achieve the desired outcomes.

Researchers also found that the financial incentives incorporated into the performance measurement system were further enhanced by performance-based contracting. Under both JTPA and WIA, contracts with local service providers, such as community colleges and nonprofits, are based on the performance of the subcontractors. Heinrich (2000), in a detailed study of an Illinois Service Delivery Area under JTPA, found that the inclusion of performance incentives in service contracts has a very strong positive effect on participants' realized wages and employment at termination and for up to four quarters after they leave the program. Based on this result and that of others (Dickinson et al. 1988; Spaulding 2001), one can conclude that performance-based contracts yield higher performance on the rewarded dimension. However, as previously mentioned, one has to ensure that incentives are properly aligned with desired outcomes.

The second lesson from the studies is that the cream-skimming problem is overstated. There has been serious concern that local administrators of the workforce system game the system by enrolling program participants with high abilities to find employment at the expense of those who truly need assistance. Administrators were also suspected of gaming the system by exiting participants only when they had achieved a positive outcome, such as obtaining a job. However, the researchers found little evidence that this had occurred in the JTPA programs. Since WIA replaced JTPA, there has been a growing industry of consultants who purport to help LWIBs maximize their outcomes, and it is unclear whether this influence has led to more gaming under WIA than under JTPA. An assessment by Barnow and King (2005) of the first five years of WIA found that gaming or "strategic behavior" took place in the majority of states studied. However, they did not analyze, as Heinrich did, the actual impact of gaming behavior on performance outcomes.

Statistical Approaches to Adjusting Performance Measures

One possibility for the low incidence of cream-skimming could be related to the methodology used to adjust for factors that lead to such behavior. JTPA used a regression approach to adjust targets for factors that affect participants' ability to find employment. By adjusting targets upward when a local program has a higher percentage of participants with characteristics more favorable to achieving positive employment and educational outcomes, the performance standards are raised for those trying to game the system by enrolling those who are more likely to find employment because of their own higher capabilities.

WIA legislation replaced the statistical approach to adjusting targets adopted by JTPA with a more subjective approach based on negotiations between the different levels of government. The reliance of WIA on negotiations to adjust for outside factors rather than using the quantifiable and transparent system adopted by JTPA led Barnow and Smith (2004) to conclude that WIA took a step backward from JTPA in measuring the contribution of the workforce system to achieving outcomes. As the performance system is adjusted more accurately for such factors, the system moves closer toward an indicator of the value-added of the program.[8]

Beginning with program year 2009, USDOL adopted a regression-adjusted approach for setting national targets for the three WIA programs and other federal workforce development programs. The regression-adjusted methodology followed the JTPA methodology to a large extent by controlling for factors related to personal abilities and local labor market conditions. However, USDOL did not return completely to using the method of setting targets under JTPA. Instead, it used a hybrid approach for states and LWIAs. As with JTPA, targets were determined for states and LWIAs using the regression methodology. These regression-adjusted targets were offered only as a starting point for negotiations, and the final targets were determined by the negotiation process (USDOL 2011). Nonetheless, by offering states and LWIBs regression-adjusted performance targets, they have objective data describing the factors that affect their performance outcomes and a transparent, objective method of understanding how these factors actually affect their performance (Eberts and Huang 2011). Several states use these data in the negotiation process.

Value-Added Performance Improvement System

Recognizing the need to provide better and more timely information to program administrators, the state of Michigan, with support from

USDOL, developed the Value-Added Performance Improvement System (VAPIS). Michigan provided VAPIS to local workforce administrators for several years (Bartik, Eberts, and Kline 2009; Eberts, Bartik, and Huang 2011). The system was similar to the regression-adjusted targets described previously, except that instead of adjusting the targets, the methodology adjusted the common measures. In this way, the performance measures themselves reflected to a greater extent the value-added of the workforce system. Performance measures were adjusted downward for participants who had a greater ability to find employment, and upward for those with less ability. The same approach was used for local labor market conditions: Performance measures in areas with favorable conditions were adjusted downward, and such measures were adjusted upward for areas with less favorable conditions. By purging the performance measures of factors unrelated to the actual effectiveness of the program services, the adjusted measures were more reflective of the value-added of the system.

VAPIS also addressed the issue of the timeliness of performance measures. Performance measures, based on UI wage records, are not available for up to a year after participants exit the program. The long lag makes it difficult for administrators to base management decisions on these measures or to use them for continuous improvement. VAPIS forecast the possible outcomes of participants currently receiving services so that local administrators could get some idea of how their current decisions may affect future outcomes.

While regression-adjusted performance measures may theoretically reflect more closely the value-added of a program, they still may not closely approximate the findings from a rigorous evaluation of effectiveness. A recent evaluation of the use of regression-adjusted performance outcomes in the Job Corps program found little relationship between these “value-added” measures and the net impact results from a rigorous randomized evaluation (Schochet and Fortson 2014). The authors attribute much of this effect to the weak associations between the unadjusted performance measures and long-term outcomes, as well as to unobserved factors. While performance outcomes were never intended to substitute for rigorous evaluations, the question still remains of whether a regression-adjusted approach provides administrators with information that can inform their decisions better than no information at all.[9]

Including Business Satisfaction Indicators

Businesses look to the workforce development system to help identify, assess, and train workers to meet their specific skill requirements. In return, the workforce development system looks to businesses to communicate their talent needs in order to assist with proper job matches and to ensure that workers are trained to meet the future needs of employers. Despite the importance of engaging businesses as customers and partners, the common measures currently adopted by USDOL do not include any direct measure of how businesses use the system, how they may benefit from using the system, or their satisfaction with the system. Obviously, the mere act of hiring a workforce-program participant is beneficial to the employer. However, the current performance measurement system does not record whether an employer used the workforce development system to find specific workers, nor does it record the length of time that employer retained the worker hired through the workforce system.

The Commonwealth of Virginia and the state of Washington considered including indicators reflecting the business use and satisfaction of public workforce development programs. Of particular interest is a measure they constructed to record the use by employers of WIA services. It measures repeat employer customers and is calculated as the percentage of employers served by WIA who return to the same program for service within one year (Hollenbeck and Huang 2008). More specifically, an employer was categorized as "satisfied" if the business hired someone who had exited from a program in the first quarter of the fiscal year and then hired another individual from the program before the fiscal year was over. The denominator for this indicator is the number of employers who hired someone in the first quarter of the fiscal year. Hollenbeck and Huang (2008) calculated the measure for the two WIA adult programs in Virginia and found that 52 percent of employers who hired someone from one of the two programs hired at least one more worker from the same program within the year. Of course, this is contingent on the number of times an employer hires during the year, but it can be normalized by a state or industry average.

The measure adopted by Virginia assumes that employers are repeat customers because the programs have provided them with job applicants with the appropriate skills and other qualifications. However, the measure, while easy to calculate and inexpensive to administer, may be a poor substitute for more in-depth information obtained directly from employers. First, it does not offer any specific information about the level of satisfaction or exactly what services businesses found helpful in their recruiting efforts. Second, the measure may not reflect what it is intended to record. Rather, it may be the case that the same business did not return to the workforce programs in search of job applicants simply because it was not hiring during the period covered by the measure. Consequently, the lack of hiring needs may be confused with lower satisfaction with the workforce services. Third, the measure may be of little use to workforce administrators seeking better ways to help guide participants with sought-after skills to the appropriate employers, and of little use to training providers in determining the appropriate curriculum and the appropriate capacity in their training facilities to meet employers' demands.

CUSTOMIZED INFORMATION AND TARGETED SERVICES

The merit of providing information customized to the personal characteristics and circumstances of individual participants is supported by lessons from behavioral economics. According to Babcock et al. (2012), job search assistance and employment services should be simplified and streamlined by making tools available that gather information on an individual's background and interests, provide feedback on the education and employment opportunities pursued by others like the participant, list job openings that may interest the participant, and provide information on the projected growth in occupations (p. 8). The next logical step then is to use that information to find the services that best meet the needs of individual participants. Therefore, initiatives that combine customized information and targeting will be discussed in this section.

Frontline Decision Support System

The Frontline Decision Support System (FDSS) pursues an approach to customizing information and targeting resources that is consistent with the lessons drawn from behavioral economics. FDSS offers a set of decision tools that provides job seekers and frontline staff with customized information about employment prospects and the effectiveness of services. Of the various initiatives considered, FDSS comes the closest to combining all five elements of an intelligent workforce system, including evidence-based decision making, and offers the possibility that the results of rigorous evaluations can be incorporated into the FDSS framework. FDSS uses existing administrative data and statistical algorithms to help staff and customers make better decisions about job prospects and about appropriate services that meet the customer's needs in finding employment. The Web-based screens guide job seekers through key decision points and provide them with easily accessible and customized information. The pilot was implemented in Georgia in 2002 as a joint effort of USDOL's Employment and Training Administration, the Georgia Department of Labor, and the Upjohn Institute (Eberts, O'Leary, and DeRango 2002).

FDSS walks job seekers through a systematic sequence of steps and presents customized information at each critical decision point. Using the case of a dislocated worker as an example, FDSS moves that individual through the reemployment process, beginning with understanding his or her likelihood of returning to work in the same industry, proceeding to explore job prospects in occupations that require similar skills and aptitudes, then accessing information about the earnings and growth of jobs in particular occupations within the individual's local labor market, and ending with an understanding of which reemployment and training services might work best for that person, if none of the previous steps leads to a job. At each of these critical decision points, personalized information is made available to help inform the decisions.

The personalized information is based on statistical relationships between a customer's employment outcomes, personal characteristics, and other factors that may affect his or her outcomes, all of which are available from workforce administrative files already collected by the various agencies. The statistical algorithms provide an evidence-based approach to determining which services are most effective for specific individuals. The algorithms also personalize labor market information so that it presents information that is pertinent to the participant's abilities and circumstances, such as the probability of someone with the observed characteristics of the specific individual returning to his or her previous occupation and industry. By using administrative data that capture the experience of all customers who have recently participated in the state's workforce system, this evidence-based approach offers a more comprehensive and "collective" experience of what works and what doesn't than relying on the narrower experience of individual caseworkers.[10]

Barnow and Smith (2004), in a critique of the performance management system of the federal workforce system, recommend using FDSS as the centerpiece for a redesign of the performance system. In what they describe as an "ideal" performance system, "randomization would be directly incorporated in the normal operations of the WIA program . . . [through] a system similar in spirit to the Frontline Decision Support System" (p. 49). They contend that such randomization need not exclude persons from any intensive services, but only assign a modest fraction to low-intensity services—that is, the core services under WIA. The randomization would then be used, in conjunction with outcome data already collected, to produce experimental impact estimates that would serve as the performance measures. However, one of the drawbacks with randomization is sample size. A relatively large sample—typically larger than the inflow of participants into many local workforce programs—would be required. Because of the need for large samples, this approach would be most applicable for state-level performance incentives, which is not the level at which contracts are administered and services delivered. Furthermore, for purposes of informing management decisions, the effect of either individual services or bundles of services is more useful than the overall effect of the program. To use randomization to estimate service-specific effects would require even larger sample sizes.

Another approach to estimating the effects of programs and services is to use propensity scoring techniques to construct counterfactuals. While this is thought to be not as reliable in estimating net impacts as randomization, it is considered a viable alternative and has been used extensively in program evaluations, most recently in evaluating the net impact of WIA programs (Heinrich, Mueser, and Troske 2009; Hollenbeck et al. 2005). For the purpose of providing pertinent information to decision makers, it has several advantages over randomization. One is the need for a smaller sample size; a second is that one need not exclude participants from any services. With randomization, a control group is constructed by randomly excluding individuals from services. With propensity scoring, the control group is constructed by identifying observationally similar individuals who were not enrolled in any of the services being evaluated. One of the drawbacks of the latter approach is that individuals may not have enrolled for reasons that are not observed and thus could bias the net impact estimates. However, finding individuals who are similar in observed characteristics helps to control for these unobserved attributes, and the previously mentioned studies have used as comparison group members those who participate in the Wagner-Peyser Employment Service. A third advantage is that propensity score matching methodologies can be "built in" to a performance system and can be refreshed periodically as new data are entered into the system. While not completely automatic and self-functioning, it does require a minimal amount of intervention during the updating phases.

FDSS has never been rigorously evaluated to determine whether the information provided and the way in which it was presented improved the effectiveness of the WIA programs compared with the typical conveyance of information within One-Stop Service Centers. However, the development and implementation of FDSS was based in part on the success of two U.S. Department of Labor initiatives, both of which were rigorously evaluated and found to be effective. These two initiatives, Welfare-to-Work and WPRS, are discussed in the next two sections.

Targeting Services to Welfare-to-Work Participants

The Welfare-to-Work referral system used a statistical methodology, similar to that used in FDSS, to target services to program participants. The purpose of the pilot was to improve the employment outcomes of participants by referring them to services that best meet their needs. Funded by USDOL and developed by the Upjohn Institute, the pilot referred Welfare-to-Work participants to one of three service providers based on a statistical algorithm that used administrative data to determine which provider offered services that were shown to be most effective for customers possessing specific characteristics and employment backgrounds. Each provider offered different services and different approaches to delivering those services. Before the pilot was established, the LWIB where the pilot took place randomly referred participants to the three different providers. Therefore, the relationships between different types of services and employment outcomes for groups of participants with different characteristics were based on a randomized sample. Using this sample, the observed employment outcomes were regressed against personal characteristics of the participants, and these relationships were then used to refer new enrollees to providers based on the enrollees' personal characteristics.

The initiative demonstrated that customizing services based on participant characteristics could increase the effectiveness and efficiency of the intervention. A random assignment evaluation of the pilot showed that targeting services in this way significantly increased the 90-day employment retention rate of participants by 20 percentage points, yielding a benefit-cost ratio of greater than three (Eberts 2002).

Worker Profiling and Reemployment Services

WPRS is a national program signed into law in 1993, which requires each state to identify UI claimants who are most likely to exhaust their UI benefits before finding employment and then to refer them as quickly as possible to reemployment programs. The purpose of WPRS is to encourage a targeted subset of UI beneficiaries to use reemployment services intensively at the beginning of their unemployment spell rather than toward the end, when they face the prospect of exhausting their benefits. The identification procedure uses statistical methods similar to some of the algorithms used in FDSS. Independent evaluations show that WPRS reduces the use of UI benefits and the length of unemployment spells by statistically significant amounts compared with appropriate comparison groups (Dickinson, Decker, and Kruetzer 2002).

Value of Information and Guidance about Training Outcomes

The training programs delivered under WIA offer fertile ground for exploring ways to guide participants through the process of determining the type of training. WIA-funded training is offered primarily through Individual Training Accounts (ITAs), which provide job seekers with a fixed amount of money they can use to pay for training from providers of their choice. With this high degree of choice, individuals are faced with a series of complex choices involving the calculations of future returns to training and the selection of the type of training and, subsequently, choice of occupation, in addition to the psychological barriers of investing time and money in training with distant payoffs. Babcock et al. (2012) suggest that training programs through One-Stop Centers should "emphasize reducing complexity and providing guidance to participants as priorities" (p. 11).

To help job seekers make more informed decisions, WIA requires states to compile and post Eligible Training Provider Lists, which provide job seekers with information about past success rates of participants enrolled with specific training providers. To be eligible to receive WIA funding for postsecondary training, a training provider must meet the criteria for being included on the list. Most pertinent for this discussion is the requirement that training providers post information on specific student outcomes, such as the percentage graduating from the program and the percentage completing the training and finding employment. To construct the Eligible Training Provider List, student data from each provider was to be linked with UI wage records. However, for many providers, this linkage was never completed. The Workforce Data Quality Initiative has rekindled interest in completing the information for training providers and educational institutions in general.

In addition to providing information about the education and employment outcomes of training providers, USDOL considered the relative effectiveness of offering different levels of guidance to prospective training participants. USDOL commissioned an evaluation that considered three models, which varied along two dimensions: first, the freedom that trainees were given in selecting a training provider, and second, the gap between the cost of training and the funds provided by WIA to pay for training.

Findings from the randomized control trial evaluation suggest that customers and society would benefit markedly from intensive counseling and higher potential ITA awards, compared with less information and direction from counselors and fixed awards. Estimates from the benefit-cost analysis indicate that society would benefit by about $46,600 per ITA customer by participants' receiving more guidance from counselors compared to less oversight (Perez-Johnson, Moore, and Santillano 2011). Results also show that customers who were given more guidance were significantly more likely to be employed in the occupation for which they trained, offering additional support for the suggestion from behavioral economics of providing guidance to participants.

EVIDENCE-BASED DECISIONMAKING

Evidence-based decisionmaking permeates many of the initiatives described in this chapter, and various methodologies of estimating the effectiveness of programs have already been discussed. One of the trade-offs inherent in providing information on the effectiveness of programs and services is between the rigor of the evaluation and the timeliness of the information. Another trade-off is between the rigor of the evaluation and the granularity of the information, such as obtaining effectiveness estimates of specific services or bundles of services for subgroups of the population. The latter is important for customizing information to individual customers and for targeting resources to individuals. Some researchers, such as Barnow and Smith (2004), have suggested embedding a randomized trial evaluation in a system such as the FDSS. Researchers at the IAB in Germany have experimented with that approach.[11] Others have explored the possibility of incorporating an evaluation instrument based on propensity scoring within a similar framework. And still others have looked at refining a regression-adjusted approach. As previously mentioned, some research has already examined the trade-offs between the different approaches, and more needs to be done to find the right balance for the different applications of evidence-based information.

EXTERNAL PARTNERS

The workforce development system depends on close relationships with other entities in order to provide effective reemployment and training services. Many LWIBs act as facilitators to bring together various local organizations, such as economic development entities, businesses, social agencies, educational institutions, and labor groups, to help address workforce aspects in their local areas. According to a Government Accountability Office report (GAO-11-506T, p. 12), One-Stop Centers provide an opportunity to coordinate the services among a broad array of federal employment and training programs. The study also points out that colocation of services affords the potential for sharing resources, cross-training staff, and integrating management information systems.

Regional Sector Alliances

Several states have initiated programs that engage businesses and form partnerships with local educational institutions and economic development agencies through a sectoral approach. Two examples are the Michigan Regional Skills Alliance and the California Regional Workforce Preparation and Economic Development Act (Eberts and Hollenbeck 2009). Typically, local areas engage in a strategic planning process that includes an analysis that identifies the key growth sectors in the region. Partnerships are formed within these sectors by bringing together key businesses within these sectors with local entities that provide training and economic development initiatives.

Beginning in 2006, USDOL funded WIRED (Workforce Innovation in Regional Economic Development), which supported the development of a regional, integrated approach to bring together workforce development, economic development, and educational activities. The goal of WIRED was to expand employment and career advancement opportunities for workers and catalyze the creation of high-skill and high-wage opportunities. WIRED consisted of three generations of regional collaborations, totaling 39 regions (Hewat and Hollenbeck 2009). The WIRED initiative was a competitive program in which selected regions received from $5 million to $15 million over three years to support the formation of partnerships. The evaluation of WIRED, funded by USDOL, found that the WIA programs within the WIRED regions had statistically significantly higher entered employment rates and retention rates than WIA programs in the comparison group (Hewat, Hollenbeck, and others 2011, chapter 5).

The information requirements to foster effective partnerships across entities external to the workforce system are similar to the information needs within the system. Partnerships work best when organizations share a common vision and strive to meet common goals. The performance of one organization, therefore, affects the success of another organization within the partnership. Consequently, each organization needs to be able to understand its contribution to the common goal, which requires each to develop value-added performance measures.

