A Frontline Decision Support System for WIA One-Stop Centers

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The Workforce Investment Act (WIA) of 1998 emphasizes the integration and coordination of employment services. Central to achieving this aim is the federal requirement that local areas receiving WIA funding must establish one-stop centers, where providers of various employment services within a local labor market are assembled in one location. A major challenge facing staff in these centers is the expected large volume of customers resulting from relaxed program eligibility rules. Nonetheless, resources for assessment and counseling are limited, and front-line staff have few tools to help them make referral decisions.

The U.S. Department of Labor is working with the W.E. Upjohn Institute for Employment Research to develop and pilot test a Frontline Decision Support System (FDSS) for workforce development staff in one-stop centers. The goal of FDSS is to assist staff in quickly assessing and properly targeting services to customers. FDSS tools are being tested in new WIA operating systems in the states of Georgia and Washington. This paper reports on the strategy, tools, and implementation efforts in the pilot states. FDSS is comprised of two main modules: (1) systematic job search, and (2) service referral.

The systematic job search module is a means to undertake a structured search of vacancy listings. The module informs job seekers about their prospects for returning to a job like their prior one, provides a realistic assessment of likely reemployment earnings, and identifies occupations related to the prior one. The first component is called the industry transition component. It provides an estimate of the likelihood that a customer can find a job in their prior industry. The second component provides a realistic assessment of likely reemployment compensation levels. This feature relies on an earnings algorithm which is a statistical model based on personal characteristics, work history, prior earnings, and educational attainment to predict earnings upon reemployment. The third component is the related-occupations algorithm. The algorithm offers individuals who have exhausted job prospects within their prior occupation a list of other occupations that are similar to their prior occupation.

The second module of FDSS is the service referral algorithm. The primary purpose is to identify the sequence of activities that most often lead to successful employment. The service referral module uses information about the characteristics and outcomes of individuals who have recently participated in and completed core, intensive, and training services. This information is used to estimate the statistical relationships between personal attributes and outcomes. This algorithm has two basic components. The first is an estimate of a person's employability, or likelihood of finding a job. The second component is a delineation of the paths, or sequential combinations of services, that lead to successful outcomes. By conditioning these paths on the employability of a specific customer, the algorithm can offer estimates of the effectiveness of various programs for individuals with specific measurable characteristics.

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Background

The Workforce Investment Act (WIA) of 1998 emphasizes the integration and coordination of employment services. Central to achieving this aim is the federal requirement that local areas receiving WIA funding must establish one-stop centers, where providers of various employment services within a local labor market are assembled in one location. This arrangement is expected to coordinate and streamline the delivery of employment-related programs and to meet the needs of both job seekers and employers more effectively than did the previous arrangement.

Successful implementation of the one-stop system requires new management tools and techniques to help staff meet the challenges presented by the one-stop environment. A major challenge is the large volume of customers expected to use the system. Increased use of services is expected because of a reduced emphasis on program eligibility as a condition for participation in the workforce investment system. Nonetheless, resources for comprehensive assessment and counseling are limited, and front-line staff has few tools with which to help them make decisions.

A prime challenge for front-line staff is to determine which set of services best meets the needs of customers who enter a one-stop center, and to do this in a consistent, rational, and effective manner. However, not all one-stop center staff may have sufficient experience to make informed decisions for clients participating in the wide variety of programs offered at one-stop centers. The coordination of services under the new one-stop arrangement now requires staff to serve customers with various backgrounds, whereas prior to the creation of one-stop centers, staff typically concentrated in a single program area and saw clients with similar barriers. An additional complication is the emphasis that WIA places on performance outcomes and accountability. WIA requires that program success be measured by employment, earnings, job retention, and knowledge or skill attainment.

The Frontline Decision Support System (FDSS) is a set of administrative tools that is being developed to help front-line staff successfully perform their duties within one-stop centers. The goal of these tools is to assist staff in quickly assessing the needs of customers and in referring customers to services that best meet their needs. FDSS includes new tools to: (1) help customers conduct a systematic search for jobs that offer the best match and to set a realistic wage goal, and (2) assist staff in determining which one-stop center services are likely to be effective in meeting the needs of specific customers in becoming employed.

The W.E. Upjohn Institute for Employment Research is working to design, develop, test and implement a FDSS in pilot sites within the states of Georgia and Washington. These states were chosen because they offer an opportunity to demonstrate the adaptability and capability of the FDSS within different one-stop center operating environments. Recognizing that the computer operating systems for the one-stop centers vary among states, FDSS is being designed so that states can easily integrate the decision tools into their specific platforms. The FDSS tools are designed to be used within the data retrieval and display systems being implemented by the states for their one-stop centers. These tools will be flexible so as to permit interface with a variety of operating systems for one-stop centers.

The design and implementation of FDSS is a cooperative effort of the U.S. Department of Labor (USDOL), the state employment agencies of Georgia and Washington, and the W.E. Upjohn Institute. After testing the system at sites in these states, USDOL intends to offer FDSS tools to other interested states. The W.E. Upjohn Institute is in a unique position to design, develop, test, and implement a FDSS. The Institute not only conducts employment-related research but also administers the state and federal employment programs that are the responsibility of the local Workforce Investment Board. The Institute has served as the administrator of federal and state employment-related programs for the Kalamazoo area since the early 1970s. During that period, the Institute has operated programs under the Comprehensive Employment and Training Act (CETA), the Job Training Partnership Act (JTPA), and currently the Workforce Investment Act (WIA). With research and operations carried out within the same organization, the Institute is uniquely positioned to coordinate the analytical and administrative tasks required to develop and test FDSS within the one-stop centers.

The purpose of this paper is to present an overview of FDSS and to give examples of the analysis underlying some of the decision algorithms that are the backbone of the FDSS tools. In the next section, we summarize the overall concept of FDSS and provide an outline of the typical client flow through the one-stop centers. We then proceed to describe examples of the statistical models that are used in the job search component of FDSS. These models include estimates of the likelihood of finding a job in the industry in which the worker was employed prior to displacement and estimates of the earnings that a displaced worker might expect when looking for reemployment. We next outline the algorithm that identifies occupations that are related to a worker's occupation held prior to displacement. The purpose of this algorithm is to provide workers who have been frustrated by their initial job search efforts with a list of occupations that have skills and attributes similar to the ones embodied in jobs held prior to displacement. This list of related occupations allows a worker to conduct a more systematic job search effort. Finally, we describe the features of the second FDSS component, the service referral algorithm, which is currently under development.

Front Line Decision Support within One-Stop Centers

FDSS provides one-stop center staff with client information and assessment tools that can be used in helping clients conduct a systemic job search and in determining the set of employment services that should work best for specific clients. To understand the role of FDSS, it is first necessary to provide a brief overview of one-stop centers, the services they provide, and the way in which staff interact with customers. The operation of one-stop centers varies across states, and even across local areas within states. Consequently, we can provide only a stylized description of one-stop centers, which however suffices for our purpose of describing how FDSS can be integrated into the general approach of these centers.

As mandated by WIA, o ne-stop centers provide a central physical location for the provision of services offered by federal and state employment programs. WIA requires that the following programs be included: Unemployment Insurance, Employment Service, Dislocated Worker and Youth Training, Welfare-to-Work, Veterans Employment and Training Programs, Adult Education, Postsecondary Vocational Education, Vocational Rehabilitation, Title V of the Older Americans Act, and Trade Adjustment Assistance. Other programs may also be included under the one-stop center's umbrella of services. One-stop centers are designed to serve customers within local Workforce Investment Areas, which usually encompass the population of one or more counties within a state. Workforce Investment Areas with large populations or which span a large geographical area may choose to establish several one-stop centers. WIA required that each state develop a system of one-stop centers that would be fully operational by July 2000. Most states met this target date.

Services provided by the one-stop centers are divided into three levels: core, intensive, and training. Services within each level are characterized by the amount of staff involvement and the extent to which customers can access the service independently. Core services typically have the broadest access and the least staff involvement of the three categories. Many core services are accessible on a self-serve basis. All adults and dislocated workers can access core services, which include assessment interviews, resume workshops, labor market information, and interviews for referral to other services.

Intensive services, the next level of services within a one-stop center, require a greater level of staff involvement and access is more restricted than for core services. Services within the intensive category include individual and group counseling, case management, aptitude and skill proficiency testing, job finding clubs, creation of a job search plan, and career planning. Training services, the third and final level of services offered by one-stop centers, use staff most intensively and are open to customers only through referrals. One-stop centers typically contract with organizations outside the centers to provide these services. Included in this set of services is adult basic skills education, on-the-job-training (OJT), work experience, and occupational skills training.

Several challenges must be surmounted for successful implementation of one-stop centers. The first is the large volume of customers expected to use the centers. Nationally, nearly 50 million people are expected to use the one-stop centers each year. Center staff will be faced with serving more people than under previous organizational arrangements. The move toward integrating services raises another challenge, staff will be asked to serve clients who may have unfamiliar backgrounds and needs. For instance, a staff person who worked extensively with dislocated workers under JTPA may now be asked to work with welfare recipients as well. Job search techniques and services that are appropriate for dislocated workers may not be as effective for welfare recipients. The lack of prior experience counseling welfare recipients, may hinder staff effectiveness. WIA does not provide additional resources for staffing or significant cross training.

Another challenge for operators of one-stop centers is to refer customers to services in the most effective matter. The efficiency and effectiveness of a center's operations are driven by the difference in cost of providing the three levels of services. As shown in Figure 1, the cost of services increases dramatically and the anticipated number of participants falls as one moves from core services to training services. Therefore, the ability to identify the needs of individuals and to refer them to the appropriate service as early as possible in the process will determine the cost effectiveness of the one-stop centers. FDSS is designed to address the need for more informed decision making and the strategic referral of services.

FDSS includes two basic modules or sets of tools. Figure 2 shows how the two modules fit into the operation of the one-stop center. The first is the systematic search module. This set of tools provides clients with customized information about several aspects of the job search process, with the purpose of assisting them in conducting a more systematic search. Initial job search activities are concentrated in the core services, and consequently this is where the systematic search module will be incorporated. A large proportion of individuals who come to the one-stop centers are looking for job search assistance in the form of labor market information, assistance with preparing resumes, and an initial understanding of the likelihood of finding a job and what wage or salary level to expect. The first prototype FDSS includes algorithms for five programs: employment service, unemployment insurance, skill training, welfare-to-work, and veterans employment and training programs. To illustrate how these algorithms are constructed, this paper focuses on the tools developed for displaced workers.

The systematic search module includes three basic components to help job seekers become better informed about their job prospects and expected earnings. The first component, referred to as the industry transition component, estimates the likelihood that a customer can find a job in the industry in which they were previously employed. Obviously, this component is designed primarily to inform displaced workers about their job prospects. Research has shown that displaced workers tend to wait for jobs to open up in the industries in which they worked before displacement. Workers prefer to return to jobs with which they are familiar, and typically salaries are higher for those who stay in the same industry. However, in many cases, a worker was displaced because of general downsizing in that industry, which reduces the chances that a job in the same industry will become available. Waiting for such an event to occur increases the amount of UI benefits the person will draw and reduces the likelihood of finding employment, even in another industry. The purpose of the systematic search module of FDSS is to help inform job seekers as to their prospects for finding jobs and to provide realistic assessments of likely compensation levels.

The need for a realistic assessment of expected reemployment earnings leads to the second component of the systematic search module–the earnings algorithm. The earnings algorithm is a statistical model that uses personal characteristics, work history, prior earnings, and educational attainment to predict earnings upon reemployment.

The third component is the related-occupations algorithm. The algorithm offers individuals who have exhausted their likely job prospects within their prior occupation with a list of other occupations that are similar to their prior occupation. We offer different algorithms based on available data and show how they differ. More detailed descriptions of these algorithms are provided below.

The second module of FDSS is the service referral algorithm. As mentioned in the overview of one-stop centers, a critical element for successful implementation of one-stop centers is staff ability to identify the needs of customers and to refer them expeditiously to services that best address their barriers to employment. Compounding this challenge is the possible lack of staff experience in serving a wide range of customers. The purpose of the FDSS service referral module is to compile and process information about the effectiveness of various alternative services in a way that better informs staff for referring customers to services. The service referral module uses information about the characteristics and outcomes of individuals who have recently participated in and completed services offered by one-stop centers. This information is used to estimate statistical relationships between personal attributes and outcomes. It should be emphasized that this algorithm does not supplant staff referral decisions. Rather, it provides a means for staff to make better informed decisions.

The primary purpose of the service referral algorithm is to identify the sequence of activities that will most likely to employment. Of course, the effectiveness of alternative service paths for each customer depends upon their initial employability. Therefore, this algorithm has two basic components. The first is an estimate of a person's employability, or likelihood of finding a job. The flip side of this estimate is an initial identification of an individual's barriers to employment. The second component is a delineation of the paths, or sequential combinations of services, that lead to successful outcomes. By conditioning these paths on the employability of a specific customer, the algorithm can rank the likely effectiveness of various programs for individuals having specific observable characteristics.

Tools for the Systematic Search Algorithm

In this section, we discuss three tools related to the systematic search algorithm: (1) the probability of return to the prior industry, (2) likely reemployment earnings, and (3) three alternative approaches to identifying occupations related to a prior one. For the first two tools, examples are provided for both Georgia and Washington using data on UI beneficiaries. The Georgia examples are for Metropolitan Atlanta and the Washington examples are for the South Puget Sound area. The third tool, identification of related occupations, is based on three sources: analyst ratings, national survey data, and Georgia Employment Service job placement data.