Moreover, since it is likely that each organization will have a different management information system, a common platform is needed upon which relevant data from the various organizations can be shared. Such platforms are available, through which organizations can share data at various levels of disaggregation and thus disclosure. Probably the most challenging barrier to sharing information is to establish trust between partnering entities and leadership to identify a common vision and act collectively toward a common goal.

SUMMARY: AN INTELLIGENT, INTEGRATED INFORMATION SYSTEM

As outlined in this chapter, customers and managers of the workforce system require more relevant and current information to make informed decisions. Job seekers ask for information that will help them identify the occupations and skills demanded by businesses, find jobs, and move into more meaningful careers. Businesses seek information about the pool of qualified workers. Workforce program administrators seek information to help them make better management decisions. To meet these needs for relevant information, an intelligent workforce system, therefore, needs to incorporate five elements: 1) a data-driven system, 2) information customized to the specific needs and circumstances of each customer, 3) an evidence-based system, 4) targeted reemployment and training services, and 5) value-added performance management. The current workforce system embodies various aspects of these elements, but significant improvements must still be made.

The WIOA, which replaces the current workforce development system, encourages states to target services, integrate data-driven counseling and assessments into service strategies, more fully integrate programs, and provide easy and seamless access to all programs. It even requires states to periodically evaluate the workforce system using comparison-group methodologies. Something like the FDSS comes the closest to incorporating these functions: It integrates administrative workforce data with education and wage data, it develops statistical algorithms that provide personalized information to help customers understand what various trends and circumstances mean to them, and it brings this information back down to the customers and frontline staff who are making decisions. Such a system incorporates some of the lessons gleaned from behavioral economics that demonstrate the benefit of customized information, feedback on the possible returns to education and training choices, and personalized employment prospects and labor market information. As Barnow and Smith (2004) suggest, this framework can be combined with counterfactuals that provide a better sense of the value-added of programs and, more specifically, the services provided within those programs. Such a system is not perfect, of course. It does not substitute for rigorous evaluations of the effectiveness of programs, nor does it guarantee that incentives are properly aligned with desired outcomes. However, it does make significant advances in getting relevant information in an easily accessible format to the customers and decision makers of the workforce system.

Development of an intelligent workforce system will not happen all at once, even though much of the foundation has already been laid by past initiatives and within the current workforce system. To begin the process, one possible approach is for the federal government to provide innovation dollars to one or two interested states with the specific purpose of developing such a system. Once the system is up and running, other states can see how it works and begin to recognize the merits of such a system. To ensure that statistical algorithms and other key innovative aspects of the system are continually updated, regional data centers could be established to give researchers who are interested in creating, updating, and improving such a system access to administrative data. Involving researchers and practitioners in the ongoing development of the system will help to ensure that the system continues to evolve to meet the current and future needs of customers and administrators of the workforce development system.

Notes

1. This chapter draws from Eberts (2013).
2. WIA was enacted in 1998, and the Wagner-Peyser was established in the 1930s. WIOA is based on principles similar to WIA (and its predecessor, JTPA) of a federal-state-local partnership with authority given to local boards to administer the programs.

3. For an example of using similar data for computing rates of return for worker training programs, see Jacobson and LaLonde (2013).
4. Some analysis has been conducted to compare the accuracy of job openings data obtained from vendors with the survey-based Job Openings and Longitudinal Time Series (JOLTS) data compiled by the BLS. While the actual numbers of job openings differ between the two sources, they both seem to track similarly, with turning points occurring at roughly the same time. Brad Hershbein has conducted this research at the Upjohn Institute, and the results are available upon request.
5. Training and Employment Guidance Letter (TEGL) 17-05, issued February 17, 2006 (USDOL 2010). The Government Performance and Results Act (GPRA) of 1993 requires that all federal programs set performance targets and establish performance tracking systems. Even before GPRA was enacted, the ETA incorporated an outcomes-based performance system into many of its programs. Today, 15 federal workforce programs, serving nearly 20 million people annually, are subject to performance measures and targets. GPRA was updated in 2010 with the enactment of the Government Performance and Results Modernization Act.
6. Performance measures of the WIA adult programs include educational attainment outcomes in addition to employment outcomes.
7. The legislation to replace WIA requires that each state periodically evaluate its workforce programs using methodologies that include comparison groups.
8. Heckman's team of researchers also found that the short-term outcomes are not highly correlated with longer-term outcomes, which suggests that the regression-adjusted targets do not substitute for a rigorous evaluation of the program, no matter how well the adjustments may move the gross outcomes toward value-added outcomes.
9. Barnow and Smith (2004), in an assessment of performance management of the WIA system, expressed concern that short-term performance outcomes mandated by WIA do not correlate with long-term program impacts. They recommended that the performance system be suspended until research identifies such short-term measures.
10. While not indicting all caseworkers, Lechner and Smith (2007) provide evidence that caseworkers do not do a very good job in referring displaced workers (in Switzerland) to services that maximize their employment prospects.
11. The German public employment service, through its research arm, the Bundesargentur fur Arbeit (IAB), used randomized experiments to develop an evidence-based system that identifies services that have been shown to contribute the most to the improvement of employment outcomes of individual workforce participants. The approach grew out of the Hartz reform to improve the effectiveness and efficiency of German's active labor market programs. Dr. Susanne Rassler was the project director.

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18
Improving the Effectiveness of Education and Training Programs for Low-Income Individuals

Building Knowledge from Three Decades of Rigorous Experiments

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While many low-income individuals have jobs—or eventually find them after periods of unemployment—many do not consistently earn wages that will foster upward mobility. To address this, a number of initiatives have aimed to help low-wage workers acquire "better" jobs, stay employed, and advance in the labor market. This chapter reviews a large body of rigorous evidence, accumulated over the past 30 years, on the effectiveness of dozens of different types of human capital development programs that had these goals and targeted public assistance recipients and other low-wage workers. It shows how knowledge gained from each set of multisite randomized control trials (RCTs) led to the development and testing of a subsequent results-based "next generation" of programs. The chapter explains how this progressive evidence-development process has led to a current focus on rigorously examining the effectiveness of programs emphasizing several approaches: the alignment of services with employer demand, longer-term advancement opportunities (rather than a focus on simply finding a job), and the provision of training that is tailored to the needs of particular industry sectors, in terms of both hard skills (such as how to operate certain machinery) and soft skills (such as how to adjust to the "culture" of employment in that sector).

The studies drawn upon in this chapter all used random assignment research designs (also called RCTs or experimental designs), which allow the effects of program strategies to be disentangled from the effects of other factors, such as participants' characteristics.[1] In this type of rigorous design, individuals who meet programs' eligibility requirements are randomly assigned to either a program group or a control group. Those in the program group are eligible for the new initiative, and those in the control group are not. Individuals in both groups are followed, and information is collected on their employment and other outcomes of interest. Random assignment eliminates systematic differences between the research groups in individuals' characteristics, measured or unmeasured (such as motivation). Thus, any statistically significant differences between the groups that emerge after random assignment—for example, in employment rates or average earnings—can be attributed to the initiatives under study.

Following an initial discussion of some broad economic trends, the next section of the chapter reviews a set of studies that first tested the effectiveness of requiring welfare recipients (recipients of Aid to Families with Dependent Children [AFDC] prior to 1996, and recipients of Temporary Assistance for Needy Families [TANF] post-1996) to engage in job search assistance, basic education, or training as a condition of receiving welfare benefits, and then tested the relative effectiveness of requiring participation in specific program components. The results of these early studies led to the testing of programs that would help people work more stably and advance in their jobs, and subsequently to examining the effects of programs that focused more on job training. The evaluation results are discussed in the next two sections. At the same time, important studies were conducted of programs using another approach—a "sectoral" strategy, the results of which are examined next. Findings from all of these rigorous studies have led to a current research focus on a hybrid program, described in detail in the following section. The final section of the chapter provides some concluding thoughts about the value of building research evidence in a systematic fashion and possible future directions.[2]

THE ECONOMIC PROBLEM

Broad economic trends have reduced the availability of high-paying jobs for people who do not have a college education. Wages at the bottom of the labor market have been stagnant and declining (in real terms) due to numerous factors, including the decline of unions, changes in labor norms, increased competition, and globalization (Howell 1997). Individuals with no more than a high school education have seen their wages remain flat in real terms for decades, and their employment is often unsteady (Mishel, Bernstein, and Shierholz 2009). These trends have implications for a broad swath of the U.S. labor market. Considering all workers today, one out of four earns less than $10 per hour (Bureau of Labor Statistics 2013; National Employment Law Project 2012). While some of these low-wage workers are teenagers, they are increasingly older workers with more education (Schmitt and Jones 2012). Moreover, the situation is particularly dire for low-wage, low-income workers with children: Only a third of them have more than a high school diploma and another third are high school dropouts (Acs and Nichols 2007).

The labor market has also restructured in fundamental ways. First, there is a proliferation of low-skill, low-wage service jobs that are often inadequate to help individuals escape poverty. Many of these jobs have little prospect for advancement, so the returns to experience can be low. Therefore, for many workers, the path to higher earnings is to work at jobs with higher skill requirements. However, middle-skill jobs that pay more are becoming harder to get. Due in part to automation, the growth rate has slowed in middle-skill job categories that employed large numbers of American workers in the early 1980s, such as "production, craft, and repair" and "operators, fabricators, and laborers." While there is substantial debate over whether middle-skill jobs are truly disappearing or instead are largely shifting to different industries and occupation types, there is a consensus that the skill requirements of jobs are increasing (Autor 2010). More and more jobs require specialized skills and the performance of nonroutine tasks (Holzer 2010). Because of these shifts, it is becoming more difficult for workers with only a high school diploma, and particularly for those who do not even have this credential, to access jobs that can help pull them out of poverty (Carnevale, Smith, and Strohl 2010).

In addition, there is evidence that employers in some industries are having trouble finding qualified applicants for some jobs (Morrison et al. 2011). Surveys show that employers feel the K–12 education system is not sufficiently equipping students with the range of skills needed in the workplace (Peter D. Hart Research Associates/Public Opinion Strategies 2005). Employers also appear less willing than in the past to absorb the training costs of providing workers with needed skills, particularly when they are considering hiring new employees (Hilliard 2013), possibly out of a concern that they may lose their investment when workers leave (Cappelli 2012). On the supply side, surveys reveal that, compared with employers, low-wage workers are less confident in the utility of training and education to help them advance in their careers, and many feel that their jobs have little potential for advancement. Workers also often lack awareness about training opportunities, and take-up rates of both employer- and government-sponsored training programs are low (Tompson et al. 2013). Finally, the availability of government funding for training through the Workforce Investment Act (WIA), as one example, has declined nearly 60 percent from 2000 to 2010, at a time when unemployment rates increased dramatically (Hilliard 2013). More recently, funding for the seven largest federal employment and training programs dropped 35 percent from fiscal year 2009 to 2013 (Center for Law and Social Policy 2014).

The result of these trends—increased skill requirements, employer reluctance to bear training costs, low levels of human capital, diminished government funding for training, and workers' doubts about the effectiveness of training—points toward a possible skills mismatch, in which the skills workers have do not match the skills needed by employers (Osterman and Weaver 2014). Whether or not this skills mismatch is as severe as is sometimes claimed, it is clear that workers who lack postsecondary education or training have more difficulty obtaining jobs that offer higher wages. As a result, programs that train individuals in areas that match the skills demanded by employers can be highly efficient, since they potentially benefit both workers and employers with minimal displacement.[3]

The lingering effects of the Great Recession are also noteworthy. In recent years, the labor market has been weak and slowly recovering, a situation in which even relatively experienced and skilled workers have struggled to find work (Kolesnikova and Liu 2011).[4] Recent studies indicate that employers have responded to this increased supply of unemployed workers by being more selective, particularly about recent work experience. Those who have been out of the labor market for six months or longer are much less likely to receive calls for job interviews—even when they have extensive relevant experience (Kroft, Lange, and Notewidige 2012). This situation presents a special challenge for training programs that seek to place such individuals into the labor market now.

THE EFFECTIVENESS OF ALTERNATIVE WELFARE-TO-WORK MODELS

Rigorous studies in the 1980s and 1990s provided the first seeds of evidence—and subsequent modification—that led to the next-generation demand-driven training model described later in this chapter. The studied programs were embedded in public benefits systems, rather than the unemployment system. Therefore, program participants were generally parents, often single parents, and usually female.

The programs studied during these two decades embodied efforts to assist applicants and recipients of AFDC into employment. The programs thus reflected the ebbs and flows in the welfare system's shifting emphases on education, training, and/or job placement alone as the best means for helping move individuals from welfare to work.

Multistate studies in the 1980s, conducted as part of the Demonstration of State Work/Welfare Initiatives, indicated that programs requiring individuals to look for jobs as a condition of receiving welfare benefits sped up the entry of individuals into the labor market, compared to imposing no requirement at all (Gueron and Pauly 1991).[5] These were low-cost interventions that also were found to provide a positive return on the government's investment. However, their positive effects were limited: Many people helped into work had difficulty staying employed, and the jobs they found were usually low paying. As a result, the programs did not improve welfare recipients' chances of escaping poverty.

Seeking to do better, policymakers and program operators in the late 1980s and early 1990s began to focus on the possible value of providing education and training in welfare-to-work programs. Two major multisite RCTs were subsequently launched to assess the effects of including these types of emphases in models. The first, launched in 1988, evaluated California's statewide Greater Avenues for Independence (GAIN) program, which required people to participate in a range of services, starting with education (provided in a regular classroom setting) for those who scored poorly on a literacy test, lacked a high school diploma or General Educational Development (GED), or were not proficient in English. Others received job search training and other services. The model designers hypothesized that this approach would produce better results than the lower-cost, job-search-focused approach of the earlier programs. GAIN's effects on employment and earnings were positive, in some respects more so than the earlier, more limited models, but impacts on increasing income over a five-year follow-up period were small (Freedman et al. 1996).

A second major multisite study—the National Evaluation of Welfare-to-Work Strategies (NEWWS)—set out to test, beginning in 1989, "What works best?" Most significantly, this study directly compared mandatory job-search-first and mandatory education-or-training-first programs in the same sites (using, as is the case for all studies cited in this chapter, RCTs). These "head to head" tests showed that both program approaches increased employment and earnings over a five-year follow-up period, compared with having no program at all. But the job-search-first approach (often called "work first" programs) got people into jobs sooner and, while people in the education-or-training-first programs eventually caught up by the fifth follow-up year, they were not more likely to get into "good" jobs as of the five-year follow-up point and, as many as 15 years later, they did not have higher earnings growth (Hamilton 2012). An indirect comparison, however, of the above two types of programs with a third type—one where some people were urged to get a job quickly and others were initially required to enroll in work-focused short-term education or training—showed that the third type (a mixed model) had the best five-year results. Nevertheless, while all of these strategies increased people's earnings within the first few years of follow-up, none produced increases in earnings that were long lasting (effects generally faded by the end of the fifth year of follow-up). And, while a number of these programs did allow people to participate in occupational skills training, *increases* in attendance in skills-building classes (comparing program group activity to control group activity) were primarily in the realm of basic education and not in the realm of occupational skills training, since participation rates in occupational skills training were often almost as high among control group members as among people in the program. As a result, the GAIN and NEWWS studies (along with others conducted at the time) pointed to a role that occupational skills training might be able to play. But it was also apparent that knowledge was lacking regarding the types of skills-building activities that might be best and the ways in which skills building could be most beneficially structured, targeted, and encouraged. Finally, additional insight into a broader range of skills-building activities came from the Job Training Partnership Act (JTPA) study described in Box 18.1.

Notably, while the studies described in this section yielded substantial knowledge about how to help low-income individuals prepare for and find jobs, many participants in the programs that successfully boosted employment over a five-year follow-up period still ended up in unstable, low-paying jobs. Thus, the research also suggested a need to focus on ways to effectively increase employment stability and wage progression.

APPROACHES TO EMPLOYMENT RETENTION AND ADVANCEMENT: THE PESD AND ERA PROJECTS

By the mid- to late 1990s, the federal government and states focused squarely on the problem of employment retention and advancement. An initial multisite RCT, the Postemployment Services Demonstration (PESD), operated in the mid-1990s. It examined the effectiveness of offering services such as counseling and support, frequent and flexible payments for work-related expenses, and other services to newly employed welfare recipients (Rangarajan and Novak 1999). The programs studied in the PESD, however, had little effect on employment or earnings.

Box 18.1 A Concurrent Evaluation: The National JTPA Study

Around the same time that the GAIN and NEWWS studies were examining the benefits of basic education and other types of services, another evaluation attempted to focus more squarely on the benefits of vocational training. The National JTPA Study measured the earnings and employment effects of several education and training services funded under Title II-A of the JTPA of 1982. The study attempted to learn which types of training and services were most effective by evaluating three individual service strategies: 1) classroom training in occupational skills, 2) on-the-job training, and 3) other services funded through JTPA. Study participants were randomly assigned after being recommended for one of these three strategies, allowing researchers to measure effects relative to a control group within each strategy. The study design, however, did not allow a direct comparison of one service strategy to another. Overall, the results indicated that adults in the evaluation experienced modest earnings gains throughout the 30-month follow-up period, with more pronounced effects seen for women than men, and substantial variability by site. For adult women, both "other" services and on-the-job training produced earnings impacts. For adult men, on-the-job training appeared to work best, but no statistically significant impacts by service strategy were found (Bloom et al. 1997). Despite these somewhat positive 30-month findings, effects on earnings had faded for both adult women and men by follow-up year five (U.S. General Accounting Office 1996). The JTPA results showed that training could work, in some places, using some strategies, and for some populations, but they also revealed that training programs were by no means a sure investment and had to be carefully designed, a theme that would reemerge several times in the years that followed (D'Amico 2006).

The next set of RCTs exploring this issue, operated in the late 1990s to mid-2000s, examined a wide variety of retention and advancement strategies, reflecting the paucity of positive results in the past. These studies, part of the Employment Retention and Advancement (ERA) project, examined programs different from the ones studied under the PESD: ERA programs, compared with the PESD ones, had greater customization of services, worked with individuals who were not employed, had more services and additional features, had greater diversity of primary service providers, and had more variation in service delivery methods (Hendra et al. 2010). ERA investigated programs that served populations at risk of needing to access welfare benefits as well as individuals already receiving them. The strategies studied under ERA, however, did not attempt to address labor market, or demand-side, issues. Rather, they all tried to address supply-side, or “worker-based,” obstacles to economic success.

The results of the ERA trials highlighted the difficulty of achieving upward mobility through simple strategic placement of people into jobs and generic on-the-job coaching alone. Of the 12 programs studied in the ERA project (those that did not target “harder to employ” enrollees, such as individuals with substance abuse issues), only 3 were found to be effective at increasing earnings for participants. The 9 unsuccessful programs offered guidance and advice after people found jobs (i.e., post-employment), but little else. All 12 programs were built upon a variety of hypotheses about what might be advantageous, for example, maintaining small caseloads; offering services at individuals’ workplaces; collaborating between welfare, WIA, and community college staff to offer services; and continuing counseling relationships from pre- to post job placement. None of these features produced sustained positive impacts on earnings, in and of themselves. (While the counseling and coaching produced a low yield on their own, researchers concluded that it was possible that these services could be very valuable when combined with other, more concrete services.) These findings suggested that more needed to be done than simply helping participants navigate the labor market better (Hendra et al. 2010).