Return to Industry

A great majority of one-stop customers will switch employers. Prior research suggests that earnings losses will be minimized if the new job is in the same industry and occupation. As suggested by Becker's (1964) theory of human capital formation, the quickest way to return to the prior lifetime earnings path is to resume employment and begin building firm-specific human capital in a new job. To help clients more realistically assess job prospects, FDSS provides an estimate of the probability of returning to employment in the prior industry.

Reliable data are available from UI wage records in both Georgia and Washington to identify the industry in which the person was employed before and after displacement. Unfortunately similar information is not available for an individual's occupation. Table 1 shows an industry transition matrix for UI clients in Metropolitan Atlanta. Industries are separated into nine categories with the prior industry category in the left column and the reemployment industry along the top row. In each row the largest element is on the diagonal of the matrix, indicating that the largest share of industry UI recipients return to work in the same industry. These aggregate average return probabilities range from 20.8 percent in agriculture, forestry and fishery to 73.3 percent in mining and construction.

Table 2 summarizes the percentage change in quarterly earnings for these industry employment changes in the Atlanta metropolitan area. The diagonal of Table 2 is positive for all industries except public administration, indicating that those who manage to be reemployed in their prior industry have earnings gains despite changing jobs. Similar patterns can be seen for South Puget Sound, Washington in Tables 3 and 4. However, a larger share of UI claimants managed to be reemployed in their prior industry and earnings growth was somewhat stronger in that region of Washington than in metropolitan Atlanta.

To provide individual estimates of the probability of being reemployed in the prior industry, we estimated logit models for each industry transition.[1] The logit model relates whether

[1] Logit models were widely used by states as a basis for Worker Profiling and Reemployment Services (WPRS) assignment rules. Eberts and O'Leary (1996) provide an example from Michigan.

or not an individual stays in the same industry to a set of explanatory variables including prior earnings, age, educational attainment, the quarter of the year in which UI was applied for, and indicators for prior occupation.[2] The logit model also included variables that indicated whether an individual was a member of the following population groups: youth, veterans, currently employed, receiving public welfare assistance, and dislocated workers.[3] For Washington we were also able to include an indicator of union membership. Because of eligibility conditions, UI beneficiaries include very few people currently enrolled in school, so that category is not included.

Tables 5 and 6 provide examples of earnings models estimated on UI recipients in Atlanta and South Puget Sound whose prior job was in the manufacturing industry. Comparing parameter estimates across the two regions in the different states shows a large degree of consistency. In all cases where parameters on similar variables were estimated with adequate statistical precision, the estimates are of the same sign and similar magnitude. As an additional way of comparing the models, Tables 5 and 6 each consider the same three examples for evaluating the probability of returning to work in the manufacturing industry. Example 1 is a person aged 35, with a high school education, who earned $30,000 per year in a clerical/sales occupation, and applied for UI in the second calendar quarter.[4] The probability of return to the

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[2]Age, gender, and race were prohibited variables in WPRS models. However, unlike WPRS the FDSS system does not set criteria for program eligibility. The graphical user interface for FDSS computer screens in one stop centers will not display age, gender and race as variables on which "what if" scenarios can be examined. These variables were included because statistical tests indicated that excluding these variables would introduce an omitted variables bias in estimation of other model parameters, following the work of Kletzer (1993) and others.

[3]These categories are defined by Employment Service (ES) practice. The dislocated worker definition is consistent with that in the Economic Dislocation and Worker Adjustment Assistance Act (EDWAA) of 1988. The EDWAA definition includes those with significant prior job attachment who have lost their job and have little prospect of returning to it or to another job in a similar occupation and industry.

[4]Note that the earnings variables in the models are quarterly figures, not annual figures.

same industry was estimated to be 0.294 in Georgia and 0.346 in Washington. The second example shows the Washington model to be much more sensitive to the prior earnings variable. Doubling prior earnings from $30,000 to $60,000 in South Puget Sound raised the chance of return to manufacturing to 0.532, while raising it to only 0.327 in the Atlanta area. The third example illustrates the same tendency for a lower prior annual earnings of $10,000 with the probability in Washington falling to 0.114 and that in Georgia falling to 0.172.

Reemployment Earnings

The WIA legislation permits intensive services to include "evaluation to identify employment barriers and appropriate employment goals" and also "the development of an individual employment plan, to identify appropriate employment goals, appropriate achievement, and appropriate combinations of services for the participant to achieve their employment goals (emphasis added)."[5] An underlying principle of WIA is that the best training is a job. Moderating wage objectives in order to win a new job may be the quickest way to return to the prior earnings path. This establishes a need for a system like FDSS and requires that outcomes be judged relative to individual targets. FDSS provides an algorithm to estimate the expected reemployment earnings for each job seeker. By providing the job seeker with a realistic assessment of earnings prospects, he or she can conduct a more informed job search that can hasten the employment process.

Displaced workers and those who have had little attachment to the workplace, such as welfare recipients, may have little understanding of the earnings level that they might expect to find in the local labor market given their skills and opportunities. Displaced workers, for example,

[5]Section 133(d)(3)(i) and (ii), Workforce Investment Act (WIA), Public Law 105-220–August 7, 1998.

may expect to receive comparable wages in their new jobs to those they held prior to being displaced. However, recent research has shown that the earnings can drop by as much as 25 percent for workers who have found jobs after being displaced. Most of the loss in earnings is due to loss in value of firm-specific skills (Jacobson, Lalonde, and Sullivan 1993). It is important to point out that the FDSS earnings assessment is only suggestive. Job seekers who find the recommended target to be out of line with their expectations may discuss their differences with a staff person in the one-stop center. The staff person may use several means in addition to FDSS to establish a realistic earnings target, including past studies and current labor market conditions.

Quartile regression models are used to estimate earnings. The upper and lower bounds on the earnings range are set at the 25^{th} and 75^{th} percentiles, so that one can think of this range as including earnings of half the people with similar measured characteristics. The model relates quarterly earnings to personal characteristics and labor market conditions. Many of these factors may be similar to those used by employment counselors to match job seekers to openings. The model assesses those factors in a systematic and consistent way, so that customers with similar needs and characteristics are treated similarly.

The earnings models were developed using quarterly earnings data from UI wage records, which are the most reliable source of earnings data. However, workers do not usually measure their compensation in terms of quarterly earnings. Rather, earnings are typically expressed as hourly, weekly, monthly, and yearly rates of compensation. Converting the quarterly earnings to any of these other units is problematic, since wage records do not indicate the number of hours worked or even the number of weeks worked during a quarter. By using the maximum earnings in the year before and the year after receiving reemployment services, we anticipate that quarterly earnings will reflect full-time hours. Conversion from quarterly earnings to hourly earnings can then be achieved by applying the usual hours of work observed in each occupation and industry group using national survey data.[6]

For consistency of exposition, we report the results from the quartile regression models for the manufacturing sector in Metropolitan Atlanta and South Puget South, the same regions and industry as used in the "return-to-prior-industry" models discussed above. As shown in Tables 7 and 8, the model includes variables typically used in earnings models, such as educational attainment, prior job tenure, occupation, and industry. Of course, the industry of reemployment is known only after a person finds a job. Since it is an endogenous variable, it would be appropriate to find an instrument for this variable, such as the industry transition regression described in the previous section. However, since our primary purpose is to construct a relatively simple model that offers the best prediction of future wages, we have not instrumented the variable. Instead, when predicting the earnings for individuals we substitute the prediction of the likelihood the person will find a job in the same industry as a predictor in the earnings equation. Earnings models for Georgia and Washington also include age and age squared to capture the earnings cycles over one's working life.

Georgia data permit the inclusion of additional explanatory variables measuring tenure on the previous job, possession of a driver's license, availability for rotating shifts, employer attachment, current school enrollment status, and an individual's self-reported reservation wage. Washington data contain an indicator of union membership. Both models include indicator

[6]Using data from the Current Population Survey for a comparable time period we computed a (9x9) industry-occupation matrix of average hours worked using one digit industry and occupation groups.

variables for population groups that are typically identified with the various programs offered by one-stop centers. These groups include youth, veterans, currently employed, receiving public welfare assistance, dislocated workers, and economically disadvantaged workers.

Results of the median regressions for the two models, as shown in tables 7 and 8, are broadly consistent with previous earnings research. In both models, prior earnings, education and age are positively correlated with future earnings, and occupation variables in prior employment are significant predictors of future earnings. In addition, returning to the industry of prior employment raises earnings by roughly 17 percent in both models and the coefficient estimates are highly statistically significant. Indicators for the various population groups are not statistically significant except for welfare recipients in Washington and economically disadvantaged and veterans in Georgia.

Coefficient estimates related to variables unique to each state add further insight into the determinants of a worker's compensation. For Georgia, results show that possession of a driver's license increases earnings. In addition, tenure on the previous job reduces earnings, which supports the results of WPRS models that detachment and subsequently loss of work experience reduces future earnings. On the other hand, those individuals with higher reservation wages receive higher future earnings, possible because they know of skills and other personal traits not measured in the data that make them attractive to employers. In the Washington model, union membership raises earnings by 9 percent.

The purpose of the earnings algorithm is to estimate an earnings range for each one-stop customer. To do this, the regression coefficients are multiplied by the individual's characteristics. Consider again the same three examples used above for evaluating the probability of returning to work in the manufacturing industry. Person 1 is 35 years old, has a high school education, earns $30,000 per year (or $7,500 per quarter) in a clerical/sales occupation, and applied for UI in the second calendar quarter. Median reemployment earnings for this individual in metropolitan Atlanta are predicted to be $6,728 per quarter with lower and upper bounds of $5,472 and $8,179. A person with the same characteristics but living in South Puget Sound area is expected to earn roughly the same amount--$7,164 per quarter with lower and upper bounds of $5,615 and $8,422. Consider person 2, who is identical to person 1, except that her prior earnings are doubled. This change has the effect of raising predicted median reemployment quarterly earnings in Metro Atlanta to $12,618 and in South Puget Sound to $12,394. Person 3 has characteristics similar to the first two, except that prior annual earnings are $10,000. For this example, predicted median reemployment quarterly earnings fall in Metro Atlanta to $3,387 and in South Puget Sound to $3,450.

Related Occupations

The FDSS algorithm identifying related occupations provides customers and front-line staff with a list of occupations that are related to the occupation that a worker most recently held. The purpose of the algorithm is to provide a customer who does not immediately find a suitable job match with job options in other occupations that require similar skills and aptitudes. Displaced workers are paid less on re-employment compared to those who change occupations voluntarily, in part because of the poor match between their current occupational skills and current job. Providing customers with reliable information on alternatives to their previous occupation may improve their re-employment earnings and reduce the amount of time spent unemployed.

A study by Markey and Parks (1989, p. 3) found that “more than half of the workers in the United States who changed occupations did so because of better pay, working conditions, or advancement opportunities; however about 1 in 8 workers changed occupations because they lost their previous jobs.” Fallick (1993) found evidence that displaced workers increase the intensity of their job search in other industries when employment growth rates in their previous industry is low. Shaw (1987) estimates that a 25 percent increase in the transferability of occupational skills leads to an 11 to 23 percent increase in the rate of occupational change, depending on the age of the worker. Taken together, these results suggest that workers concentrate their search efforts in industries and occupations similar to their own. A reasonable re-employment strategy might include identifying related occupations and providing clients with timely information on the prospects for work in those areas.

Two methods are used to identify related occupations. The first methodology, based on the O*Net system, chooses occupations that are considered to be closely related to the previously held occupation with respect to a person’s qualifications, interests, work values, and previous work activities, to name several of the attributes. O*Net, developed by the U.S. Department of Labor, incorporates the expert opinions of human resource professionals and analysts as to the characteristics of each of more than 1,000 occupations and then relates the various occupations by prioritizing the importance of these attributes for each occupation. This methodology addresses the decision to change occupations by asking the question: “What occupations are most related to my previous occupation with respect to my qualifications, interests, and aspirations?” This approach assumes that the person was qualified for the job that he or she previously held. O*Net matches the characteristics of the previous job with the characteristics of other related occupations. However, these transfers are hypothetical and are not based on actual occupational transfers. It does not take into account the actual demand for a worker's skills.

The second methodology is based on actual occupational changes and addresses the transfer decision with the following question: "For workers who switch out of my occupation, into which occupations do they most frequently move?" This methodology provides a worker with insights into the set of jobs that people like him most often obtain. It incorporates both the qualifications of workers and the demand for their skills. Two data sets are used to record job changes and to compile the list of occupational transfers. The first data set is the Current Population Survey (CPS), which is a national survey of households taken each month. The second data set is the administrative files from the Georgia employment service, which includes self-reported work histories of each participant. Unfortunately, Washington employment service records could not be used because they do not include occupation codes.

Each methodology has its advantages and disadvantages. The first methodology is based on extensive information about the characteristics required by an occupation. Furthermore, because of its comprehensive assessment of skill requirements for specific occupations, this methodology allows one to link this information to possible course offerings at local training and educational institutions in order to fill specific skill gaps. The information can also be used to assist in determining the services that best meet the individual's needs and then to make the appropriate referral. The tools can help determine not only which programs are appropriate for the customer but also which services within a particular program may be most effective.