Lessons from the three ERA tests that *did* produce positive effects also provided ideas for ways programs could move forward. A studied program in Texas, for example, provided former welfare recipients with wage supplements of $200 per month for working full time. The supplement provided a strong incentive to work and also gave participants some extra cash to better handle work-related financial issues, such as emergency car repairs. When combined with high-quality post-employment services (as was the case in one Texas site), the program produced long-term effects on earnings and employment that were sustained through the fourth year of follow-up, the last year when data were available. The Texas findings were consistent with those found for many other wage supplement programs (Martinson and Hamilton 2011). One implication of these results is that when effective take-home pay is higher, participants may work more stably. However, apart from using wage supplements, few job placement programs have been able to increase participants' wage rates.

An ERA test in Chicago also suggested ideas to pursue. In this studied program, a for-profit employer intermediary provided job matching services, which enabled participants to move from very low-paying informal jobs to jobs in the higher-paying security and health care sectors. The Chicago results suggested that organizations that have close relationships with local employers in high-growth sectors can foster positive effects, even for program participants already employed. These findings also provided experimental evidence that proactive job change—taking the initiative to move from one employer to another, prompted by a desire for higher wages and/or a more suitable work arrangement and not by a negative event—can increase earnings.

Finally, positive effects in an ERA test of a program in Riverside, California, suggested the worth of providing assistance to rapidly reemploy individuals who lose their jobs. These findings suggested that it might be more effective to focus on helping people to quickly replace lost employment, that is, assist people to retain overall employment, as opposed to concentrating on helping people retain particular jobs.[6]

The ERA project also provided important insight into employment dynamics. Analyses of the ERA data set revealed that employment spells for low-income populations are highly unstable. Importantly, there is negative duration dependence of spells, meaning that the probability of job loss is highest in the period soon after a job start. Intensive intervention during this critical period thus could be cost effective (Dorsett et al. 2013). While rapid intervention seems critical here, other analyses pointed to the need to provide long-run follow-up as well, as rates of job loss stay high well past the six-month period that most performance measures capture (Riccio et al. 2008). The ERA results also implied that strategies should focus on *employment* stability rather than *job* stability, that is, on developing multiple job placements over an extended time frame as opposed to solely on the initial job placement. Finally, the analyses showed that proactive job change was associated with advancement among low-wage workers, particularly among those who held jobs with smaller employers and had little prospect for advancement (Miller, Deitch, and Hill 2009).[7]

A REFOCUS ON VOCATIONAL TRAINING AND SKILLS: THE UK ERA AND WASC STUDIES

As results from the PESD and ERA evaluations unfolded, some programs moved to incorporate more job training, acknowledging that some kind of vocational skills building was needed in order to increase wages for low-wage workers. One initiative that attempted this was studied as part of the United Kingdom's Employment Retention and Advancement project (UK ERA). This UK program was similar in many ways to the Texas program studied within the United States' ERA project, but it added tuition assistance while individuals remain engaged in training and financial incentives for training completion.

The UK ERA results supported a long-standing lesson in the field of employment and training: training does not work if it is not aligned with employer demand.[8] The UK ERA program boosted training engagement, but labor market benefits attributable to training were not found, suggesting that there was a mismatch between the training undertaken and the labor market demand for individuals with that training (Hendra et al. 2011).[9] The leading explanation for this result related to the program staff's capacity. The UK ERA advisory staff functioned as employment "generalists"—they offered participants general advice and guidance on adapting to work, encouraged them to consider seeking full-time work, helped them address issues of balancing work and family life, advised them on seeking promotions and finding better jobs, and urged them to enroll in training courses in whatever areas interested them. However, UK ERA advisory staff did not have in-depth knowledge of particular occupations or industries or expertise on the career ladders and training requirements for jobs in those areas. Nor did they steer participants assertively toward particular occupations known to offer real advancement opportunities. They were also not positioned to connect participants who had trained in particular occupational areas with relevant employers who were hiring people with the new skills those participants had acquired. These limitations likely undermined the benefits of the extra participation in training that UK ERA caused. The findings point toward providing career advice that is sector-specific and more narrowly focused on opportunities available in the local labor market.

A subsequent test of an approach with a more deliberate demand-driven focus occurred in the late 2000s, in the Work Advancement and Support Center (WASC) Demonstration. The programs examined in WASC aimed to increase the incomes of low-wage workers by stabilizing employment, building skills, increasing earnings, and easing access to work supports. One of the central hypotheses of WASC was that providing training through WIA One-Stops would result in better alignment between training and work. Two of the WASC programs increased (relative to control groups) participation in education and training and also increased earnings in the third follow-up year (Miller et al. 2012). In one program, these effects faded somewhat in the subsequent follow-up year; in the other, longer-term follow-up was not available. In both programs, the level of staff capacity to provide employer-informed advice was lower than anticipated. Still, because funding for training was mainly through WIA, there were conditions in place to try to assure that training was in high-demand fields. In particular, in one of the programs, many of the training vouchers were used to pay for training in the rapidly growing health care field. These results suggested the promise of focusing training in high-demand areas, a central aspect of the sector-based programs discussed in the next section.[10]

PROMISING EVIDENCE FROM SECTOR INITIATIVES: THE SECTORAL EMPLOYMENT IMPACT STUDY

The idea that increases in skills lead to increases in earnings is one of the most established ideas in labor economics (Mincer 1974). But many programs for low-income individuals have been designed with an apparent optimism that any kinds of skill increases will reliably lead to earnings increases, a view that does not fully consider local labor market demand. In particular, the capacity of most social services programs to work effectively with employers and properly read the labor market is an open question.

"Sector strategies" approaches in workforce development programs, pioneered by community-based organizations across the United States beginning in the late 1980s, attempt to keep local labor markets in focus (Magnat 2007). Although programs employing sector strategies vary widely, the Aspen Workforce Strategies Institute defines a sector-based strategy for workforce development as one that

- targets a specific industry or cluster of organizations;
- intervenes through a credible organization, or set of organizations, crafting workforce solutions tailored to that industry and its region;
- supports workers in improving their range of employment-related skills;
- meets the needs of employers; and
- creates lasting change in the labor market system to the benefit of both workers and employers (Conway 2007).

Importantly, sector-based strategies go well beyond simply specializing in one area of training. By Aspen's widely accepted definition, a training provider that trains in a specific field, but does not have strong relationships with employers and/or industry associations in that field, would not be considered a sector-based provider. To qualify as a sector-based program, an initiative must bring together multiple employers in a given field to collaborate on developing a qualified workforce (Woolsey and Groves 2013).

While nonexperimental work by the Aspen Institute (Zandniapour and Conway 2002) and others (Henderson, MacAllum, and Karakus 2010) have produced some encouraging evidence on the benefits of the sector-based approach, the most powerful evidence to date comes from the Sectoral Employment Impact Study, an RCT of four sector-focused training programs conducted by Public/Private Ventures (P/PV) (Maguire et al. 2010). The study finds that the programs, targeted to low-income workers and job seekers, increased earnings, employment, job stability, and access to benefits for participants over the two-year period for which follow-up was available. Participants' earnings over two years were $4,500 (or 18 percent) higher than earnings for the control group. Earnings in the year after training were 29 percent higher than the control group average. In addition, there was evidence of increases in wage rates, which rarely had been found in prior RCTs. The effects of prior programs were generally much more modest than these, which led to enthusiasm about sector-based programs (National Network of Sector Partners 2010) and several attempts to promote the strategy in Congress.[11]

Key elements of the sector-based programs studied by P/PV included the maturity of the service providers, their strong relationships with local employers, the provision of job readiness training in addition to occupational skills training, a stringent screening and intake process, and the provision of individualized services. Although the programs aimed to place workers in “good” jobs—jobs that are higher paying and more stable, there was no “advancement” component. Some of these same elements, however, particularly the small size of the programs, the heavily screened participants, and the experienced and community-rooted nature of the program providers, caused some policymakers to view the results as having limited generalizability. Therefore, while the P/PV results are encouraging, it is critical to test sector-based programs with a more representative set of providers, larger and more disadvantaged samples, and in a broader range of sectors and economic conditions (and some of that testing is under way, as discussed below).

Thus, a “next stage” of research—one part of which is described below—is attempting to understand sector-based programs better, confirm whether they are effective, and determine how they perform at a larger scale and under different conditions, for example, when operated by a more typical range of providers, in weaker economic demand conditions, and for a different sample of workers. Longer-term follow-up is also investigating whether participants in sector-based programs stay in the sector in which they were trained and whether they are able to advance over time, beyond their initial placement. Finally, this next stage of research will consider whether it appears possible to embed sector-based approaches in national training systems and community colleges without losing the local/focal emphasis that is so critical to the strategy.

WORKADVANCE: A "CURRENT GENERATION" MODEL INFLUENCED BY PRIOR RESEARCH FINDINGS

One of the consequences of the above research findings and open questions has been the development of the WorkAdvance model, a sector-based training program. First and foremost, the model reflects a belief, informed by several studies mentioned above, that only through deep knowledge of and relationships with employers in a particular sector can staff in programs serving low-income individuals provide the required level of specialized guidance needed for participants to succeed in their jobs and advance in their careers while also meeting employers' demand for specific skills. The model also reflects a reading of the evidence that, while required job search and required attendance at classes in basic reading and math skills instruction can produce earnings gains, more is needed to truly produce long-term impacts on employment advancement. Finally, the model is an effort to address matching problems in the labor market, in which many individuals are having trouble meeting the skill and experience requirements of middle-skill jobs, and employers are having trouble filling those positions with qualified workers.

A fundamental focus on employer input and long-term career advancement is reflected in each of the five WorkAdvance program elements:

1) Intensive screening of program applicants prior to enrollment—a practice not common in training programs offered to low-income individuals—is intended to assure that program providers select participants who are appropriate for the sector and the particular training programs offered. From one perspective, the brokering and screening role played by sector-based programs might seem duplicative of what happens in a normal, well-functioning labor market. These are tasks typically performed by employers, but disadvantaged workers often have difficulty competing for jobs with advancement potential. Sector-based programs can help workers who would ordinarily not make it through employer screening to obtain the hard and soft skills needed to gain access to better positions (after they receive training at the provider). Providers seek to

identify low-income applicants who have the ability to complete the program services and be attractive to employers, but who are not so qualified that they will likely find high-quality jobs in the sector on their own. This was identified as one of the key elements of success in the P/PV sector study.

2) Sector-focused *preemployment and career readiness services* include an orientation to the sector, career readiness training, individualized career coaching, and wrap-around services that sustain engagement and assist participants to complete their training and find employment.
3) Sector-specific *occupational skills training* seeks to impart skills and lead to credentials that substantially enhance workers' employment opportunities. Providers offer training only in particular sectors and for occupations that the providers, in ongoing consultation with employers, have identified as being in high demand with the potential for career advancement.[12]
4) Sector-specific *job development and placement* facilitate entry into positions for which the participants have been trained and for which there are genuine opportunities for continued skills development and career advancement. To ensure that job development and placement are linked with the occupational skills training, the providers' job developers (or "account managers") maintain strong relationships with employers who hire individuals with the kinds of skills the program has imparted.
5) Postemployment *retention and advancement services* assist participants to advance in and retain their jobs. Providers maintain close contact with workers and employers to assess performance, offer coaching to address any "life issues" that might arise for workers, help identify next-step job opportunities and skills training that could help participants move up career ladders over time, and help with rapid reemployment if workers lose their jobs.

The WorkAdvance model is currently being implemented via four programs, operated in three cities by four local organizations that focus on a range of sectors and bring differing backgrounds to the project. Sectors of focus include transportation, information technology, environmental remediation and related occupations, health, and manufacturing.[13]

Reflecting a continuing need for clear evidence about the best ways to promote the upward mobility of low-income individuals, MDRC is evaluating the WorkAdvance model using an RCT. Through rigorous testing, the study will determine whether a strategy that integrates the most promising features of sector-based and retention/advancement strategies can produce larger and longer-lasting effects on employment, earnings, and career paths than either strategy might produce on its own. The RCT is following individuals who qualified for the WorkAdvance programs between mid-2011 and mid-2013. Program participants will receive program services for up to two years after enrollment.

The WorkAdvance demonstration seeks to assess whether providing sector-based training will lead to advancement by establishing a pipeline from training into work. Several pieces must fall into place for that to happen, however. First, the programs have to find the right participants, those who—*with the benefit of the training*—are within reach of the targeted jobs. Then, participants, many of whom are low-income and disadvantaged, have to finish training and earn a credential. At the same time, job developers have to build relationships with employers who will recognize the earned credentials and hire employees into jobs with future advancement opportunities. Once on the job, participants have to apply both their soft and hard skills training in order to excel in their jobs and pursue advancement opportunities. While the economic effects of the WorkAdvance programs will not be known until late 2015, the WorkAdvance implementation analysis is currently examining the extent to which all of these conditions for advancement are being put into place.

Finding the Right Participants

As was the case with the P/PV Sectoral Employment Impact Study, marketing and outreach to potential WorkAdvance enrollees has required a substantial investment of time and resources in all four of the WorkAdvance programs. This is not surprising, since one of the key contributions of sector-based programs (from the perspectives of businesses) is to reduce screening and acquisition costs by identifying job applicants who (with some training) are qualified for the positions that they are seeking to fill. On average, only one in five program applicants have been found to be eligible and qualified for WorkAdvance. Program providers are using both objective selection criteria (such as income guidelines and test scores) and subjective criteria (such as staff assessments of potential barriers to employment) to screen applicants.[14] Most commonly, however, individuals who do not eventually enroll in the program either withdraw on their own accord during the screening process or fail to achieve a required score on assessments of their academic level; the screening out of applicants as a result of staff discretion has been rare.

Reflecting the minimum level of education required in some of the targeted sectors, almost all applicants who have actually enrolled in WorkAdvance programs have at least a high school diploma or GED, and over half have at least some college education. Thus, the population being served in WorkAdvance, though still disadvantaged, is different from that served in many of the above-discussed studied programs. Among those training in the information technology sector, for example, less than 1 percent lack a high school diploma or GED. Almost all enrollees also have preenrollment work experience, although only one in five were working as of enrollment. At the same time, over a third of enrollees were unemployed for at least seven months prior to enrollment—a likely indication of the lingering (and damaging) effects of the Great Recession. Another possible barrier to finding work posttraining is enrollees' past involvement with the criminal justice system: One quarter of all enrollees have had a previous criminal conviction, and the rate is even higher (40 percent or above) among enrollees training in the transportation and manufacturing industries.

Implementation of Various Components of WorkAdvance

As mentioned above, past research has suggested that programs need to address several issues in order to convert training into advancement. One concern is whether individual programs can handle all of these components (versus a networked approach where several programs coordinate). Thus far, the findings from the implementation analysis suggest that WorkAdvance program providers have been able to implement all of the major elements of the WorkAdvance model, including preemployment and career readiness services, occupational skills training, job development and placement, and retention and advancement services, but the last-listed services have taken the most time to develop, particularly in a robust way, and are still being strengthened.

The preemployment coaching has sought to help enrollees set and follow through on career advancement goals, while the career readiness classes are teaching enrollees about their sector of focus and helping them acquire “soft skills.” The structure and manner of delivering these services differ across program providers, but the content is similar: introductions to the sector, advice on resumes and cover letters, job interview preparation, and development of individualized career plans. These services are demand driven: two of the programs use employer advisory groups to help develop the curricula for these classes, another program receives help from existing business intermediary groups, and the fourth program relies on input from individual employers to serve this function. In many cases, these employer partners come to the program offices to conduct mock job interviews, and they also host worksite visits to give program enrollees firsthand exposure to the type of environment in which they can expect to work.

In WorkAdvance, occupational skills training varies across providers and sectors in terms of its duration, whether it is on-site at the provider or contracted with an off-site provider, and the breadth of training offerings. Examples of occupations for which trainings are being provided include help desk technician, environmental remediation technician, pest control technician, aviation manufacturing assistant, computer numerical control operator, diesel maintenance technician, and patient care assistant. Depending on the material and certification requirements, training course duration ranges from two weeks (for example, for patient care assistant training) to eight months (for example, for diesel mechanic training). All programs offer training in cohorts, but the programs differ in terms of whether WorkAdvance enrollees are in training with or without non-WorkAdvance students. Combined with the career readiness classes, the skills training classes usually require full-time involvement, and training takes place during regular business hours or, in two of the programs, optionally during evenings. In previous programs, getting occupational training aligned with ever-changing employer demands has been a struggle. Thus far, the implementation research suggests that WorkAdvance providers have been responsive to demand fluctuations and have adapted the training offerings as the local economy changes.

The Sectoral Employment Impact Study identified "brokering" on the part of job developers as a critical element of sectoral programs. For the most part, in WorkAdvance, job developers appear to have the understanding of local labor markets and of the specific needs of employers necessary in order to prepare enrollees for the best jobs in particular sectors that are available in the localities. The job developers have been able to maintain close relationships with employers and to provide program management with timely feedback on employer needs. Job developers use a mix of networking and cold calls to make initial contact with employers, pitching the value that WorkAdvance programs offer: prescreening of job applicants, career readiness training, and, in some cases, supplying job applicants who already have certifications that employers might otherwise have to arrange and pay for (such as Occupational Safety and Health Administration certification). This raises a potential concern that this type of intervention is simply subsidizing employers by enabling them to shed legitimate training costs. One possible justification for public or private investment in these services is that programs such as WorkAdvance provide disadvantaged workers with an opportunity to enter better-paying jobs than they typically have access to. By providing these individuals with assistance to obtain important certifications, the program makes them more marketable to employers. There are also benefits to employers and the local economy if these investments promote a better-trained workforce.

Most of the previous studies described above find that labor market programs often have short-term effects. The goal of postemployment services is to extend these effects into long-term career trajectories. This is currently the weakest link in the implementation of WorkAdvance. While postemployment services are being delivered, they are currently focused mostly on job retention (for example, addressing relationships with supervisors by coaching workers while they are encountering on-the-job conflicts or issues) and much less on advancement (for example, identifying each participant's next career goals and establishing the steps the worker needs to take to reach those goals). To strengthen this component, the programs are currently focusing on the following: establishing an intentional follow-up plan to contact and communicate with enrollees at strategic points after they start employment, updating career plans periodically to focus on advancement, and maintaining regular contact with enrollees' employers.

Early Training Participation and Completion Rates

In previous programs, getting participants to complete training and other services has been a struggle. Given all of the components of WorkAdvance, and the fact that participants are often in poverty and have little economic support, an open first-order question has been the extent to which participants will complete program services. Results at this point indicate that all of the WorkAdvance providers have been able to engage a substantial share of enrollees in program services, particularly in career readiness activities and occupational skills training: More than 93 percent of enrollees have participated in career readiness activities, and about 70 percent of enrollees have started occupational skills training—all within six months of enrolling. Dropout rates from the training programs have also been low: Only about one in eight of those who started training have dropped out within six months of program enrollment. These high rates may be attributable, at least in part, to the screening done at the beginning of the program.

Finally, and perhaps most critically, most enrollees who have completed training have obtained an industry-recognized credential. (Given the length of the training, statistics on six-month training completion rates are not reliable.) In three of the four programs, over 90 percent of individuals who completed the program have earned a license or certificate. In the fourth program, focused on the health and manufacturing sectors, about half of those who completed training have earned such credentials. Two of the programs have worked with local employers and/or training providers to abbreviate and adapt some formal certifications in the manufacturing sector that normally require years of training. These new credentials are unique to the local employers in the specified industries and have created a certified and viable way for program enrollees to enter that sector's workforce.

Variations in the WorkAdvance model have also suggested an early lesson, one that echoes some of the findings from earlier studies. Two of the WorkAdvance programs initially implemented the program model with two separate tracks: one track emphasized gaining skills first through training (similar to most other sector-based programs), and the other sought to place people into jobs first. The placement-first track was intended to be less expensive than the training-first track, but one that would still impart skills, albeit through work experience and on-the-job training. However, both of these programs eventually shifted mostly to the training-first approach, since the job-placement-first track often resulted in participants' entering low-wage jobs that in practice did not lead to on-the-job acquisition of skills. These shifts were made before a robust set of postemployment services was in place, and it is possible that the placement-first track could have been more effective with the underpinning of those types of services.

CONCLUSIONS AND FUTURE DIRECTIONS

As discussed in this chapter, evidence suggests that skills building can be a means of increasing earnings in the long run for disadvantaged workers, as long as it is well aligned with the needs of employers. Several generations of experiments have also made it clear, however, that there are limits as to what can be done on the worker side of the equation. Sector-based programs, in contrast to many programs from the past, are heavily demand-driven and bring workers and employers together in ways that solve local and regional economic challenges. The evidence suggests that future programs and evaluations thus should continue to include and examine this potentially promising demand-side focus.

WorkAdvance is not the only program under evaluation that is designed to use more of a demand-driven skills acquisition approach as a means toward advancement for low-income individuals. Several programs in the Innovative Strategies for Increasing Self-Sufficiency demonstration use a broadly similar strategy (Martinson and Gardiner 2014).[15] In addition, evaluations are under way of some programs funded through Health Programs Opportunities Grants that also use a demand-driven training approach to help TANF recipients advance in the health care sector (Lower-Basch and Ridley 2013). Finally, some programs undergoing evaluation in the U.S. Department of Labor's Social Innovation Fund portfolio use a similar strategy.[16] The fact that so many agencies and foundations are operating or supporting programs that have evolved in this direction suggests that the interpretation of the evidence presented in this chapter reflects a commonly held view. Therefore, in coming years there should be much more evidence available on the reliability and scalability of this demand-driven skills-building approach. These projects have a strong potential to inform workforce policy.

Even if the results of these studies are positive, however, the difficulty of implementing successful sector-based interventions, coupled with the small size and specific focus of some of the models, raises questions about scalability. WorkAdvance in particular is a difficult model because individual providers have to implement several components on their own. An alternative approach, which might aid scalability, would be to have different organizations coordinate to implement different components of the model. For example, a key way to scale the model may be to take advantage of the ability of the community college system to provide some program components, as some of the WorkAdvance providers have done.

Another challenge with scaling this strategy is that sector-based programs are inherently small and local, owing to the specialization that is necessary to truly understand the high-demand niches of the local labor market and to match appropriate individuals to job openings. While programs may need to stay small to maintain this specialization, it is possible to view them as being part of broader sectoral systems (or "career pathways" systems). In some cities and some labor markets, sector-based programs have been embedded in much broader initiatives (which also take advantage of feeder systems from "bridge" programs to enable a broad segment of disadvantaged workers to enter the initiative). Project Quest (Osterman and Lautsch 1996), or the initiatives implemented by the Instituto del Progreso Latino in Chicago (Martinson and Gardiner 2014), are some programs that apply some of the sector-based strategies on a larger scale and/or for a more disadvantaged set of workers. So, while these programs can seem "boutique," they can be parts of larger systems.

Future directions should explore incorporating the involvement of employers even more centrally into program operations and research. A recent study, for example, has shown the promise of paying employees more or providing better benefits (so-called high-road employment practices), not only for workers but also for the bottom lines of employers (Ton 2012). This is an example of work where employers are central to the intervention and the evaluation. While past experience has made it clear that it can be difficult to engage employers in programs and research (Schultz and Seith 2011), the results of recent studies have indicated that it is possible to work with employers quite directly to implement innovative advancement strategies and determine their effectiveness (SRDC 2013). One challenge of implementing advancement programs at employers, however, is that the goals of employers do not always align with the needs of employees. For example, in some settings an employer's goal may be retention, but the best way for employees to advance is to change employers (Miller, Martin, and Hamilton 2008). It can also be challenging to study programs within employers, particularly using random assignment designs, which might give one segment of employees an unfair advantage. Despite all of these challenges, it seems critical that future advancement programs work closely with employers, who ultimately have the resources and pathways in place to help provide for meaningful advancement in the labor market.

This chapter is an effort to demonstrate what has been learned from the rich, diverse, and many rigorous past studies that have tackled the long-standing problem of lack of upward mobility among disadvantaged workers. Though the context has changed, the studies provide several salient lessons that should inform future program designs and trials. This chapter has presented one reading of the body of evidence that has accumulated regarding the effectiveness of dozens of different types of human capital programs, and has tried to illustrate how the evidence and lessons have been used to develop a recent initiative, called WorkAdvance.

Therefore, to conclude, we would like to emphasize the need to systematically build evidence and draw upon it when designing new programs. The economic problems discussed in this chapter have evolved, but they are essentially old problems. Thus, the findings from well-designed evaluations, accumulated over time, can inform future policy designs. As an example, when one of the authors of this chapter was recently asked to help develop a new model that combines sector-based training with subsidized employment, it quickly became apparent that this was essentially the same model that had been rigorously researched (and found to be promising) in the 1980s Homemaker-Home Health Aide Demonstration (Bell, Burstein, and Orr 1987). Without closely considering what we have learned in the past, we risk relearning old lessons and not realizing the vision of policy *evolution* put forth by Donald Campbell (1973) and other pioneers of the "experimenting society" approach to policy making.

Notes

1. Many of the studies were also conducted by MDRC, the nonprofit, nonpartisan social policy research organization that employs the authors.
2. Some aspects of this chapter, particularly the description of the economic problem and the section on the WorkAdvance program, draw from an MDRC report on WorkAdvance (Tessler et al. 2014).
3. Displacement in employment programs occurs if programs have effects only by favoring some workers over others who would have gotten the job without the program. In a general equilibrium sense, there is no improvement. However, if programs help fill vacancies with better-trained employees, then there would be positive effects that go beyond simply switching workers in the employment queue.
4. It is also very important to recognize that the previous recovery was notable for the lack of job creation and earnings growth. The period up to 2007 was sometimes called the *jobless recovery*. Thus, low-wage workers have confronted an extended period of labor market stagnation.
5. See Gueron and Rolston (2013), which also discusses these early studies, but importantly, in addition, provides a comprehensive history of RCTs in the welfare reform field.
6. It also may be relevant that the program providers in this particular Riverside test were mostly well-rooted community-based organizations, whereas the program providers in several other tested ERA programs were local government offices.
7. This finding is also consistent with the earlier work of Holzer, Lane, and Vilhuber (2004).
8. For example, this was a central argument regarding the effectiveness of the Center for Employment and Training program in San Jose, California, which was evaluated as part of the JobStart evaluation (see Meléndez 1996).
9. The UK ERA program did have labor market effects, but the effects do not appear to be attributable to training. It is more likely that the effects were due to the combination of a wage supplement and retention and advancement services (similar to the ERA Texas program). For the long-term unemployed, the UK ERA program had long-term impacts on employment (similar to the effects found for the Corpus Christi, Texas, program).
10. Another finding from the WASC study was that increasing access to work supports (such as food stamps and child care subsidies) does not necessarily lead to advancement. Part of the theory of change in WASC was that by providing more access to work supports in the short- term, the program would give participants the

financial stability to help support longer-term labor market advancement. However, although the intervention increased work support take-up and earnings in some sites, no association was found between the two effects. Put differently, in some sites and for some subgroups, the intervention increased earnings, but these were not necessarily the same sites or subgroups in which work support take-up was increased.

11. The National Network of Sector Partners (2010) found that 47 percent of sector initiatives profiled were less than five years old. The Strengthening Employment Clusters to Organize Regional Success (SECTORS) Act, which proposed to amend WIA to include additional funding for sector initiatives, was introduced in Congress in 2008, 2009, 2011, and 2013 without ever moving out of committee (*SECTORS Act of 2013*). The Workforce Innovation and Opportunity Act was passed with bipartisan support in July 2014, reauthorizing WIA from 2015 to 2020. The bill promotes sector strategies, specifically requiring states to implement industry or sector partnerships and career pathways (*Workforce Innovation and Opportunity Act* 2014).
12. During the program design phase, providers were asked to provide career advancement "maps" that outlined the necessary steps for advancement in targeted occupations and to justify that targeted positions had a reasonable prospect for advancement. Providers were discouraged from placing participants in "dead-end" jobs. There was also a goal to place participants in "better" paying jobs (for this population, wages beyond $12–15/hour are a reasonable goal, depending on the local labor market) and jobs that provided benefits such as health insurance. Some targeted jobs initially offered low pay, but were deemed to have strong advancement potential.
13. Some of these sectors overlap with ones in the programs studied in P/PV's Sectoral Employment Impact Study. In the P/PV-studied programs, sectors included construction, manufacturing, health care, medical billing and accounting, and information technology.
14. For WorkAdvance, applicants needed to be adults who had a monthly family income below 200 percent of the federal poverty level and earned less than $15 per hour at the time they entered the study.
15. This evaluation has been renamed "Pathways to Advance Career Education."
16. See http://www.doleta.gov/workforce_innovation/ (accessed October 9, 2014).

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19
Doing More with Less

Leveraging Advances in Data Science to Support an Intelligent Workforce System

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In the aftermath of the Great Recession, shrinking budgets and high caseloads all but guarantee that the workforce system of the twenty-first century will have to serve more job seekers with fewer resources. Maximizing the system's efficiency and effectiveness will require the U.S. workforce system to evolve into an intelligent workforce system, where data drive the decisions of all stakeholders—from policymakers to workforce program staff, education and training providers, job seekers, and employers. For the system to be truly intelligent and data driven, state workforce agencies (SWAs) and local workforce areas must be able to extract meaning from multiple types of data, including numeric, location, and text data, stored across multiple state agencies; properly analyze these data to generate accurate insights and integrate them into stakeholder decision making; and foster an organizational culture that values data collection, quality, analysis, and dissemination.

Advances in data science, coupled with the ever-expanding capabilities of open-source and low-cost software, offer the workforce system a genuine opportunity to do more with less. Specifically, developments in two areas—mining information that states have collected for years but examined only infrequently (such as location data and textual data), and analyzing their data in such a way as to generate more accurate insights, especially in the field of prediction—can be harnessed to help states deliver services more effectively to workforce system customers. This chapter describes how SWAs can adopt tools to analyze nontraditional data sources such as geospatial and text data and to improve their predictive practices.

During the past several decades, SWAs have developed tools to analyze more traditional types of data, such as numbers (0, 1, −27.15) and categories (male and female). In addition to numeric and categorical data, however, SWAs also store important geospatial (location) and textual information. Examples of geospatial information include addresses of job seeker customers when they register for services, the addresses of employer customers and the establishments where they have job openings, and the Internet protocol addresses—which can be linked to physical locations—of job seekers who are using state online job boards to search for employment. At the same time, SWA data systems capture vast amounts of textual information. For example, every time a counselor enters a comment or note about a customer into an SWA database, the database records critical qualitative information about the job seeker, such as his skill deficits, the counselor's assessment of his job readiness, and possibly his attitude toward his job search. Although SWAs have made little use of either location or text data, open-source and low-cost software are available to help SWAs extract meaning from them. Incorporating location and textual data can support learning about how SWAs serve their customers, the effectiveness of their programs, and strategies for program improvement.

In an intelligent workforce system, data analysis adds value in many different ways, including performance metrics for tracking program implementation, scorecards for public accountability, rigorous evaluations to identify the programs that most benefit customers, and predictions of which customers are most in need of services and most likely to benefit from them. For SWAs, one of the most widely used data applications is prediction: learning from the data so that when a new customer enters the workforce system, the SWA knows what the experiences of thousands of customers like her have been and can therefore predict how she is likely to fare and what services might benefit her the most. To be more specific, an intelligent workforce system can use prediction to assist SWAs in better serving customers by identifying customers likely to experience an adverse event such as prolonged unemployment, matching customers to the job openings for which they are best suited, or identifying the set of reemployment and job training services that are likely to be the most effective at helping a customer achieve a positive labor market outcome. Of course, prediction cannot foresee the future perfectly. On the contrary, prediction is almost always prone to at least some error. But high-quality prediction can allow us to see the future more clearly than with no prediction at all, and this extra insight can significantly improve program outcomes.

While innovations in data science hold the promise of greatly improving the ability of SWAs to serve their customers, realizing this promise requires the effective use of their resources and capabilities. Fortunately, states already possess the resource that is the most costly and time consuming to develop—namely, detailed customer-level data that they have collected for decades. Effective use of individual-level data begins with high levels of data security to safeguard the privacy and confidentiality of the information the SWAs have collected from the public. Once data security is established, combining data from many different programs affords SWAs a fuller understanding of each customer they serve and allows for more detailed analyses than have generally been possible before. Through the Workforce Data Quality Initiative, the U.S. Department of Labor (USDOL) has funded 32 states to securely link data that have traditionally been housed in separate databases and maintained by multiple state agencies. We aim to introduce SWAs to a number of methods for leveraging this wealth of existing data.

The chapter is organized into two parts. In the first, we examine how location data and then textual data can be analyzed to yield value for SWAs. For each data type, we walk through an application to illustrate how SWAs and local areas can derive insights from these data. In the second part of the chapter, we describe the prediction process and the steps that these agencies need to follow in order to be able to generate accurate predictions and incorporate them into service delivery. We then illustrate how SWAs can improve their predictive practices by applying predictive modeling to identify job seekers who are most likely to experience long-term unemployment.

GEOSPATIAL AND TEXT DATA IN WORKFORCE DEVELOPMENT

Modern analytics involves using a variety of different types of data. The more traditional types, such as numeric and categorical data, are now found alongside data types such as geospatial (Burrough and McDonnell 1998) and text data (Schutt and O'Neil 2014). Geospatial data, which refers to address and location information, and large collections of text—such as online job listings, job seeker profiles, and counselor notes on individual customers—are increasingly available to workforce development professionals. A challenge workforce counselors face is deciding how to make use of these valuable data collections.

Geospatial Data

Spatial data are features—roads, buildings, and addresses—whose locations can be mapped onto the earth's surface along with the feature's descriptive characteristics. Workforce data systems often store data elements on customers and employers that are spatial in nature, such as an employer's address, along with attributes such as current job openings and contact information. Data visualization through geographic information systems (GIS) can be a powerful tool for helping SWAs and workforce boards turn this geospatial data into innovative new service solutions. Specifically, SWAs and local areas can improve their targeting of workforce services to better meet job seekers where they are, including making decisions about where to locate satellite offices and where to concentrate outreach efforts.

While workforce professionals have been using maps to improve services for decades, the last few years have produced an exponential increase in mapping possibilities. As a result of innovations in both workforce data and mapping software, powerful maps need not be costly or time-intensive to create. Through programs such as the Workforce Data Quality Initiative, state and local governments are increasingly linking administrative data that are housed across multiple agencies. This allows governments to create powerful maps that display not only workforce information, such as wages and WIA participation, but also data related to education and human services programs.

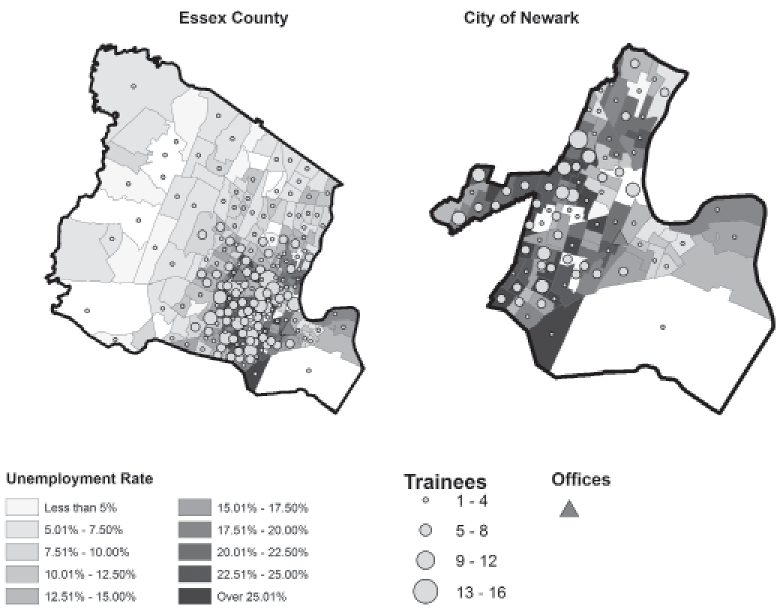
Regarding innovations in mapping software, applications such as ArcGIS easily combine location-based information with workforce data. This software can be preloaded with local census-based labor market information and demographic characteristics, while local infrastructure information, such as roads and public transportation routes, is easily integrated. With so much data already assimilated into the software, workforce agencies need only provide a single piece of information: customer location. Finally, due to the proliferation of geospatial data use in the public sector, trained GIS professionals are often available at all levels of government, as well as in local colleges and universities. Thus, governments frequently already employ all the staff necessary to leverage geospatial data for making workforce policy decisions, making data visualization tools that use geospatial data accessible and affordable, even at the local level.

Application: customer outreach

We illustrate the value of geospatial data by mapping workforce information from Essex County, New Jersey, and the city of Newark. The map below (Figure 19.1) plots the location of occupational training participants, aggregating the information by census tract to protect customer privacy (U.S. Census Bureau 1994). The trainees are represented by circles, with larger circles signifying more trainees within a given census tract. The unemployment rate of each census tract is also represented, with darker-shaded tracts representing higher unemployment rates. Finally, American Job Center (AJC) offices are represented with triangles.

Created for the Newark Workforce Investment Board (WIB) to assist with recent exploration into strategies for customer outreach, these maps quickly convey a large amount of information that is critical to identifying the areas where the WIB can most efficiently target its efforts. For example, the areas with the most customers in need of services are concentrated in close proximity to the city of Newark, with the areas farther out in Essex County benefiting from relatively low levels of unemployment. So while there are currently no offices in the outer tracts of the county, there is also not necessarily a need to increase outreach efforts in this region. Within the city itself, there is substantial variation in unemployment, and many of these areas are underserved. Specifically, the tracts with high unemployment but few trainees could

Figure 19.1 Number of Trainees by Census Tract, Essex County, New Jersey, 2012



be prime candidates for outreach efforts. And, in determining where to place a new outreach center, GIS software can easily overlay roads and public transportation routes onto this map to find a location that would be accessible to the underserved customers in need of assistance.

Perhaps most importantly, the WIB needed to provide only a single piece of workforce information to create this map: the location of trainees. All other data were either publicly available or integrated into the GIS software application. Thus, the maps are not only powerful in their ability to quickly convey information that is critical to developing an outreach strategy but also relatively undemanding to create.

Text Data

Like geospatial data, text information holds a great deal of unlocked potential for improving SWA services. In a workforce system, text data can include titles of job openings, descriptive information on skill requirements and job duties from job postings, counselor comments on job seeker skills and aptitudes, and customer feedback on their satisfaction with the services they have received.

Although many states are moving to apply text analysis algorithms to match job seekers to the jobs with the skill requirements and job duties that most closely align with their experience, nearly all of them use commercial products to do so. A number of companies have developed proprietary algorithms that allow job seekers to use a search function that automatically reviews job postings and notifies them of jobs that match the skills listed in their resumes. Whether organizations analyze text data themselves or enlist the services of a private sector firm, an understanding of the basic tools of text mining aids the use and interpretation of these methods. In addition, advances in computer software have made text mining methods accessible to a wide range of practitioners, increasing opportunities for organizations to conduct "in-house" analyses of text.