However, one of the major drawbacks of this first methodology is that it does not consider the demand by employers for those skills embodied in the occupation. For instance, the occupation that O*Net determines to be highly related to a worker's previous occupation may be a good match with respect to skills but there may be little demand for that occupation in the local labor market.

The primary advantage of the second methodology is that it incorporates both supply and demand considerations inherent in job changes. By using local data, it can provide a convenient perspective on the occupations within which a person is most likely to find a job. Its drawback is the lack of detailed information about the occupation. There is little information about the qualifications of those who hold a job in that occupation, except for information about educational attainment. Some of the deficiencies of this methodology with respect to detailed occupation information may be addressed by combining the two approaches.

To illustrate the two approaches, we found occupations related to the occupation of bookkeeping, accounting and auditing clerks (O*Net Occupation Code 43-3031.00).[7] As shown in Table 9, O*Net identified occupations that appear to be closely related in terms of the type of tasks required and the level of autonomy in executing the tasks–elements which O*Net focuses on in categorizing occupations. Table 10 shows the matches of people who switched from Computing and Account Recording to other occupations, as recorded in the Georgia employment service records. While the majority of job switchers stayed within the same occupation, the next most prevalent job change was to the occupation of packaging, materials handling. This choice of a related occupation seems strange, but it most likely reflects the prevalence of job openings in the

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[7]In making the comparisons, considerable effort was required in converting the occupation codes from ONET to the occupation codes used in the CPS and by the Georgia Employment Service. Complete matching was not possible, but we came as close as possible. See DeRango, et al. "Development of the Transferable Occupations Algorithm," for more details.

area for people with the skills embodied in the occupation of computing and accounting. Changes to occupations more related to record keeping also took place. Job changes recorded using CPS data as reported in Table 11 reveal occupations more closely aligned to record keeping than found for the Georgia data. Most of these occupations are considered clerical, except for teachers. The difference between the two data sets results perhaps from the prevalence of industries in local labor markets, which are not apparent using national data such as the CPS.

Service Referral Algorithm

The second module of FDSS is the service referral algorithm. As mentioned in the overview of one-stop centers, a critical element for successful implementation of one-stop centers is the staff's ability to identify the needs of customers and to refer them expeditiously to services that best address their barriers to employment. Compounding this challenge is the possible lack of experience among the center's staff in serving a wide range of customers. The purpose of the FDSS service referral module is to compile and process information about the effectiveness of various programs in a way that better informs staff when referring customers to services.

The service referral module is based on information about the characteristics and outcomes of individuals who have recently participated in services offered by one-stop centers. This data is used to estimate statistical relationships between personal attributes and outcomes. The service referral module uses these models to identify the sequence of services that most often leads to successful employment outcomes for individuals with specific characteristics. It should be emphasized that this algorithm does not replace the staff's referral decisions. Rather, it provides additional information to better inform the decision.

The effectiveness of alternative paths for each customer depends upon their employability. Therefore, the service referral algorithm has two basic components. The first is a model to estimate a person's employability, or likelihood of finding a job. Conceptually, this is the flip side of WPRS models which identify the chance of UI benefit exhaustion. The second component is a delineation of the paths, or sequential combinations of services, that lead to successful outcomes. By conditioning alternative services on the employability of a specific customer, a ranking can be produced of the effectiveness of various programs for individuals with specific measurable characteristics. This ranking would be a suggested ordering of service participation.

Since it is based on prior values of exogenous variables, the employability index can be viewed as a summary of client characteristics. Interacting the employability index with service indicators is a type of sub-group analysis (Heckman, Smith and Clements 1997). The planned approach is analogous to that used by Eberts (2001) for assigning welfare-to-work clients to alternative bundles of reemployment services. This method is also similar to the procedure applied by O'Leary, Decker, and Wandner (2001) who essentially interacted an unemployment insurance benefit exhaustion probability index with reemployment bonus intervention indicators to identify the best exhaustion probability group for targeting a bonus.

The exercise of O'Leary, Decker and Wandner (2001) reexamined treatment and control group data generated by random trials in a field experiment. However, service referral algorithms for FDSS are based on administrative data in which program participation is subject to selection bias. So that their effectiveness may be ranked for customers with alternative employability scores, impact estimates of alternative services will be computed while correcting for selection bias. We plan a simple single equation least squares methodology, which will be validated by a matching approach which accounts for all possible non-linear influences of observable factors on selection for program participation (Rosenbaum and Rubin 1983, Heckman, Ichimura and Todd 1997, Heckman, LaLonde, and Smith 1999, and Smith 2000).

Employability Estimates

This algorithm estimates the likelihood of an individual finding employment based upon prior work history, personal characteristics and educational attainment. The estimate is based on the experience of individuals who have recently enrolled with the employment service or with other programs provided through one-stop centers. However, since we are assessing their initial employability before receiving services, we estimate the model using only those persons who have not yet received services within their current enrollment period when estimating the model.

The data come from the same administrative records that are used to estimate the components of the systematic job search module described in the previous section of this paper. The employability model is similar to the earnings algorithm, except that employment is used as the dependent variable instead of earnings. Thus, the sample includes individuals who have worked just prior to enrolling in one-stop programs as well as those who have not held a job prior to enrolling. In this way, we are able to compare the measurable attributes of those with and without recent employment as they enter a one-stop center. The presumption is that those with more recent work experience are more employable, even before they receive services.

For illustrative purposes, an employability model for welfare recipients in the state of Washington is discussed. The explanatory variables include prior work history, educational attainment, participation in public assistance programs, and their primary language. As shown in Table 12, the coefficients display the expected signs and many are statistically significant. For instance, people who have experienced longer periods of unemployment are less likely to hold a job at the time of intake. People with more education are more likely to hold a job. Those who are willing to relocate are also more likely to find employment. Based on these variables and others, the probability of employment is predicted for each individual who enrolls in Work First. The next step is to determine whether or not some services are more or less effective for individuals within certain ranges of the distribution of employment probabilities.

Path Analysis

The second component of the service-referral module is an analysis of the various services that individuals receive to assist their efforts in searching for and obtaining a job. As discussed in the section on the flow of clients through one-stop centers, it is apparent that individuals typically receive more than one service during their participation period and that they receive those services in various sequences. For instance, a welfare recipient may start his or her participation in the Work First program by being referred to the program by the welfare (or social service) agency, then being referred to a job search workshop, next to a basic education program, and then back to a job search initiative. The final steps would be a job interview and employment. Even after obtaining a job, the individual may participate in post-employment activities. Another welfare recipient entering the same program may take a different route to employment.

Therefore, for programs that offer a sequence of services, the analysis must identify the predominant paths that participants typically follow. Considering a collection of individual activities, such as attending a job search workshop or enrolling in an education program, without taking into account how they relate to other activities, does little to capture the cumulative nature of the delivery of services. Once the pathways, or sequence of service activities, have been identified, the effectiveness of these strings of services will be analyzed with respect to each individual's estimated likelihood of employment. One would expect to find that specific paths are more effective in leading to employment for some individuals than others, depending upon the individual's propensity for employment as measured by the estimated employability.

For Work First, the pathways are relatively short. In some cases, participants receive only one service before finding employment or otherwise exiting the program. Table 13 shows a sample of paths from two starting points. The top panel of Table 13, Section A, includes those who were referred to the Employment Security Department (ESD) during their participation in Work First. The bottom panel, Section B, includes those who returned to Work First after working for a while but then losing their job. The specific activities are not important for the purpose of illustrating the paths.[8] Rather, the important point is that definite sequences of activities occur and that many of these paths consist of only one recorded activity.

Estimates of the Effect of Services on Employment Outcomes

To illustrate the effect of specific services on employment outcomes, we estimate a model that relates employment in the quarter after exiting from the program to participation in services and other characteristics, including the predicted probability of employment derived from the employability model. We focus on the two most prevalent services received by those returning to Work First–employment retention services (RS) and labor market exchange or WPLEX (PS). We interact the predicted employability estimate for each individual with a variable indicating whether or not they received either one of the two post employment services.

[8]A detailed discussion of these paths is given by Eberts, O'Leary, and Huang (2000).

Results in Table 14 show that returnees who have participated in WPLEX and post employment retention services are more likely to find a job and stay off welfare system than those who do not participate. Furthermore, WPLEX is more effective for those who have a higher probability of employment than those with a lower probability, according to the employability estimate. Therefore, while the magnitudes of the effects are small, the estimates do offer information about the appropriate services for individuals with certain characteristics. The service referral algorithm will follow a similar approach in estimating the effect of services offered by other programs.

Summary

The Workforce Investment Act of 1998 calls for the creation of a national network of one-stop centers where intake and referral of job seekers to various programs will be done in a coordinated fashion. Resource constraints dictate that each workforce development program can serve only a portion of the population which might benefit. Funding levels, from state and federal sources, determine how many workers can be served. Choosing which individuals are served depends on decision rules applied by frontline staff in one-stop centers. Statistical tools can help make these decisions more cost effective for society, by targeting services to job seekers who will benefit the most, thereby maximizing the net social benefit of program expenditures.

The Frontline Decision Support System (FDSS) offers a variety of tools that can help inform staff and customers in their job search efforts and in their selection of reemployment services. The tools are based on statistical techniques that use administrative data to estimate likely earnings prospects, industry transitions, related occupations, and outcomes associated with participating in specific reemployment services. The technique is an extension of the Worker

Profiling and Reemployment Services system, which all states have implemented, and with a Work First pilot which was implemented at the Kalamazoo-St. Joseph, Michigan Workforce Development Area and in Broward County, Florida. At the time of this writing, the W.E. Upjohn Institute is working closely with the states of Georgia and Washington to design and implement FDSS in selected one-stop centers.

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Table 1. Industry of Employment Transition Matrix; Percent of Unemployment Insurance Clients, Metropolitan Atlanta, Georgia

	Reemployment Industry								
Prior Industry	Agriculture Forestry Fishery	Mining Construction	Manufacturing	Transportation Communication Utilities	Wholesale Trade	Retail Trade	Finance Insurance Real Estate	Services	Public Administration
Ag., For., Fish	26.3	10.1	10.9	4.9	10.5	11.7	3.2	20.6	1.6
Mine, Const.	0.5	60.1	5.8	3.9	5.3	5.1	2.5	15.0	1.6
Manufacturing	0.3	3.8	40.1	5.7	11.7	8.9	3.0	24.8	1.6
Trans., Comm., Util.	0.4	2.9	6.4	41.8	8.0	7.2	4.7	26.6	2.0
Wholesale Trade	0.4	4.5	14.2	7.4	28.6	11.7	3.9	27.8	1.5
Retail Trade	0.3	2.4	6.2	5.5	7.3	45.5	4.7	26.6	1.5
FIRE	0.3	2.5	4.2	4.7	5.1	6.8	38.3	35.7	2.4
Services	0.3	2.6	6.2	6.2	6.2	8.4	5.9	61.6	25.3
Public Admin.	0.5	3.6	5.4	7.9	4.0	7.8	6.1	39.4	25.3

Table 2. Mean Percentage Change in Earnings for the Industry of Employment Transition Matrix, Metropolitan Atlanta, Georgia

	Reemployment Industry								
Prior Industry	Agriculture Forestry Fishery	Mining Construction	Manufacturing	Transportation Communication Utilities	Wholesale Trade	Retail Trade	Finance Insurance Real Estate	Services	Public Administration
Ag., For., Fish	1.6	1.6	-3.0	-0.9	32.4	-12.1	12.8	-3.5	-16.6
Mine, Const.	-30.6	6.4	-7.8	-0.9	-2.1	-25.4	3.3	-9.9	-25.5
Manufacturing	-34.3	-14.3	6.6	-0.5	-2.1	-29.4	-9.0	-15.7	-21.4
Trans., Comm., Util.	-25.8	0.1	-2.1	6.2	-4.3	-25.2	-9.3	-15.8	-19.0
Wholesale Trade	-28.3	-2.0	-2.0	1.3	7.1	-21.4	-0.7	-7.4	-26.8
Retail Trade	-12.1	0.8	9.0	6.0	10.1	1.9	10.2	-3.1	-9.7
FIRE	-28.3	-9.9	-6.6	-10.1	1.4	-26.4	8.6	-11.2	-23.4
Services	-20.3	6.3	8.7	9.3	14.4	-20.0	6.7	3.9	-8.4
Public Admin.	-22.7	-7.7	1.7	2.2	12.2	-21.5	-8.6	-2.4	-4.2

Table 3. Industry of Employment Transition Matrix; Percent of Unemployment Insurance Clients, South Puget Sound, Washington

	Reemployment Industry								
Prior Industry	Agriculture Forestry Fishery	Mining Construction	Manufacturing	Transportation Communication Utilities	Wholesale Trade	Retail Trade	Finance Insurance Real Estate	Services	Public Administration
Ag., For., Fish	20.8	11.3	13.5	8.8	5.3	12.8	3.5	21.4	2.6
Mine, Const.	0.9	73.3	4.5	3.6	3.8	3.7	1.6	7.6	1.1
Manufacturing	1.0	5.7	54.8	4.7	7.1	6.9	1.7	16.9	1.2
Trans., Comm., Util.	0.7	4.2	4.9	61.0	5.9	5.7	2.3	14.0	1.4
Wholesale Trade	0.4	7.7	15.9	7.2	29.2	12.1	3.3	22.8	1.4
Retail Trade	0.7	3.7	6.7	4.7	7.2	50.9	3.9	21.0	1.3
FIRE	0.6	3.8	4.3	4.6	2.8	7.2	48.9	26.2	1.6
Services	0.7	3.3	5.9	4.6	4.1	8.9	4.6	65.1	2.9
Public Admin.	0.3	5.2	8.2	8.0	6.6	9.2	3.6	28.9	30.0