Text mining is a collection of analytic methods used to extract useful information from large volumes of text (Sebastiani 2002; Witten 2005). These methods are particularly suited for large text collections whose size makes human reading and coding prohibitively costly. Computer algorithms automate the process of searching the texts for patterns and information. Text mining methods can be used for text summarization and document retrieval, for clustering texts into predefined or previously unknown categories, and for extracting structured information such as Web addresses from texts.

This section reviews several text mining methods that are well suited to workforce development applications.[1] Often, the first challenge is deciding how to summarize the text in a collection. We highlight several text mining methods that can help workforce professionals summarize large text collections and organize similar documents into a set of categories. Then, to give a sense of how these tools might be applied, we analyze open-ended survey responses from a survey of individuals who received services from AJCs in a state in the eastern half of the United States.

Summarization and classification of text

Faced with a large collection of text, an organization may first need a simple method for summarizing the content of the collection.[2] One of the simplest methods that an organization can use is count-based analysis. As the name implies, it involves calculating the most frequently used words in both a text collection and in individual documents. A count-based approach can reveal, for example, that the words *transportation* and *warehouse* are the two most frequently used words in a collection of job ads.

A next step toward summarizing a text collection is to calculate word associations. Word associations reveal which words are highly correlated with the use of a selected word. For example, an organization may calculate associations for both *transportation* and *warehouse*. Word association can reveal that *full-time* and *truck* are strongly associated with the words *transportation* and *warehouse*. In this example, these two simple methods have given the organization preliminary evidence that its collection of jobs ads features many ads for full-time, tractor-trailer truck drivers.[3]

Classification and clustering

Many text mining problems involve grouping documents into natural clusters of similar documents. Consider a scenario in which a workforce organization has a database of thousands of job postings and wants to group them by industry of employment. Human-based coding of these job ads is prohibitively expensive: the organization likely lacks the staff and the time to read and code thousands of job ads. Text mining classification methods offer an automated approach to accomplish this task.

One of the first steps in text classification is choosing the approach that is appropriate for the task. Generally, this choice is determined by the large variety of classification methods, which can be grouped into two general approaches: supervised and unsupervised (Grimmer and Stewart 2013).

Supervised methods

In the phrase "supervised learning methods," the term *supervised* is used to refer to methods where the categories are known in advance. The researcher supervises the automated classification process by providing the computer a training set of documents already labeled with the known categories. The supervised method estimates the words or phrases predictive of the label. The researcher then uses the estimates from the training set to infer the labels for documents in the test set. Popular supervised methods include k-nearest neighbor classification, support vector machines, string kernel clustering, and the Naïve Bayes classifier.[4]

Dictionary methods are a relatively simple and intuitive way to organize texts into known categories (Neuendorf 2002). To assign texts to a given category, dictionary methods use the rate at which certain predefined key words appear in the text. More specifically, a dictionary method takes a list of words (the dictionary) and counts the proportion of words in a text that are also in the dictionary. An organization may use a sample of existing job ads to create a dictionary of keywords that identify the likely industry of new job ads. Another common application of dictionary methods is sentiment analysis, where the goal is to assess degree of positive, neutral, or negative language in text.

When using dictionary methods, organizations must choose dictionaries appropriate for the application, such that the meaning of the words in the dictionary corresponds to the way words are used in the text (Loughran and McDonald 2011). The word *work*, for example, can be positive in many contexts, such as *the machine works*. In workforce context, work is more often a neutral term: *looking for work*, *I worked as a machinist*. Organizations can acquire free text analysis dictionaries on the Web, or construct their own dictionary tailored to the specific application.

Unsupervised methods

In some applications, the categories may not be known in advance, making the application of supervised methods infeasible. Unsupervised learning methods apply when no predefined categories are available and the researcher still seeks to group similar documents into clusters. Unsupervised methods can also help to explore a large collection of text documents by summarizing its thematic content.

Since the methods are fully automated, they can discover both expected categories (e.g., health care jobs) and unexpected categories. For example, the method can reveal that multiple categories define the broader health care industry; one category may feature the words *hospital*, *surgery*, and *nurse*, while another category features *home*, *health*, and *nurse*. In this example, the unsupervised model infers that two broad categories of jobs are prominent in the collection of job ads: hospital-based surgical nurses and nurses employed in home health care services. If the organization were to use a supervised method, it would have to know these two categories in advance. It is possible that the organization may be unaware of the extent of local demand for home health care nurses. If the organization were to rely solely on supervised methods, it would overlook an important piece of information about the local labor market.

Unsupervised methods range from fully automated clustering algorithms (Grimmer and King 2011) to computationally demanding topic models (see Blei [2012] for a review and discussion of topic models). With all unsupervised methods, the goals are generally the same: either explore the categories (or thematic topics) that constitute a text collection, or cluster similar documents together into previously unknown categories.

Application: analysis of open-ended survey responses

Organizations often employ surveys that ask respondents to rate a service along some preset scale, such as poor to excellent. However, these closed-ended responses, while useful, are often too coarse to answer questions such as why respondents selected the rating they did. In contrast, open-ended survey questions allow respondents to elaborate on previous answers, suggest improvements, or offer praise in their own words, rather than in the predefined language of the survey developer.

One challenge that responses to open-ended survey questions present to researchers is how to analyze large amounts of text data. Generally, organizations require a team of human coders to read the responses and code them in a manner consistent with the organization's goals. Human coding is a time-consuming task. An alternative strategy for systematically analyzing open-ended survey responses is to use simple, computationally based text mining tools.

In a recent survey of individuals who received workforce services in a state in the eastern half of the United States, we asked respondents a closed-ended question: *How valuable was this service to you—not at all valuable, somewhat valuable, or very valuable?* We followed this question with an open-ended question:

Is there anything else that you would like to add about your experience, either positive or negative, that could inform the improvement of aspects of the program that did not work as well, or ensure the retention of those things that did work well?

We sought to use the open-ended question to analyze why respondents gave the rating that they chose. In particular, we wanted to know which aspects of the program were prominent in more negative reviews compared to the aspects mentioned in more positive reviews.[5] Rather than human coding of all the responses, our first analysis involved the use of text mining tools provided in the “tm: Text Mining Package” in the open-source statistical software R (Feinerer, Hornik, and Meyer 2008). The tm: Text Mining Package includes tools to download and analyze the data, as well as to implement standard text preprocessing steps such as removing punctuation and numbers, and changing words to reflect their stems or roots.

Even this basic application of text mining revealed several differences across respondents who rated their overall experience negatively compared to those who rated it positively. Respondents who offered a negative rating were more likely to write longer responses and focus their comments on particular aspects of the program: the classes, courses, and the AJC counselors. In contrast, respondents who rated their experiences positively were less likely to identify any particular aspect of the program that they found helpful. Rather, the positive respondents were more likely to use the open-ended question as an opportunity to voice their general satisfaction with the services and the help they received finding a job.[6] The information gained from the open-ended survey responses can help organizational leadership strategically target improvement efforts to the aspects of service that contributed to customers’ negative evaluations.

PREDICTIVE ANALYTICS

Although states have been using data to make predictions for over a decade, primarily to implement the Worker Profiling and Reemployment Services (WPRS) system, technological advances in predictive analytics, together with shrinking financial resources and demands for increased performance accountability, have precipitated wider interest in and adoption of predictive analytics for workforce development applications (the White House 2014). Many states and organizations, for example, have contracted with proprietary firms to leverage text data in resumes and job advertisements to make better predictions concerning which applicants are most likely to succeed in a given job.

Applications in predictive analytics generally share a common goal: to generate accurate predictions that contribute to improved organizational performance or service delivery. To meet this goal, SWAs must be able to measure the performance of their predictive analytic applications and design or modify them to improve prediction.

There are three ways in which SWAs could generate more accurate predictions. First, they could increase the accuracy of their predictions by comparing the performance of predictions based on multiple different predictive algorithms.[7] Second, SWAs could improve the predictive power of their models by regularly evaluating the accuracy of their predictions and adjusting their models over time.[8] Finally, they could improve predictive accuracy by including more diverse sets of predictors in their models.

The Prediction Process

When most people think about prediction in the context of workforce development, they probably think about something like the following example. John has worked for 10 years as an accountant at a retail store. He loses his job and files for UI. In filing the claim, he provides information about his occupation and industry, how long he worked for the company, and why he lost his job. John also lists his age, race and ethnicity, and level of education. The SWA might then use this information to estimate such items as how likely he is to suffer prolonged unemployment, the jobs for which he is the most qualified, and/or which services are likely to afford the most help in returning to work.[9] Although this example illustrates an important part of the prediction process—the assignment of a prediction to a current SWA customer—it is incomplete because it omits other parts of the process.

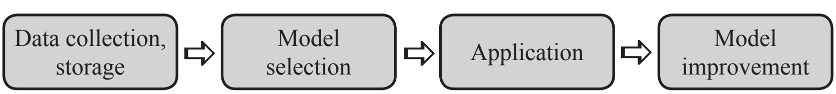
The prediction process actually begins with the identification of a substantive problem to which the application of predictive modeling might help the SWA overcome (Finlay 2014). In the case of workforce development, these problems largely revolve around identifying at-risk customers, matching customers to open jobs, and matching them to the most appropriate services.

After identifying a problem suitable for predictive modeling, the task of using prediction to improve service delivery involves a four-step process: 1) collecting, storing, and preparing for analysis data on the individuals whom the SWA serves; 2) testing many different predictive models on the data and selecting the one that generates the most accurate predictions;[10] 3) using the best model to generate predictions for each new customer and applying the predictions to serve customers better; and 4) assessing and improving the predictive model over time. Figure 19.2 depicts this process.

The more complete the data on workforce system customers, the more diverse the predictors that SWAs can include in their models and the more accurate their predictions are likely to be. Preparing data for analysis involves extracting data from diverse data systems, transforming the data so they can be analyzed using statistical software, and loading them into a database for analysis.

During model selection, researchers learn from the data by engaging in retrospective prediction (Siegel 2013). A SWA may want, as in the example we present below, to be able to predict which newly unemployed individuals are likely to remain unemployed for an extended period. SWA researchers would begin by examining a *subset* of the SWA's existing data, looking only at what was known about the unemployed individuals at the time they became unemployed, and use this information to "predict" who is likely to be unemployed a year later. The challenge is to find patterns that hold not just with the available data, but also in new data. So the researchers then test several predictive models for accuracy on a second subset of data, validate the results on a third subset of the data, and select for deployment in the field the predictive model that emerged from the validation phase with the highest accuracy. While this phase may provide the greatest challenge for

Figure 19.2 Predictive Modeling Process



SWAs in terms of developing new expertise, we demonstrate below that these challenges are not as large as they appear. Additionally, this phase of the prediction process does not need to be repeated on a regular basis, providing SWAs with the opportunity to hire an outside party to perform model selection if they are not equipped to perform this task internally.

In the application phase, the organization uses the winning predictive model to predict which new customers are likely, in our example, to have long spells of unemployment and takes some action based on the predictions. This means that when a newly unemployed worker enters personal information on a UI claim application or an AJC intake form, a predictive model examines the worker's characteristics and predicts how likely the worker is to have a long spell of unemployment. The SWA could then target services to this customer based in part on the predictive score.

Finally, because economic conditions change over time, predictive models must be updated regularly to remain accurate. In addition, the effect of assigning services based on the predictions of the model needs to be rigorously evaluated to ensure that the predictive system not only makes accurate predictions but also positively affects the outcomes it was designed to improve.

Current SWA Uses of Prediction

In this section, we review the substantive problems to which SWAs currently apply prediction and examine how SWAs engage in prediction. To date, SWAs have used predictive models to assist in addressing two substantive problems. First, nearly all states apply predictive modeling to identify the newly unemployed workers who are most likely to remain unemployed for so long that they exhaust their UI benefits. Individuals are then assigned to various services, a process known as worker profiling (USDOL 2000). SWAs can also use predictive models to target services and place customers into programs that are most likely to assist them with labor market reintegration. As discussed in the first section, SWAs are also starting to mine text data and combine it with other data on job seekers in order to develop predictive job matching systems.

Worker profiling

In 1993, Congress passed the Unemployment Compensation Amendments, establishing a federal mandate for the WPRS initiative (Wandner 1997). The law requires SWAs to develop either characteristic screening processes or statistical models to identify the individuals who have been permanently laid off and who are most likely to exhaust their UI benefits, for the purpose of referring them to reemployment services. This process, known as worker profiling, produces a prediction of a UI claimant's probability of exhausting his or her UI benefits based on a set of personal and economic variables that differs from state to state, though five variables are recommended by USDOL—education, job tenure, industry, occupation, and unemployment rate (USDOL 2000).[11] The legislation, as well as subsequent guidance from USDOL, requires states to use data on the outcomes of individuals referred through WPRS to update their models over time. The WPRS Policy Workgroup called on states to "update and revise their profiling models regularly, as well as add new variables and revise model specifications, as appropriate" (WPRS Policy Workgroup 1999, p. 16).

Identifying optimal services

In 2001, with support from USDOL, the W.E. Upjohn Institute built and pilot-tested the Frontline Decision Support System (FDSS) in two Georgia workforce centers with the objective of improving customer and workforce staff decision making with respect to reemployment. The system consists of a series of tools to provide customers with better information on their employment prospects, their job search, and the services that would be the most effective at helping them to return to work. The system generates the probability of a worker being reemployed in the same industry, a list of occupations related to the job seeker's previous occupation, and the services that are likely to be the most effective at helping the job seeker return to work (Eberts and O'Leary 2002). Because FDSS was not implemented on a statewide basis, a rigorous evaluation of the program's effect on reemployment has not been conducted. The FDSS is discussed in more detail elsewhere in this volume.

How states conduct predictive modeling

Although SWAs have applied predictive modeling to various substantive issues, they most commonly use prediction in implementing WPRS. Through WPRS, nearly every SWA in the nation uses a predictive model on a daily or weekly basis to assign a probability of UI benefit exhaustion to newly unemployed UI claimants and to refer individuals to services based on their scores. Since WPRS is the biggest predictive modeling enterprise that the SWAs undertake, we sought to learn how states engage in predictive modeling by surveying them about their WPRS predictive modeling practices. Specifically, we were interested in learning about three aspects of how they engage in predictive modeling: 1) the variables they include in their predictive models, 2) the algorithms they use to calculate predictions, and 3) the frequency with which they update their predictive models.

In April 2014, we e-mailed the survey to the UI directors in the SWAs of all 50 states, the District of Columbia, Puerto Rico, and the U.S. Virgin Islands. We received 34 responses, which enabled us to draw three primary conclusions with respect to how SWAs engage in predictive modeling.

First, states primarily include in their models the variables recommended by USDOL (education, job tenure, industry, occupation, and unemployment rate). Of the 34 responding states, 27 use at least the variables recommended by USDOL. The majority of states, however, include few variables beyond this list. The results of our survey are consistent with what others have previously learned about how SWAs conduct predictive modeling. The U.S. Government Accountability Office (2007); Sullivan et al. (2007); and Black, Smith, Plesca et al. (2003) find that many states do not include in their models a number of variables, such as the number of previous employers, past wages, and previous UI receipt, that might improve the predictive power of their worker profiling models. In their reanalysis of Kentucky's UI claims data, Black, Smith, Plesca et al. (2003) conclude that states could improve the predictive power of their models by incorporating more variables, including whether the customer received welfare benefits, the office where the individual received services, and whether the customer was enrolled in postsecondary education at the time of filing a claim. They note, however, that most states' models do not include these variables, and neither did many of the respondents to our survey.

Second, states primarily use a logit model to predict benefit exhaustion. Of the 34 responding states that use predictive models to assign claimants to services, 23 of them use a logit model. While one state used a neural network model, two states did not use a statistical model at all, and instead assigned customers using a characteristic screen, which selects individuals for services based on a handful of individual attributes.

The third conclusion is that many states do not regularly update their models. Despite the requirements of the original legislation and the guidance issued by USDOL, states are not regularly updating their profiling models. In their survey of state profiling models, Sullivan et al. (2007) find that many states had not updated their models in years. In some cases, states were using models estimated possibly 10 years previously to predict worker employment outcomes in the present day. Our survey from this year finds that updating of profiling models remains infrequent, with 16 of the 34 responding states indicating that they have not updated their models since before 2008. In other words, despite the substantial changes in the U.S. labor market over the past six or more years, these states have used models based on the prerecession period to predict job seeker outcomes during the recession and for the postrecession period.

Many of the states that had not updated models since before the recession cited an inability to update due to a lack of resources. This was particularly the case for states that have no in-house statistical staff and those that had their existing models set up directly by USDOL. Nevertheless, when model coefficients are not updated, it increases the chances that the predictive model misallocates services away from those most in need. Indeed, the U.S. Government Accountability Office (2007) finds that not only were many states not updating their profiling models, but also that neither USDOL nor the states had conducted any recent study to evaluate whether assigning individuals to services based on the predictions of the profiling models was having any positive effects on UI claimants' outcomes. The studies that have been conducted (e.g., Black, Galdo, and Smith 2007; Black, Smith, Berger et al. 2003; and Black, Smith, Pleasca, et al. 2003), although they employ rigorous methodological designs, are using data from the 1990s. Without updated research, it is impossible to know whether the states' profiling models are having the desired effect of reducing the duration of unemployment.

Application

In this section, we present an application of predictive modeling to a substantive workforce problem, predicting which customers are likely to have difficulty finding employment and need more extensive services before falling into long-term unemployment. Although our application addresses a substantively important issue, we have selected this application to illustrate the predictive modeling *process*. In particular, we present three approaches that states can take to improve the accuracy of their predictions using three different predictive algorithms, use the results to show the importance of updating predictive models over time, and describe some steps for diagnosing problems with and improving a model's predictive accuracy.

In our application, we assess the predictive accuracy of three algorithms—logit, regularized regression, and neural network—encountered both in our survey of the states and in the statistical literature on predictive analytics.[12] These algorithms represent three different approaches that states can use to improve the accuracy of their predictive models. We present an example in which the predictive accuracy varies only slightly across the three models, in order to highlight a cautionary point for states acquiring data for predictive applications: big data and sophisticated statistical models are not enough to solve every problem. If the statistical model is a poor approximation of the real-life process (e.g., long-term unemployment) that is being modeled, then neither more data nor more complicated methods will greatly improve predictive accuracy. We discuss this issue in more detail below.

Data

We use two primary data sources from the state of New Jersey to construct the sample for this chapter: America's One-Stop Operating System (AOSOS) and UI Wage Record data. AOSOS records the enrollment of customers in the workforce system, their demographic characteristics, the services they receive, and their exit from the system. AOSOS also tracks the participation of workforce system customers in the three largest welfare programs that serve working-age adults: Temporary Assistance for Needy Families (TANF), Supplemental Nutrition Assistance Program (SNAP), and the General Assistance (GA) program, a state-funded program that serves adults without dependent children. The UI wage data system records the wages of all employees at employers that report wages every quarter in the course of paying their UI taxes.

Sample

The sample for this chapter consists of all individuals who interacted with a New Jersey AJC for the first time in 2012. However, we exclude certain groups of individuals from the sample when they differ significantly from other AJC customers both in how they enter and how they interact with the workforce system. Specifically, we remove individuals who had any interaction (in terms of application for benefits or receipt of benefits) with TANF, SNAP, or GA, as well as customers under the age of 25. For both welfare program recipients and youth customers, it is more appropriate to run a separate predictive model for these individuals. In order to highlight the usefulness of predictive models for smaller geographic units than the state-level, we limit the data to a single state workforce investment area. The results presented below are substantively similar when analyzing statewide data.