Table 4. Mean Percentage Change in Earnings for the Industry of Employment Transition Matrix, South Puget Sound, Washington

	Reemployment Industry								
Prior Industry	Agriculture Forestry Fishery	Mining Construction	Manufacturing	Transportation Communication Utilities	Wholesale Trade	Retail Trade	Finance Insurance Real Estate	Services	Public Administration
Ag., For., Fish	7.4	8.1	11.1	24.4	7.6	-2.5	13.3	-5.1	-4.6
Mine, Const.	9.1	9.0	14.1	16.5	13.4	-0.9	16.9	3.7	10.1
Manufacturing	5.5	-0.3	1.2	-8.0	-5.9	-9.5	-0.7	-9.0	1.9
Trans., Comm., Util.	0.1	8.4	16.9	8.4	1.8	-0.1	7.2	0.6	-2.6
Wholesale Trade	4.1	16.9	2.4	3.2	1.6	-3.8	2.5	-2.0	5.0
Retail Trade	-1.6	24.7	29.2	20.7	12.5	3.4	10.7	8.3	27.3
FIRE	-15.9	8.8	14.5	10.5	3.5	-1.1	4.3	-4.0	-0.8
Services	-0.5	18.6	22.3	17.8	15.6	2.6	16.2	3.7	11.2
Public Admin.	-24.2	-11.5	6.1	3.8	-3.0	-21.1	3.5	-11.9	8.8

Table 5. Logistic Regression Summary for the Probability of Returning to the Same Industry (Unemployment Insurance Clients in Atlanta Whose Prior Industry is Manufacturing)

Variable Description	Parameter Estimate	Standard Error	Marginal Effect	Hypothetical Workers 1	Hypothetical Workers 2	Hypothetical Workers 3
Log of Maximum Prior Earnings	0.663**	0.061	0.159	8.923	9.616	7.824
Age as of Reference Date	0.017**	0.003	0.004	35.000	35.000	35.000
Education, Less than High School	0.032	0.058	0.008	0.000	0.000	1.000
Education, More than High School	-0.304**	0.060	-0.070	0.000	1.000	0.000
Youth, Age 14-21	-0.173	0.202	-0.041	0.000	0.000	0.000
Veteran	-0.161**	0.073	-0.038	0.000	0.000	0.000
Welfare Recipient	0.052	0.239	0.013	0.000	0.000	0.000
Dislocated Worker	-0.123**	0.054	-0.029	0.000	0.000	0.000
Employed	-0.036	0.144	-0.009	0.000	0.000	0.000
Reference Date in 2nd Quarter	-0.043	0.063	-0.010	1.000	1.000	1.000
Reference Date in 3rd Quarter	-0.086	0.068	-0.020	0.000	0.000	0.000
Reference Date in 4th Quarter	-0.098	0.073	-0.023	0.000	0.000	0.000
Prior Occupation, Clerical and Sales	-0.062	0.092	-0.015	1.000	1.000	1.000
Prior Occupation, Services	0.408**	0.150	0.101	0.000	0.000	0.000
Prior Occupation, Ag, Forestry, Fishing	1.144**	0.436	0.277	0.000	0.000	0.000
Prior Occupation, Processing	0.937**	0.132	0.230	0.000	0.000	0.000
Prior Occupation, Machine Trades	1.021**	0.096	0.249	0.000	0.000	0.000
Prior Occupation, Bench Work	0.988**	0.106	0.242	0.000	0.000	0.000
Prior Occupation, Structural Work	1.089**	0.110	0.264	0.000	0.000	0.000
Prior Occupation, Miscellaneous	0.795**	0.088	0.196	0.000	0.000	0.000
Intercept	-7.291**	0.549	-0.400	1.000	1.000	1.000
Return to Same Industry Probability:				0.294	0.327	0.172

Example 1: Age 35, high school education, earning $30,000 per year in a clerical/sales occupation, entering in the 2nd quarter of the year.
Example 2: Age 35, post-high school education, earning $60,000 per year in a clerical/sales occupation, entering in the 2nd quarter of the year.
Example 3: Age 35, less than high school education, earning $10,000 per year in a clerical/sales occupation, entering in the 2nd quarter of the year.
* Parameter significant at the 90 percent confidence level in a two-tailed test.
** Parameter significant at the 95 percent confidence level in a two-tailed test.

Table 6. Logistic Regression Summary for the Probability of Returning to the Same Industry (Unemployment Insurance Clients in South Puget Sound, Washington Whose Prior Industry is Manufacturing)

Variable Description	Parameter Estimate	Standard Error	Marginal Effect	Hypothetical Workers 1	2	3
Log of Maximum Prior Earnings	0.733**	0.092	0.182	8.923	9.616	7.824
Age as of Reference Date	0.026**	0.004	0.006	35	35	35
Education, Less than High School	0.077	0.095	0.019	0	0	1
Education, More than High School	-0.275**	0.086	-0.068	0	1	0
Youth, Age 14-21	0.208	0.188	0.051	0	0	0
Veteran	-0.167	0.109	-0.042	0	0	0
Welfare Recipient	-0.402**	0.148	-0.100	0	0	0
Dislocated Worker	-0.102	0.174	-0.025	0	0	0
Employed	0.530**	0.090	0.125	0	1	0
Union	-0.298*	0.168	-0.074	0	0	0
Reference Date in 2nd Quarter	-0.035	0.097	-0.009	1	1	1
Reference Date in 3rd Quarter	-0.186**	0.091	-0.046	0	0	0
Reference Date in 4th Quarter	0.207	0.149	0.051	0	0	0
Prior Occupation: Clerical, Sales	-0.306**	0.152	-0.076	1	1	1
Prior Occupation: Services	0.173	0.221	0.042	0	0	0
Prior Occupation: Ag, Forestry, Fishing	1.048**	0.278	0.228	0	0	0
Prior Occupation: Processing	0.842**	0.160	0.190	0	0	0
Prior Occupation: Machine Trades	0.891**	0.142	0.199	0	0	0
Prior Occupation: Bench Work	1.064**	0.145	0.230	0	0	0
Prior Occupation: Structural Work	0.841**	0.146	0.190	0	0	0
Prior Occupation: Miscellaneous	0.817**	0.134	0.185	0	0	0
Had Job Last Quarter	0.618**	0.116	0.157	1	1	0
Intercept	-8.419**	0.838	-2.085	1	1	1
Return to Same Industry Probability:				0.346	0.532	0.114

Example 1: Age 35, high school education, earning $30,000 per year in a clerical/sales occupation, entering in the 2nd quarter of the year.
Example 2: Age 35, post-high school education, earning $60,000 per year in a clerical/sales occupation, entering in the 2nd quarter of the year.
Example 3: Age 35, lest than high school education, earning $10,000 per year in a clerical/sales occupation, entering in the 2nd quarter of the year.
* Parameter significant at the 90 percent confidence level in a two-tailed test.
** Parameter significant at the 95 percent confidence level in a two-tailed test.