Predictors

The predictors for the model consisted of demographic characteristics that appeared in the AOSOS data and wage history variables constructed from the UI wage data. Although AOSOS has the capacity to accommodate the entry of hundreds of different job seeker attributes that could be significant predictors of labor market success, in practice a much more limited set of characteristics is available for most job seekers. These include sex, race/ethnicity, education level, and date of birth.

We create wage histories for each workforce system customer relative to their date of entry into the workforce system. The wage history consists of each customer's earnings in each of the 24 quarters prior to enrollment in the workforce system, except for the first 2 quarters prior to enrollment, as the six-month lag in the UI wage data means that these quantities would not be available for inclusion in a predictive model at the time a customer enrolled. We then created additional variables, including the total number of quarters worked in the past six years and the number of consecutive quarters the job seeker was employed before entering the workforce system.[13]

Comparison of predictive models

In the predictive models presented below, we operationalize long-term unemployment as collecting zero wages in the four quarters after a customer's initial AJC visit. We then compare the predictive accuracy of three competing models. When the outcome variable is dichotomous, one of the first classification methods that researchers apply is logistic regression, which often achieves high predictive accuracy. However, when the model includes few observations and many variables, some of which may be highly correlated with each other, a statistical problem called *overfitting* may reduce the model's accuracy on new data sets. When a model overfits, it is fitting the random noise in the data and not the underlying relationship between the variables, meaning that it is likely to perform poorly when called upon to make predictions on new data. Numerous and highly multicollinear variables are features of large administrative data sets in workforce development. Regularized regression models, such as the ridge and lasso, were developed to improve predictive accuracy in situations where models are overfitting the data. Thus, in addition to the logit model, we estimate a modified regression model called ridge regression (Hastie, Tibshirani, and Friedman 2009; Kuhn and Johnson 2013).

The third model we show is called a neural network, which at least one state uses for its worker profiling model. The chief advantage of the neural network is its ability to model complex relationships between the predictors and the outcome, which can lead to improved predictive accuracy when compared to competing models. States can implement a neural network, as well as the logit and the ridge regression, without a substantial investment in technical capacity. The models can be estimated using freely available and easy-to-use software such as R (discussed in the Predictive Analytics section on p. 452).

In estimating the models, we follow common practice in predictive analytics by splitting the customer data into three separate data sets: a training set, a test set, and a validation set. The reason we split the data involves choosing models that have high predictive accuracy on new observations. The danger of the overfitting phenomenon mentioned above is that the model estimates may have excellent predictive accuracy on the data set used in estimation while having poor predictive accuracy on any new data. A predictive model should not be assessed on how well it predicts outcomes on the data that were used to estimate the model, but rather on new data for which the outcomes are unavailable. For example, a model may perform well predicting outcomes on past One-Stop customers while poorly predicting outcomes on any new customers. Splitting the data set into a training, test, and validation set helps reduce the possibility that our models overfit the data and thus have poor predictive accuracy on new customers.

Specifically, we follow these four steps:

1) Estimate the logit, ridge, and neural network models on the training data
2) Assess the predictive accuracy of each model on the test data
3) Choose the logit, ridge, and neural network specification with the highest predictive accuracy on the test data[14]
4) Assess predictive accuracy of each model on the validation set to establish final benchmark model accuracy

In practice, a predictive model should produce at least higher predictive accuracy than an alternative strategy of using no model at all. For example, workforce agencies can simply classify all customers as likely to be unemployed. The predictive accuracy of this system will equal the average of the outcome variable for averages above 0.5 and 1 minus the average for values below 0.5. If 60 percent of customers in the data are unemployed, then this system would achieve a predictive accuracy of 60 percent, since it would classify all the 60 percent of unemployed individuals correctly and all of the 40 percent of employed individuals incorrectly. We call this system the *null model*. At a minimum, we want to choose predictive models that have higher predictive accuracy than the null model.

Note that we estimate and validate the model using 2012 customer data. The estimates thus reflect the most current data available for this application. However, as we found in our survey of the states' predictive modeling practices, some states are not updating their models with the most current data. For example, many states are using 2008 customer data to predict 2012 customer outcomes, despite the large differences in the labor market conditions and typical customer profiles across this period of time.

To illustrate the consequences of not updating predictive models, we follow the same steps as those listed above but train and test the models using data from 2008 only. With the estimates from the 2008 data, we measure predictive accuracy using the same 2012 validation set as that used above.

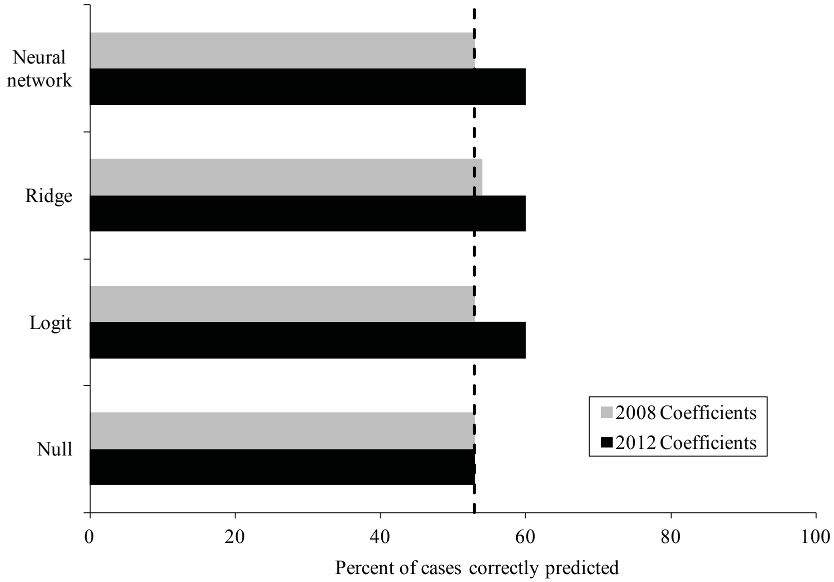
The results are shown in Figure 19.3. The black horizontal bars mark the predictive accuracy of the models that are fit to the 2012 data, with the bottom horizontal black bar representing the null model's predictive accuracy. The three models achieve similar predictive performance on the validation data. The logit, ridge, and neural network models correctly classify 60 percent of customers as experiencing a long spell of unemployment. Each model does significantly better than the null model, which features only 53 percent of customers correctly classified.

The grey horizontal bars in Figure 19.3 represent predictive accuracy for the models estimated using the 2008 data. Recall that the expectation is that the predictive accuracy of a model will decrease when the model's estimates are not updated with more current data. The results confirm our expectation. Across all three models, the predictive accuracy on the validation data is approximately equal to the accuracy of the null model. In other words, when we estimate models using older data, we achieve results no better than simply assuming every customer who enters an AJC will experience a long spell of unemployment.

A natural question to ask is why the performance of the three models is so similar. Why, in other words, do the more sophisticated ridge and neural network models provide little improvement over the logit model? The answer relates to the concepts of the bias and variance of a predictive model.

The variables included in the application we present are only weakly associated with the outcome variable of unemployment. These variables thus do a relatively poor job representing the complex process that leads individuals to experience long-term unemployment. This phenomenon—the failure of a model to be a good approximation of a real-life process—is called *bias*. Rather than overfitting the data, the logit model is underfitting, so the ridge regression offers little or no gain

Figure 19.3 Predictive Performance of Neural Network, Ridge, and Logit Models



over the logit. In addition, even the complex neural network is unable to model the complexity in the data in a manner superior to the logit and the ridge regression. The result is three models that perform similarly and achieve prediction accuracy at only about 60 percent when, ideally, the model should achieve much higher accuracy. This suggests that additional work needs to be done collecting not more data but more high-quality variables that are associated with the outcome of interest.

A crucial point about a high-bias model is that more data will not substantially improve predictive accuracy. Even when we expand our data set to include hundreds of thousands of additional observations, the results change little. Big data will help primarily when the model has an opposite problem called *high variance.* A high variance model features poor predictive accuracy on data that were not used to estimate the model. Generally, more data can reduce the variance of the model by reducing overfitting, but more data will not reduce its bias.[15] Bias reduction requires the inclusion of additional predictors in the model.

CONCLUSIONS

Building an intelligent workforce system requires high-quality data and the ability to mine insights from all types of data, not just numeric and categorical data, and to analyze that data as accurately as possible. Data science and low-cost software offer SWAs and local workforce areas a series of valuable tools for improving the labor market outcomes of AJC customers. When described using terms such as geospatial analysis, text mining, predictive analytics, or big data analytics, these models can appear new and intimidating. However, despite states' limited experience examining location and text data, the tools for mining these data for insights are within the capabilities of SWA research staff—possibly in collaboration with state university partners or private sector firms. Moreover, many states are already quite familiar with predictive modeling, as nearly every state already implements predictive models through their UI programs. While it is true that the field of predictive modeling offers a wide range of algorithms for predicting workforce outcomes, SWA staff do not need to understand their mathematical intricacies any more than they do the basic logistic regression models currently in use for worker profiling because existing statistical software does most of the heavy lifting.

What SWAs *do* need to ensure is the proper expertise in the application of location and text analysis and in predictive modeling. For location and text data, this requires identifying staff capacity internal to the SWA or available in other agencies of state or local government, universities, or the private sector. In the case of prediction, this may require some training for staff members who currently oversee worker profiling models or hiring an outside party to develop and implement a new predictive model, as setting models up the first time requires careful design and evaluation. But once the models are established, they need to be updated with new data only on an annual basis, which is a much less costly process. In short, while states will need to find resources to develop new models, these resources need not be extensive.

Beyond resource constraints, the much larger and more crucial impediments to an intelligent workforce system are data limitations. If address information is not updated regularly or textual data are collected only sporadically, then these potentially useful sources of information may not be available in an accurate or complete enough form to provide the type of value they could potentially provide. The chapter has also demonstrated that having a large quantity of data is not enough to produce highly accurate predictive models. The *quality* of workforce data is just as important. In order to fully leverage the power of location-based analyses, text analysis, and predictive models, SWAs need not only a large number of observations but also a multitude of variables that are related to workforce outcomes. In the current state of the workforce data, these variables are often not available because state agencies silo their data into separate systems. Furthermore, states often only collect the bare minimum of variables necessary to meet federal reporting requirements.

Data quality is an area where the workforce system needs to strive for improvement, and to some extent this process has already begun. The need for high-quality data is becoming more apparent to public officials, and a limited number of projects are under way at all levels of government to foster improvements in data quality. For instance, the USDOL Workforce Data Quality Initiative has provided grants to 32 states to integrate administrative data systems, breaking down silos and providing the diversity and number of variables that make accurate predictive modeling possible. Other examples of data integration projects include the Workforce Innovation Fund projects in Chicago and Newark, as well as recent efforts to create a federal workforce data system.

In order to derive insights from location and textual data and develop accurate predictive models, the collection of high-quality workforce data must begin now, and an intelligent workforce system should look beyond data integration to further improve the quality of workforce data. For instance, a key component of data quality is data completeness, and in our experience performance metrics have had a significant effect on which fields of data are the most thoroughly recorded and least missing. Those that are required for SWAs to meet their federal reporting requirements are the fields that are the most complete. Data quality improvements may therefore depend on how the federal system holds states and local areas accountable. A system that genuinely incentivizes states, local areas, and workforce counselors to collect and record a greater variety of data elements may be the essential first step to building a truly intelligent workforce system. SWAs can also take other steps to improve data quality, such as designing new customer intake procedures that collect additional variables and provide training to ensure consistent data entry across AJCs. Location data, text data, and predictive models hold much promise for the future of workforce development, and states can capture the benefits that these models provide only by improving data collection in the workforce investment system.

Notes

1. More extensive reviews of the field can be found in Grimmer and Stewart (2013) and Witten (2005).
2. Generally, before any analysis begins, a researcher must preprocess the text for analysis. This step usually involves stemming words, removing punctuation and common stop words such as *the* and *than*, removing numbers, and converting words to lower case. Analysts often apply a weighting scheme to words, such as *tf-idf* weights.
3. For a detailed R example as the count-based method and word associations, see Feinerer, Hornik, and Meyer (2008).
4. Monroe, Colaresi, and Quinn (2008) and Taddy (2013) discuss methods for estimating words that are predictive of category or group labels.
5. At alternative strategy is to look at specific aspects and assess their overall positivity and negativity (Liu 2010). Our research question here is focused on understanding aspects that factor into respondents' overall evaluation of the program rather than understanding variation in ratings across different services.
6. For a discussion of more advanced analyses of open-ended survey items, see Roberts et al. (2014). The result presented here is consistent with the informational negativity effect in psychology whereby individuals are better able to identify more precise justifications to support a negative reaction than a positive one (Lewicka 1997; Peeters and Czapinski 1990).
7. An algorithm is a step-by-step process for making a calculation.
8. A model is a mathematical equation that expresses a formal relationship between variables. In the case of predictive modeling, the model expresses the mathematical relationship between the predictors and the outcome being predicted.
9. To prevent discrimination, federal laws and regulations may prohibit the inclusion of some personal characteristics, such as age, race, sex, and disability status, in models that automatically assign individuals to services.
10. There are many different criteria that a researcher may use to guide her choice of the "best" model. For classification problems where the dependent variable is not skewed, accuracy is a good model evaluation parameter, as is the area under the receiver operating characteristic (ROC) curve. With a skewed dependent variable, it may be necessary to use other metrics, such as precision, recall, the F-score, etc. For models that predict continuous outcomes, the researcher might compare models based on their root mean squared error. For a detailed analysis of model evaluation, see Japkowicz and Shah (2014).

11. USDOL prohibits states from including some personal characteristics, including age, race, sex, and disability status, from the worker profiling model.
12. We define predictive accuracy as the percent of customers that the model accurately predicts as remaining unemployed.
13. We have no data on individuals who earn wages outside New Jersey. In an effort to partly mitigate the out-of-state employment problem, we delete from our list customers without any recorded education or employment history in New Jersey. Of course, this also removes weaker job seekers who are living in New Jersey but have poor employment histories. The results presented here are substantively similar to the results we obtain when we include those individuals.
14. We choose the ridge regression regularization penalty and the neural network decay parameter and node size to optimize predictive accuracy on the test data.
15. For more information about diagnosing bias and variance, see the concept of learning curves in the statistics and machine learning literature.

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Chicago's Journey toward Better Data and Performance for the Workforce Development System

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The recent economic downturn has led many job seekers and policymakers to ask questions about which workforce development programs are effective at helping people acquire skills and obtain employment. In Chicago, as in many other jurisdictions nationwide, the local workforce development system is a complex array of public and private organizations that provide services ranging from job search assistance to education and occupational training (Chapin Hall at the University of Chicago 2010). Information about program performance is inconsistent and difficult to obtain, given fragmented program funding silos coupled with various data and reporting requirements. Even when data to assess programs are available, they are often limited to participants within a particular service provider agency or public funding stream, providing only a partial understanding of program outcomes. Furthermore, data quality and access can be inconsistent, since organizations are often required to use multiple cumbersome data management systems with limited reporting capacity (Weigensberg et al. 2013).

The need for better data to understand program performance is not only shared among policymakers and job seekers but is also expressed by workforce program administrators and frontline practitioners seeking more information about their outcomes (Corporation for a Skilled Workforce and The Benchmarking Project 2013; Weigensberg et al. 2012). The demand for data to make informed decisions about workforce development programs created a culture of desired change in Chicago. Since 2009, numerous public and nonprofit agencies, local policymakers, foundations, and researchers have collaborated to engage in several strategic and innovative initiatives to improve organizational governance and the structure of the local workforce system as well as to access, create, and analyze data to assess programs and inform decision making.

CHICAGO WORKFORCE INVESTMENT COUNCIL AND CWIC*STATS*

In 2009, Chicago Workforce Investment Council (CWIC), a nonprofit, was created to help align programs and promote effectiveness of the local workforce development system. CWIC was chaired by Mayor Richard M. Daley and governed by a board of influential businesses and community partners to provide cross-systems oversight of key public agencies, including high schools, community colleges, and workforce development programs. CWIC's mission was to ensure that Chicago had a skilled and educated workforce to keep Chicago's businesses, economy, communities, and families thriving. It aimed to improve the skills and earning potential of residents, meet the labor needs of local businesses, and strengthen Chicago communities. The council focused on aligning the diverse public agencies and program funding streams within the workforce development system and was charged with ensuring that programs were effective for both residents seeking employment and businesses needing to hire a skilled workforce. It monitored over $350 million in annual workforce investments and coordinated resources across numerous city agencies to maximize the return on public investment.

To support the information needs of CWIC and other stakeholders, numerous workforce development policymakers, program administrators, and foundations partnered with Chapin Hall at the University of Chicago to establish a Chicago workforce data and research initiative called CWIC*stat*s. The model for CWIC*stats* emerged from the need for a workforce data consortium that could provide reliable data from the diverse and fragmented local workforce development system. CWIC-

stats researchers worked with state and local public agencies to access and analyze administrative data on program participants and outcomes, including data on Workforce Investment Act program participants and secondary students in the Chicago Public Schools, and then to link that information to employment earnings. CWIC*stats* produced program performance measures, reports synthesizing local labor market indicators, and periodic research studies providing an in-depth understanding of targeted populations and programs. The CWIC*stats* initiative served as an innovative model of cross-system data integration and analysis to address data and research gaps, assisting policymakers with data-informed decision making (Weigensberg 2013).

CHICAGO-COOK WORKFORCE PARTNERSHIP AND IWIS

In 2012, building on recent political transitions, the local workforce development system evolved along with the approach to address the need for data on program performance. Mayor Rahm Emanuel and Cook County Board President Toni Preckwinkle established the Chicago Cook Workforce Partnership (the Partnership) to oversee the local workforce development system. The Partnership combined city and county resources to promote collaboration and efficiency for services supported by the federal Workforce Investment Act (WIA), which were previously administered by three separate local Workforce Investment Boards that covered Chicago and Cook County. Since its inception, the Partnership has reduced administrative and programmatic redundancy within the local system and helped to align local training opportunities with the needs of businesses. To achieve its goals of effective and streamlined workforce services, the Partnership also saw the need for improved data for workforce programs.

Although CWIC*stats* made great progress to link and analyze data across multiple programs and data sources to assess program performance and pursue research, the fragmented and incomplete nature of workforce development data remained a challenge, especially for program management purposes. With support and recommendations from research efforts conducted at Chapin Hall (Weigensberg et al. 2012) and Public/Private Ventures (Miles et al. 2010), a growing need for an improved data system for local workforce development programs emerged. Furthermore, the need for better data was being voiced from community-based service providers, not just public agency administrators. In 2013, the Partnership, in collaboration with public agency partners and service providers, embarked on a three-year project to develop and implement a comprehensive integrated workforce information system (IWIS) to capture and report data on all participants served by workforce development programs in Chicago and Cook County. This effort, which is funded by a U.S. Department of Labor Workforce Innovation Fund grant and several local foundations, is the first attempt to create a management information system to integrate administrative data across public and private agencies, as well as funding streams, to provide data on all individuals served by local workforce development programs. IWIS will reduce the need for frontline staff to enter data with numerous management information systems because it will serve as an interface among multiple data systems. IWIS will also promote the use of data through customizable reporting for agency staff and program administrators, as well as common reporting among private funders. In addition to the robust reporting features, IWIS will benefit frontline staff by creating a dashboard where they can easily navigate data entry, obtain information across numerous backend data systems, share referrals, and assess outcomes that were previously unavailable or labor-intensive to obtain. Once in operation, IWIS will allow for the comprehensive assessment of workforce development programs for the first time, while also streamlining data processes for improved program management. Although these technical advances with IWIS will assist policymakers, administrators, and frontline staff, the system will also ultimately benefit job seekers by providing enhanced information sharing, efficient referrals, and better data to improve services.

LESSONS LEARNED

The CWIC*stats* and IWIS initiatives to improve data and program performance in Chicago have provided several key lessons that could benefit others embarking on similar efforts to improve workforce data.

Shared Need and Vision for Improved Data

The CWIC*stats* and IWIS efforts emerged from a common need for better data on the workforce development system, which was shared among multiple stakeholders, including policymakers, public agencies, community-based service providers, private foundations, advocates, and researchers. CWIC*stats* was developed as an excellent strategy to link and analyze data to address the initial need to provide periodic performance measures and research on the overall effectiveness of the system. However, stakeholders wanted more comprehensive data, particularly on those individuals served by the workforce development system, yet not supported by public funds and not typically included in those corresponding data systems. Therefore, stakeholders, especially the frontline provider organizations, rallied around the need for IWIS as a comprehensive data system that could be used not only for analysis purposes but also for program management.

Strong Leadership and Partner Collaboration

To build on a shared vision of improved workforce development data, strong leadership and partner collaboration were essential to implement strategies to achieve this vision. For both CWIC*stats* and IWIS, political leadership and local public agency leaders helped to champion the work and engage partners. Also, with both efforts, an advisory council of key stakeholders was established to assist with oversight and to provide input. In addition to leadership, collaboration with public agencies and community provider partners was essential to implementing both data initiatives. Specifically, collaboration among public agency partners, such as the Illinois Department of Commerce and Economic Opportunity and the Illinois Department of Employment Security, was essential to establishing data sharing agreements to access and use their program data. Also, in regard to IWIS, extensive stakeholder engagement efforts were used to solicit input from public agencies and community providers to help define the system requirements and to ensure IWIS will meet the data collection and reporting needs of users (Weigensberg et al. 2013). Strong leadership and collaborations among partners were key to overcoming many challenges with both CWIC*stats* and IWIS, including obtaining buy-in, securing legal data permissions, data sharing and interface development, identifying common measures and reporting, and executing effective implementation plans.

Data and Research Expertise

Another important aspect of both data initiatives was the engagement of partners with data and research expertise in using administrative program data from the workforce development system. CWIC*stats* was housed at Chapin Hall at the University of Chicago, where experts could apply their many years of experience analyzing administrative program data, while serving as a third-party entity to provide unbiased research for partners. With the development of IWIS, data expertise was provided by Chapin Hall, the Chicago Jobs Council, and independent consultant Marty Miles, who helped to develop the system requirements plan with the input from public agencies and private providers. Leveraging expertise from experienced researchers and data partners was essential to promote innovation, ensure a high level of rigor, and lend authority for these data efforts.

Data Linkages across Multiple Programs

The innovation with both CWIC*stats* and IWIS was to link data across programs to look at the workforce system holistically rather than operating within fragmented program and funding silos. Data from workforce programs, educational institutions, and earnings were linked to assess program outcomes but also to pursue research about the experiences and trajectories of participants over time. These efforts highlighted the importance of focusing on a more systemwide and longer-term perspective to understand how programs can support the pathway and outcomes of individuals as they moved through the workforce development system and into employment.

Meaningful Analysis for Decision Making

Another important element of these data initiatives was to ensure data reports and analysis were useful and meaningful to policymakers and program administrators, who needed this information to make decisions. The analysis and research products from CWIC*stats* were often shared in a variety of formats, including presentations and policy briefs, to convey data in a user-friendly format to help make applied decisions. IWIS was also designed to ensure practical reports were included in the data system along with the ability for users to develop their own queries to analyze data, assisting users with obtaining what information they needed for management as well as service provision purposes.

Diverse Funding

Given the array of staff and resources needed to implement data initiatives, funding should be diversified among numerous sources. CWIC*stats* operations cost approximately $500,000 annually, which was supported by numerous grants from foundations as well as contracts with public agencies.[1] These funds supported the role of researchers at Chapin Hall at the University of Chicago to perform the data and analysis aspects of CWIC*stats*. However, the development of a new data system with IWIS cost significantly more, with the initial development costing approximately $3 million. The main financial support for the development of IWIS was provided by the U.S. Department of Labor and augmented by additional funds from private foundations.[2] Although developing a new data system is expensive, the investment is expected to lead to substantial savings with program management and service provision, owing to less redundancy, more efficiency with data entry, and anticipated improvements in program performance through an increased ability of providers to assess and improve services. Despite generous investments for development, obtaining funding to maintain and grow IWIS past the initial implementation will be a challenge. Future financial sustainability will likely come from a combination of funding from participating public agencies, private providers, and foundations. After the initial development, continued support costs for IWIS are estimated to be about $500,000 per year.

These lessons learned from Chicago's experience with CWIC*stats* to link data and conduct research, along with the current development of IWIS, can help other jurisdictions that are also struggling to obtain improved data to assess and manage their workforce development systems.

Notes

1. Numerous organizations provided funding for CWIC*stats* development and research efforts, including the Chicago Cook Workforce Partnership, Chicago Workforce Investment Council, the Chicago Community Trust, the Searle Funds at the Chicago Community Trust, the Boeing Company, the Ford Foundation, the Joyce Foundation, the Annie E. Casey Foundation, the Lloyd A. Fry Foundation, the Chicago Department of Family and Support Services, and the Steans Family Foundation.
2. In addition to the U.S. Department of Labor Workforce Innovation Fund grant, funding for IWIS was provided by the Chicagoland Workforce Funder Alliance.

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Piloting and Replicating What Works in Workforce Development

Using Performance Management and Evaluation to Identify Effective Programs

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What can cities do to identify and build evidence for effective strategies in workforce development, and how can they use these findings to drive funding decisions and improve workforce delivery systems? The New York City Center for Economic Opportunity (CEO) addresses poverty by developing, implementing, and evaluating innovative approaches to better understand what works and what does not.

Low-wage workers, and by extension workforce providers, face a tough job market. Unemployment remains high following the Great Recession, and the unemployment rate of 8.6 percent in New York City in late 2013 hides the great variation across the boroughs; for example, in the Bronx, unemployment climbs as high as 12 percent (Bureau of Labor Statistics 2014). According to CEO's research, 1.7 million New York City residents are in poverty. Many of the poor are engaged in the world of work yet still struggle to make ends meet. In New York City, there were nearly 685,000 residents in poverty who live in a household with at least one full-time year-round worker (CEO 2014).[1]

Nationally, a majority of the new jobs created in the aftermath of the recession are in low-wage occupations, while midwage industries have nearly a million fewer jobs than at the start of the recession (National Employment Law Project 2014). In addition, low-income workers face wage stagnation (Shierholz and Michel 2013).

This is the context in which New York City has worked to promote the economic well-being of low-wage workers, both through workforce development initiatives and through strategies that enhance low-wage workers' economic security, such as uptake of Food Stamps and creation of local tax credits and paid sick leave policies. New York City has a robust system of workforce services provided by multiple city agencies in partnership with service providers; CEO's goal has been to develop and assess new strategies, address gaps, and bring new resources and evidence-based approaches to improve systems and service delivery.[2]

HOW DOES CEO PILOT AND EVALUATE WORKFORCE PROGRAMS?

CEO works like a research and development lab within city government to try new strategies, determine which are effective, and scale up what works. CEO's work was shaped by a 2006 commission that was established by the mayor to comprehensively review poverty in the city and to recommend areas for investment and intervention. The commission—composed of leaders of government, business, nonprofits, academics, and philanthropy—prioritized workforce development efforts to help the working poor enter and advance in the labor market. Other focus areas included young adults (aged 16–24) who were out of school and out of the labor market ("disconnected youth"), people with a history of involvement with the justice system, and young children.

The center was quickly established to implement the commission's recommendations, and from 2007 through 2013, it piloted over 60 initiatives with a mix of public/private funding. Substantial investments focus on helping disconnected youth and the working poor to enter and advance in the workplace, and since its start, CEO has invested hundreds of million dollars in human capital development and workforce strategies. Programs represent new strategies, expansions of strong local programs, and replications of evidence-based models.

CEO is housed in the mayor's office, giving it a cross-agency vantage point, and its programs are implemented in partnership with city agencies. Most workforce programs are contracted out to local providers that deliver services to the community. All programs undergo rigorous results-focused performance monitoring, including monthly narrative reports and quarterly data reports that track progress toward targets.

Regular meetings with agency partners and site visits to providers complement the data. Performance data focus on outcomes rather than just process measures and are tracked against performance targets. Common measures, such as participant demographics, are aligned across programs to the extent possible. For CEO's workforce programs there is an emphasis on what is important: placements, wages, job quality (e.g., full-time/part-time, benefits), and promotions.

Data are periodically reviewed, with the recognition that context matters. Staff consider the range of information known about the program's performance (e.g., have there been recent staffing changes, are particular providers struggling compared to others), the labor market context, and changes in performance over time. CEO and agency partners, informed by the data, adjust and improve programs as needed. For example, a weak provider may receive a corrective action plan and assistance tailored to its shortfalls, or data showing weak job placements in particular occupations could cause a shift in focus to new areas. Meetings that convene providers often highlight the best practices of strong performers to promote peer-to-peer learning. Annual awards are given to high-performing providers that hit target outcomes and demonstrate ongoing use of data to strengthen their service delivery, as a positive strategy to encourage a data-driven culture.

Data are also shared externally. CEO shares aggregated data publicly via its Web site on an annual basis.[3] In recent years CEO began working with its partner agencies to share site-level data back to providers so that they can see how their program performance compares to fellow nonprofits operating the same model. This process also provides an opportunity for the city agencies to ensure that partners are defining and reporting variables consistently and accurately.

Once fully operational, promising program models are also evaluated to document outcomes and impacts on job placement rates and wages. Key factors in determining the shape of the evaluation include the length of program operations, the timing of expected outcomes, existing knowledge in the field, CEO's level of financial investment, and the quality of the data available. Evaluations range from qualitative assessments to quasi-experimental data analyses, up to random assignment studies that measure program impacts. CEO works with nine external evaluation partners to conduct independent evaluations, and these reports are made public.[4]

The center's overall approach is characterized by evidence-based policymaking, and accountability is built into the system. Data from performance monitoring and evaluation findings have been used to determine annual funding decisions. Successful programs are continued with the focus on bringing the program to scale and promoting system changes, while unsuccessful programs are discontinued.

WHAT SPECIFIC MODELS HAVE WORKED?

CEO's workforce development programs served more than 43,000 participants across nearly 25 programs in 2013. Its workforce strategies have spanned a range of approaches, targeting specific populations (e.g., probationers or young adults), industries (e.g., health care or transportation), or communities (e.g., particular public housing developments). Service delivery is adapted to reflect these different characteristics in recognition that there is no one-size-fits-all solution. For example, an initiative focused on a particular industry tailors its job readiness services and employer engagement strategies to that particular sector, and a program targeting people with a criminal history tailors services to address the particular needs and challenges faced by that group. CEO has documented a number of successful or promising strategies, which are discussed in the sections below.

Sector-Focused Career Centers

These centers deliver services to job seekers and employers tailored to specific industries and have demonstrated success in helping participants achieve higher wages and job placements relative to customers of the typical One-Stop Career Center. The centers are similar to One-Stops but they focus on a narrow range of occupations that help them build robust employer relationships and enable them to tailor all services to the particular industry. Starting in 2008, CEO has worked with the Department of Small Business Services (SBS) to create New York City's first sector-specific career center focusing on transportation. The results were powerful: placement rates and wages increased when compared to the traditional One-Stops that did not have an industry specific focus. Additional sector centers were added in manufacturing and health care, and a recent evaluation comparing the city's sector centers to the One-Stops found that the sector approach increases the likelihood of participants finding employment, and achieves substantially higher wages for those placed (an estimated $5,800 increase in earnings in the first year), and participants had a 39 percent increase in steady employment (working all four quarters in the year after exit from the program). Of those who received services at the sector centers, those that received hard-skills occupational training services had the greatest income gains (Gasper and Henderson 2014).

WorkAdvance

Building on its experience with sector-focused workforce programming, as well as earlier incumbent worker initiatives that had focused on career advancement, CEO worked with partners to create WorkAdvance, a new sector-focused career advancement program for low-wage workers being replicated nationally through the Social Innovation Fund.[5] WorkAdvance addresses the need for quality workforce services that go beyond the initial placement to help workers keep their jobs and to continue to advance. Each WorkAdvance site focuses on a narrow range of occupations and provides robust participant screening, job readiness services, occupational training, job placements, and retention/advancement coaching beyond the initial placement. Each component of the program model is closely tailored to the target industry and informed by employer feedback. A randomized control trial is under way by MDRC to evaluate the impact of WorkAdvance, with results expected in late 2015. An early look at the program's implementation yielded important lessons about the challenges for providers in operating these programs, including the difficulty in keeping training offerings aligned with changes in the target industry, and in recruiting potential workers who meet the educational and other background screening criteria set by training providers and employers (Tessler 2013).

Jobs-Plus

This cross-agency initiative takes a geographically based approach to connect public housing residents at targeted developments to employment opportunities. The strategy delivers on-site workforce services, promotes neighbor-to-neighbor outreach, and offers rent-based financial incentives through the housing authority to “make work pay.” A seven-year evaluation of the program by MDRC in the late 1990s finds that housing developments that had fully implemented the program experienced earnings growth of $1,141 on average for *all* residents, regardless of whether they participated in Jobs-Plus (Riccio 2010). The results endured even after the program had closed its doors. Specifically, residents in Jobs-Plus sites had increased their earnings 16 percent more than residents of non-Jobs-Plus sites (Riccio 2010). Based on MDRC’s research and an initial pilot site that CEO launched in 2009, the city expanded the program to 10 sites through funding from the federal Social Innovation Fund and the city’s Young Men’s Initiative, a mayoral initiative to address disparities faced by young African American and Latino men.

Business Solutions Training Funds

This program engages directly with employers as a strategy to help incumbent low-wage workers advance in their current jobs, while also helping businesses stay competitive. It works by providing grants for customized training to businesses in exchange for their commitment to provide wage gains to their low-wage workers (with a particular focus on businesses that propose upgrading workers who earn less than $15 an hour). The current program grew out of SBS’s existing Workforce Investment Act (WIA) customized training funds program. CEO funds and partnership brought a greater priority focus on low-wage workers and more flexibility in the program structure and training offerings. The program is now supported by a blend of CEO, WIA, and employer funds, and a recent independent evaluation of the program found that the model successfully led to increases in wages for the employees that received training. Program participants earning less than $15 an hour at the start of the program benefited from an 11 percent wage gain post-training and had greater wage gains than a group of similar workers at the standard career centers when compared six months after training (Hamilton and Chen 2014).

Subsidized Jobs for Young Adults

Although subsidized jobs programs for the general adult population have had mixed results in terms of their impact on helping workers enter the labor market, subsidized jobs and paid internships have been an important strategy for CEO's young adult programs. In particular, CEO has found that these programs are successful when the workforce focus of a subsidized job is added to educational programs that help young adults learn skills or advance toward their educational goals. Several recent evaluations have found promising results for disconnected youth. Sixty percent of participants in the Young Adult Internship Program complete the subsidized job program, and 50–60 percent remain in employment, education, or training after the program (Westat and Metis Associates 2009).[6] Participants in the Youth Adult Literacy Program who also held a paid internship while in pre–General Educational Development classes were more likely to graduate, attend class, and stay enrolled in the program longer than students at sites that did not offer internships (Meisch and Tunik 2011).[7]

Scholars at Work

A workforce program for students that connects the education and workforce systems, Scholars at Work draws on the employer engagement expertise of the sector-focused One-Stop to set up relevant paid internships for high school Career and Technical Education students. While the program has not yet been formally evaluated, performance monitoring suggests that the program has resulted in several participants' obtaining job offers from their internship. Interestingly, a large percentage of participants chose to go to college following the program, even though recruitment targeted students who were not considered college bound and had been planning to go directly into the workforce. Since 2010, Scholars at Work expanded the number of students placed in internships from 17 to more than 100 in 2013, grew to include community college students, and expanded its reach from 11 partner employers to 43 in 2013.

All of these programs are examples of models that have been shown to help low-wage workers enter and advance in the labor market. They are complemented by a range of other CEO initiatives that promote completion of high school (or its equivalent) and community college, as well as strategies to promote financial and asset development, and to lift the floor for low-wage workers.

LESSONS LEARNED FROM PERFORMANCE MANAGEMENT AND EVALUATION

Over the years, CEO has gleaned a wide range of lessons from doing this work. These lessons are cross-cutting and derive from multiple pilot initiatives.

Lesson 1: Programs Need to Be Labor Market Driven and Tailored to Employer Demand

While this lesson is now commonly accepted in the workforce world, it is less commonly well implemented. Program staff need to develop strong relationships with employers and use information from them to develop appropriate program screening criteria, tailor their hard- and soft-skills training offerings, and learn about career ladders within targeted occupations to provide appropriate retention and advancement services. Sector programs are a strong model for serving two constituencies: they help job seekers obtain quality employment while also meeting the human resource needs of local businesses. The approach has rigorous evidence behind it (Maguire et al. 2010) and has been increasingly embraced at the federal level.

Demand-driven hard-skill occupational training investments show particularly robust results in helping low-wage workers obtain good jobs. For example, CEO's recent sector program evaluation noted that participants in the program who received training were more likely to work the entire year after program exit, and they increased their annual earnings by $9,071 on average over those who used standard career centers. They also earned nearly $3,500 more on average than those who used sector-focused career centers but did not receive hard-skill training.

A cautionary note: programs that are too narrowly tailored can fail. Two of CEO's discontinued workforce programs were built around the needs of specific employers or a single occupation. An initiative to train young people in green jobs related to arboriculture and landscaping failed to place graduates when demand at the Parks Department and other local employers failed to materialize. A Licensed Practitioners Nursing training program built to meet the demand for nurses in the city's public hospital system was unable to place its graduates when the economy shifted and the demand for nurses (particularly those without significant relevant work experience) lessened as fewer nurses retired because of the recession. While these programs were well delivered and had high graduation rates, they did not move enough people into employment. Because they were built around a single occupation, they were not well designed to nimbly adapt to rapid changes in the labor market.

Lesson 2: Subsidized Jobs Are an Important Service Element for Young Adults

Several CEO young adult programs have found that incorporating subsidized jobs or paid internships into their educational interventions have been an effective tool to help young people get a foothold in the labor market while keeping them engaged in their classes.[8] By adding a subsidized job, programs help meet a young person's immediate need for income and also provide opportunities for exploring careers and learning valuable basic job-readiness skills. When programs are well designed, they incorporate youth development principles, match students to opportunities that meet their expectations, tailor strategies to the skills and level of job readiness of the young person, and provide both skill instruction and social/emotional support through mentoring and supervision.[9] These subsidized work opportunities often have a community service element and thereby contribute to local neighborhood improvements as well.

Lesson 3: Funders Must Invest in Building the Capacity of Workforce Providers

Operating quality workforce programs requires capacity in the field to implement. CEO programs utilize competitive requests for proposals (RFPs) to select providers that have experience with the target population or sector and demonstrate an experienced and well-qualified staff. Skilled providers are necessary to run a robust program, particularly when they are being asked to implement a specific program model that is new for their organization or represents a change in their historical way of operating. While some providers are able to continuously adapt and develop locally tailored strategies, many require the help of specialists to implement a well-delivered program. This often requires workforce funders to support technical assistance that builds needed skills to help nonprofits launch and operate new service strategies. CEO has supported the work of several experts in providing technical assistance to community groups.

Lesson 4: Performance Management and Evaluation Are Key from the Start

Low-wage workers deserve quality programs, and funders want to ensure they are getting robust outcomes for their investments. While a focus on outcomes and evaluation has grown tremendously in the workforce field broadly since CEO's creation in 2006, there is still a lack of clear and consistent focus on measuring results. While strong providers have systems in place to regularly collect data, measure progress against targets, and review data regularly to inform programmatic changes, many organizations need support in managing their data, learning from them, and using them to make programmatic changes effectively. Agencies need a functional management information system that can produce dashboards to help program staff see program data in real time, and all staff need training in data entry and metric definitions. The Benchmarking Project can provide a valuable resource for program managers in interpreting performance by showing how completion, placement, and retention measures stack up to similar workforce programs around the nation.[10] Federal agencies also provide valuable performance management resources online, such as the U.S. Department of Labor's Employment and Training Administration online training and tutorials for frontline staff, and the Department of Health and Human Services' Results Oriented Management and Accountability framework.[11]

Some additional key lessons in performance management of workforce programs include the following:

- Assessing program performance must factor in the job readiness and barriers of the target population, and how long the program has been operating. While funders are tempted to compare programs to each other, some populations need more assistance, time, and resources to move into self-sufficiency. In weighing program performance, CEO takes into consideration the context of the population served (e.g., low-literacy young adults and criminal justice system involvement), the types and intensity of services provided, how long the program has been operating, and the size of the budget. Evaluations often conduct regression analyses using individual-level data to further illustrate how work history, demographics, and other individual-level characteristics shape how a program impacts a given group of participants.
- Targets need to be revisited periodically with partners to ensure they are in line with the level of investment, the past performance of the program, the context of what is happening in the labor market, and other factors.
- Numbers alone do not tell the full story; performance monitoring and improvement requires both qualitative and quantitative information. CEO collects both narrative and data reports, conducts site visits, holds meetings with agency partners, and reviews budgets. Client profiles, case studies, and qualitative evaluations can provide valuable insights into how programs work and communicate impacts to the public in a way that resonates.
- Having evaluation partners with an expertise in particular methodologies and issue areas helps ensure the findings will be relevant. Not every program needs a random assignment study, and the size of the investment and the existing knowledge base in the field are key factors. In addition, the timing of evaluations is an important consideration, and programs should be mature before investing in evaluation. Rather than only conducting single evaluations, CEO often conducts multiple evaluations of a program, each building on the previous study's learnings. For example, the Young Adult Literacy program's first evaluation tested the impact of adding paid internships to the program model that delivered literacy, numeracy, and support services. Based on findings showing increased attendance and retention at literacy

sites that provided internships, paid internships were added to the model at all sites. A second evaluation of the program looked at longer-term reading and math gains of participants, and most recently, a third evaluation provided a qualitative study of high-performing sites to identify best practices.[12]

- Program participants need information about available training options and their value, and more work needs to be done in this arena. CEO is committed to sharing data about programs, and its Web site shows high-level aggregate outcomes annually. One of the center's early initiatives in partnership with SBS was to create the New York City Training Guide to help consumers find the best local training program.[13] CEO also supported an interagency public information campaign to educate consumers about for-profit job training schools/colleges. The effort highlighted the cautions needed with proprietary and for-profit institutions and encouraged consumers to research programs, to use free or low-cost educational options, to be cautious about taking on excessive debt, and to report negative experiences. Components included online resources, connections to free financial counseling, free review of loan applications by volunteers, and intake of complaints.[14]

Lesson 5: Innovation Requires Flexible Funding

Flexible City and private funds have enabled CEO to quickly pilot innovative approaches and allowed city agencies to try new strategies without threatening their ability to meet their outcomes for WIA or other existing funding streams. Once programs demonstrate success, agency partners have been able to dedicate federal grants funds to support them, as with the sector-focused career centers and the Customized Training program. Given ongoing threats to federal funding streams, this can be a challenging path to sustainability without continued local and philanthropic support.

Although the strategies above contribute to a robust system to help low-wage workers advance, workforce development alone cannot address the needs of all low-wage workers. CEO has funded strategies such as expanding and promoting uptake of the EITC and supporting a local child care tax credit as ways to lift the floor and enhance the incomes of low-wage workers. As an example, the center worked with the city's Department of Finance to mail prepopulated amended tax returns to New Yorkers who potentially qualified for the EITC but had not filed for it (a strategy that has since been replicated in other states). In tax year 2009, this initiative helped over 6,239 households receive the EITC that would not have otherwise, cumulatively receiving $6.09 million. Recently, New York City passed expansions of paid sick leave policies and launched a universal prekindergarten expansion. Furthering policies such as these is a vital part of the strategy to support the working poor and address long-term mobility.

There is significant work still to be done. With limited public funding, even programs that demonstrate positive impacts can be challenging to maintain and expand. As a promising development, the Obama administration increased its emphasis on encouraging federal agencies to direct funding toward evidence-based programs (Executive Office of the President 2013). At the local level there is also a need to continue working to bring successful pilot programs to scale by integrating them (wholly or in part) into the larger workforce delivery system that is shaped by federal, state, and city funds, as well as private philanthropy. Some CEO pilot programs have achieved this; for example, a program that connected the One-Stops to low-income clients at community nonprofits was successful, and SBS subsequently integrated it fully into the standard operating practices of all of New York City's WIA-funded career centers (see Henderson, MacAllum, and Karakus [2010]).

With so many workforce initiatives supported through diverse funding streams, it remains a challenge to create a system where unemployed and underemployed can easily access the program that best meets their particular needs. Building stronger connections between education and workforce systems can also further the goal of longer-term engagements that help people advance along their career pathway over time.

CONCLUSION

Government is increasingly outcome driven and focused on investing in evidence-based strategies. CEO's leadership in these realms was recognized in 2011 with Harvard's Innovation in Government award (see Ash Center for Democratic Governance and Innovation [2012]). While workforce development initiatives are an important component of a strategy to help low-wage workers, they are a piece of a larger strategy to promote economic opportunity. CEO has had success, for example, in increasing graduation from community college through its Accelerated Study in Associates Program (ASAP) program, which more than doubled the graduation rate while saving the system much needed funds (Levin and Garcia 2013). Recognizing the fact that many people work full time but still remain in poverty, CEO is testing an expansion of the EITC for single tax filers without children in an effort to see if a more generous benefit will help increase incomes and draw more men into the labor market.

Incorporating lessons from successful pilots can improve workforce systems and reach scale to achieve greater impact. By sharing what has worked and what has not, local government has the potential to affect public policy and help increase economic opportunity.

Notes

The views expressed in this case study solely reflect the opinions of the author and do not represent any other person or entity. The author extends his gratitude to his colleagues from the Center for Economic Opportunity who provided feedback on this chapter, and especially Courtney Jones for her outstanding research assistance.

1. Based on 2012 data. CEO developed a more accurate measure that takes into account the local cost of living as well as the impact of government benefits for low-income populations. See nyc.gov/ceo for more information.
2. For an overview of New York City's workforce system, see City of New York (2011).
3. See http://www.nyc.gov/ceo (accessed January 20, 2015).
4. Evaluation reports are available at http://www.nyc.gov/html/ceo/html/data/reports.shtml (accessed January 20, 2015).
5. The Social Innovation Fund is a public/private funding initiative of the federal Corporation for National and Community Service to identify and expand promising programs.
6. The Young Adult Internship Program helps out-of-school and out-of-work young adults obtain needed skills through a combination of educational workshops, counseling, short-term paid internships, and postinternship support to obtain further education, advanced training, or employment.
7. The Young Adult Literacy Program provides literacy and numeracy services,

social support, and paid internship opportunities to 16–24-year-olds who read below the 8th grade level.

8. CEO programs that have provided subsidized job opportunities for young adults include Project Rise, Scholars at Work, Young Adult Internship Program, Young Adult Literacy Program, Work Progress Program, and NYC Justice Corps. See nyc.gov/ceo for more details.
9. A youth development approach is one that incorporates youth leadership into programming, sets a culture of high expectations, ensures young people are matched with caring adults who provide individualized attention, focuses on young adults' assets rather than deficits, provides support to young people to overcome barriers and develop positive coping skills, emphasizes key academic and/or occupational skills, and supports community connections to additional programs and services.
10. See http://www.skilledwork.org/benchmarking-project-workforce-benchmarking-network for more information the Benchmarking Project (accessed November 18, 2014).
11. See the USDOL ETA Web site: http://www.doleta.gov/performance/training tutorials/PEP.cfm; see also the HHS ROMA training and technical resources Web site: http://www.roma1.org/557/interior.html (accessed November 18, 2014).
12. All evaluation reports are available on CEO's Web site at www.nyc.gov/ceo (accessed November 18, 2014).
13. See www.nyc.gov/trainingguide (accessed November 18, 2014).
14. See http://www.nyc.gov/html/ohcd/html/policy/know_before_you_enroll.shtml for more information (accessed November 18, 2014).

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Scorecards for Postsecondary Education and Training Programs

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Individuals, government, and businesses make significant investments in postsecondary training programs that are designed to prepare adults for employment or careers. Despite the magnitude of these investments, there is often limited information on the effectiveness of these programs, leaving most students to choose a training program and a training provider based on anecdotal information, word of mouth recommendations, and marketing materials from training providers. As a result, the market for postsecondary training functions inefficiently.

While the Workforce Investment Act of 1998 (WIA) attempted to address this inefficiency by requiring states to develop a consumer report card for training programs and an eligible training provider list (ETPL) based on performance data, a significant majority of states failed to implement these requirements for a wide variety of reasons (Van Horn and Fichtner 2011). However, a small number of states, most notably New Jersey, Washington, and Texas, have more than a decade of experience of successfully implementing these systems. This case study profiles New Jersey's online consumer report card for training programs. The experience and lessons learned from New Jersey and other successful states can provide a roadmap for other states to follow.

DESCRIPTION AND IMPORTANCE OF POLICY PROBLEM

Almost four out of five jobs in the United States (78 percent) require some form of postsecondary education. Middle-skill jobs are those that require education and training beyond a high school diploma but less than a bachelor's degree. Educational attainment can serve as a proxy to define middle-skill occupations; however, analysis that takes into account education plus formal postsecondary training as well as significant on-the-job training estimates that half of the jobs in today's economy are middle-skill jobs (Achieve 2012). Middle-skill jobs are projected to increase at a rate faster than other types of jobs in the United States. According to the Bureau of Labor Statistics, jobs requiring more than a high school diploma but less than a bachelor's degree will increase 15.8 percent between 2012 and 2022, compared to just 10.8 percent for all occupations. Occupations requiring a bachelor's degree are expected to increase 12.2 percent, while those needing a high school diploma or less will increase just 9.1 percent.

Government programs, individuals, and businesses spend significant amounts each year to prepare individuals for these middle-skill jobs. The federal government spends over $18 billion on the administration of close to 50 employment and training programs (U.S. Government Accountability Office 2011). Much of these investments are spent on short- to mid-term, postsecondary occupational training. In addition, a recent survey estimated that U.S. companies spend more than $164 billion annually on training and development, including both internal expenses and tuition reimbursement programs (American Society for Training and Development 2013). These investments estimate the expenditure by government and private businesses; however, additional significant monies are spent by individuals to improve their preparation for employment.

A wide variety of entities, from for-profit proprietary schools to nonprofit organizations and public institutions of higher education (including community colleges), provide this training, marketing their services to individuals, managers of government programs, and businesses. In addition, there are many different types of training programs offered. These programs vary by length, by cost, by whether they offer a credential, or by whether they offer college credit. Within this context, individuals must first choose which program is the right one for them to pursue, and then they must choose which provider is best able to provide that training.

NATIONAL CONTEXT

WIA required states to create consumer report cards (CRCs) in order to foster informed consumer choice in the public workforce system. It also required that states use performance data from all students in a program, regardless of the funding source, to certify those training providers and programs that would be eligible to receive funding. In addition, WIA required states to maintain an ETPL of these providers and programs. Many states expressed concerns that the CRC and ETPL requirements were too onerous to training providers and would thus limit the number of programs and providers available to WIA customers. As a result of these and other concerns, 39 states received waivers from the U.S. Department of Labor to ease implementation by extending the period of initial eligibility of providers on their lists.

In recent years there has been increasing attention to data on outcomes for education and training programs. In early 2013, the Obama administration introduced a College Scorecard, which includes data on college costs, student loans, default rates, and graduation rates. There are plans for the site to also include employment outcomes of graduates. At the state level, a limited number currently provide information online.

The federal government has increasingly recognized the importance of scorecards by funding states to develop data systems to support them. Since 2006, the U.S. Department of Education's State Longitudinal Data System Grant Program has supported state efforts to develop K–12 and P–20W (early childhood through the workforce) data systems. The U.S. Department of Labor's Workforce Data Quality Initiative provides support to states to integrate workforce development and employment data with K–12 and postsecondary education data. Both efforts are designed, in part, to help states develop employment outcomes for education and training programs.

New Jersey Solution

This case study reviews the CRC used by the New Jersey Department of Labor and Workforce Development (NJLWD). The CRC, which has been provided as an online tool to job seekers and workforce development professionals for over 15 years, is a strategy that can increase the efficiency of the training provider market by providing consumers with information on program quality. The experience of New Jersey and of other states such as Washington and Texas can provide important lessons for states as they implement WIOA and postsecondary training scorecards.

New Jersey's CRC for training providers (www.NJTopps.org) is an online searchable directory of more than 1,000 training providers offering over 9,000 programs. The site is an important tool included on the state's workforce services portal, known as Jobs4Jersey.com. The site is also promoted through NJLWD's Web site and through the New Jersey Career Assistance Navigator (NJCAN.org) Web site, a career awareness resource for high school students. During the 12 months from June 2013 through July 2014, the NJTopps site received over 63,000 hits.

NJTopps.org allows individuals to search for training programs using a variety of search terms, including program of study, occupation, and location. The result of the search is a list of the training programs that meet the user's needs. For each training program, users can view information on the provider, including a description, costs, and information on program performance. The provider and program descriptive information is developed by the providers themselves and is reviewed by state staff before it is posted online.

Program performance information includes the employment rate, retention rate, and average earnings of training programs. Labor market outcomes are shown at the program level, the cluster level (grouping together similar programs offered by the same provider), and the provider level. Data are reported for the first, fourth, and eighth quarters after program completion.

While most states found it difficult to implement these systems, New Jersey was able to create a successful system by reducing the burden on training providers while increasing the incentives for their participation. That approach has ensured that students have a broad array of choices of training programs and providers through the ETPL. Additionally, the approach has shown that the CRC is a valuable resource to a wide range of individuals and companies as they choose a training provider and program.

Broad Scope of the System

Unlike many other states, the New Jersey ETPL is not solely used by WIA programs. State legislation passed in 2006 requires all training providers who receive federal *or* state training funds to be listed on the state ETPL. By applying the ETPL requirements to more than 50 separate workforce development programs, the law creates a stronger incentive for training providers to participate in the system.

The state law also requires NJLWD to develop a CRC to disseminate information on the labor market outcomes of all students who participated in the training program, and not just of those students who received government assistance. As a result, any individual or company interested in selecting a training program or provider, even those who plan to use their own resources to pay for that training, can find value in the NJTopps Web site. This broader audience of potential users of the CRC further increases the incentive for providers to be listed on the ETPL.

Reliance on Existing Student Record Data

The New Jersey system relies heavily on existing data sets to calculate employment outcomes for participants. This has two benefits: it reduces the data collection burden on training providers, and it helps to ensure greater data quality.

Instead of conducting expensive surveys of their program participants, training providers report student records to NJLWD, using NJTopps.org to securely upload data files on a quarterly basis. Those providers who report their student records to other government agencies are not required to report their student records to NJLWD. The department, through data sharing agreements with other state agencies, is able to obtain data on students who attend institutions of higher education or on adults who attend programs funded by the Carl D. Perkins Act.

New Jersey, through a partnership with Rutgers University's Heldrich Center for Workforce Development, combines all three sources of student records with administrative data from the state's workforce development programs to create a comprehensive file of a significant percentage of all the students who have attended postsecondary education and training programs in the state.

To obtain employment outcomes for the programs on the ETPL, Rutgers University matches the student records with New Jersey Unemployment Insurance (UI) wage records and with wage records from other states through the Wage Record Interchange System. These UI wage records are collected by all states during the collection of UI payroll taxes and include wages earned in a particular quarter for individuals and information on their employers. As a result, UI wage records provide a significant record of the employment and wage experiences of the vast majority of individuals working in the state.

By combining these data sets, New Jersey can efficiently calculate employment and earnings outcomes for large numbers of programs in a standardized manner. New Jersey continues to expand and refine the use of these various data sets to calculate employment outcomes for training providers. In 2012, NJLWD was awarded a three-year grant from the U.S. Department of Labor as part of the Workforce Data Quality Initiative program. The scope of work builds on the partially developed longitudinal data system (the ETPL) by incorporating data from additional LWD administrative data systems, including UI, vocational rehabilitation, and more comprehensive adult basic education data. Links are also made to postsecondary programs and are planned for pre-K–12 public education. Three additional years of funding were awarded in 2014, which supports the addition of more data from partner agencies and expands research efforts in order to help job seekers make better training choices, program staff apply more effective workforce strategies, and policymakers support the most effective programs.

Reducing the Burden on Training Providers

To further lessen the burden on training providers, providers can use the NJTopps Web site to apply to be on the ETPL. Department staff review all applications online and can approve the applications online as well. They compare the information submitted online with information provided to the state through the licensing process for training providers, allowing for an important cross-check of the data.

Use of the System

New Jersey workforce development partners, specifically, staff at local Workforce Investment Boards and American Job Centers, use

NJTopps.org to manage and monitor training programs and use the site to help job seekers make more informed decisions on training providers. Some local Workforce Investment Boards have, at different points during the system's history, required funded providers to meet specific performance thresholds. For example, one area currently uses a 65 percent placement rate requirement, and when clients want to use providers with a lower rate, the request is given additional review by staff.

Finally, the inclusion of the NJTopps Web site on the Jobs4Jersey portal helps to expand the use of the CRC beyond those students served by the American Job Centers. In turn, the Jobs4Jersey Web site is promoted through marketing and public information efforts that have included advertising on transit buses, partnerships with community colleges and libraries, and partnerships with the state's talent networks.

FUTURE DIRECTIONS

New Jersey continues to implement improvements to the NJTopps .org system to ensure better data quality and to expand the use of the Web site. New Jersey is preparing to implement a state law that requires all private and nonprofit career schools to be included on the CRC as a condition of licensing. In addition, in early 2014, legislation was signed that expands the required data to be displayed on the CRC, including licensing and examination information, which will include information on the number of students who obtain industry recognized credentials.

CONCLUSIONS AND NATIONAL IMPLICATIONS

The Workforce Innovation and Opportunity Act (WIOA), signed into law in July 2014, continues many of the CRC and ETPL provisions of WIA, thus signaling to states that they must find new solutions to the challenges they faced in implementing WIA.

The successful efforts in New Jersey, Texas, Washington, and a handful of other states have shown that states can effectively implement CRC systems to provide individuals and employers with valuable information that can be used to choose a training program and a training provider. Such systems have the potential to create a more efficient market for postsecondary training by helping consumers to make more informed training decisions and to take into account the labor market experiences of former students when they make those decisions. Given the significant investment in money and time that students make in training, this information can be particularly valuable to students.

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