Table 7. Quartile Regression Coefficient Estimates, and Examples of Predicted Earnings from an Earnings Model for Recent Manufacturing Employees Among UI Recipients, Metropolitan Atlanta, Georgia

	25th Percentile		Median		75th Percentile		Hypothetical Workers		
Variable Description	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	1	2	3
Log of Maximum Prior Earnings	0.412**	0.019	0.466**	0.014	0.503**	0.012	8.923	9.616	7.824
Age as of Reference Date	0.009**	0.005	0.003	0.004	-0.001	0.003	35	35	35
Age Squared	-1.3E-04	5.4E-05	-5.2E-05	4.3E-05	-5.6E-06	3.8E-05	1225	1225	1225
Education, Less than High School	0.014	0.014	-0.008	0.011	0.012	0.010	0	0	1
Education, More than High School	0.058**	0.014	0.062**	0.012	0.063**	0.010	0	1	0
Youth, Age 14-21	-0.039	0.047	-0.057	0.038	-0.122**	0.034	0	0	0
Veteran	0.011	0.017	0.036**	0.014	0.028**	0.012	0	0	0
Welfare Recipient	-0.071	0.056	-0.048	0.045	-0.065	0.040	0	0	0
Dislocated Worker	0.011	0.013	0.009	0.010	0.006	0.009	0	0	0
Employed	0.003	0.034	-0.012	0.028	-0.014	0.025	0	0	0
Education Status	-0.015	0.043	0.002	0.035	-0.011	0.031	0	0	0
Economically Disadvantaged	-0.046**	0.015	-0.031**	0.012	-0.031**	0.010	0	0	0
Exhausted Prior UI Claim	0.014	0.051	-0.006	0.040	0.062*	0.035	0	0	0
Weeks of UI Collected Prior Claim	0.002	0.002	0.003**	0.002	0.001	0.001	0	0	0
Workforce/Employer Attachment	0.053	0.037	-0.002	0.030	0.014	0.027	0	0	0
Does Not Have Driver’s License	-0.077**	0.024	-0.079**	0.020	-0.072**	0.017	0	0	0
Available for Rotating Shifts	0.027	0.017	0.024*	0.014	0.041**	0.012	0	0	0
Months of Tenure, Most Recent Job	-0.002**	2.2E-04	-0.001**	1.8E-04	-0.001**	1.6E-04	24	48	8
Months of Tenure Squared	3.2E-06	6.9E-07	3.6E-06	5.9E-07	2.6E-06	5.2E-07	576	2304	64
Required Hourly Salary	0.022**	0.002	0.024**	0.001	0.023**	0.001	12	23	5
Reference Date in 2nd Qtr	0.014	0.015	-0.002	0.012	-0.001	0.011	1	1	1
Reference Date in 3rd Qtr	0.005	0.017	0.003	0.014	0.002	0.012	0	0	0
Reference Date in 4th Qtr	-0.001	0.018	-0.012	0.015	-0.013	0.013	0	0	0
Ref Date 3 Qtrs After Max Wage	0.008	0.015	0.004	0.012	0.017	0.011	1	1	1
Ref Date 4 Qtrs After Max Wage	0.005	0.016	-0.003	0.013	-0.002	0.012	0	0	0
Ref Date 5 Qrtrs After Max Wage	0.010	0.015	0.034**	0.012	0.029**	0.011	0	0	0
Days Left in Current Quarter	3.5E-04	2.2E-04	0.001**	1.8E-04	0.001**	1.6E-04	40	40	40
UI Reference Date	-0.004	0.003	-0.004*	0.002	-0.006**	0.002	13581	13581	13581
UI Reference Date Squared	1.4E-07	1.0E-07	1.6E-07	8.6E-07	2.2E-08	7.7E-08	184523177	184523177	184523177
Unemployment Rate, t-3	0.022	0.667	0.135	0.547	1.141**	0.480	0	0	0
Post Industry Same as Prior Industry	0.206**	0.013	0.181**	0.010	0.140**	0.009	0.292	0.325	0.171
Occupation, Clerical and Sales	-0.070**	0.021	-0.045**	0.017	-0.031**	0.015	1	1	1

Table 7. (Continued)

Variable Description	25th Percentile Parameter Estimate	25th Percentile Standard Error	Median Parameter Estimate	Median Standard Error	75th Percentile Parameter Estimate	75th Percentile Standard Error	Hypothetical Workers 1	Hypothetical Workers 2	Hypothetical Workers 3
Occupation, Services	-0.090**	0.036	-0.034	0.029	-0.050**	0.025	0	0	0
Occupation, Ag, Forestry, Fishing	-0.320**	0.105	-0.193**	0.087	-0.272**	0.075	0	0	0
Occupation, Processing	-0.104**	0.033	-0.076**	0.027	-0.017	0.023	0	0	0
Occupation, Machine Trades	-0.059**	0.024	-0.041**	0.019	-0.015	0.017	0	0	0
Occupation, Bench Work	-0.102**	0.026	-0.086**	0.021	-0.056**	0.018	0	0	0
Occupation, Structural Work	-0.015	0.027	0.009	0.022	0.048**	0.019	0	0	0
Occupation, Miscellaneous	-0.105**	0.022	-0.078**	0.018	-0.038**	0.015	0	0	0
Intercept	30.072	19.087	32.627**	15.802	45.345**	14.170	1	1	1
Predicted 25th							5472	9636	3020
Predicted 50th							6728	12618	3387
Predicted 75th							8179	15557	4078

Example 1: Age 35, high school education, earning $30,000 per year in a clerical/sales occupation, entering in the 2nd quarter of the year.
Example 2: Age 35, post-high school education, earning $60,000 per year in a clerical/sales occupation, entering in the 2nd quarter of the year.
Example 3: Age 35, less than high school education, earning $10,000 per year in a clerical/sales occupation, entering in the 2nd quarter of the year.
* Parameter significant at the 90 percent confidence level in a two-tailed test.
** Parameter significant at the 95 percent confidence level in a two-tailed test.

Table 8. Quartile Regression Coefficient Estimates, and Examples of Predicted Earnings from an Earnings Model for Recent Manufacturing Employees Among UI Recipients, South Puget Sound, Washington

Variables	25th Percentile Parameter Estimate	25th Percentile Standard Error	Median Parameter Estimate	Median Standard Error	75th Percentile Parameter Estimate	75th Percentile Standard Error	Hypothetical Workers 1	Hypothetical Workers 2	Hypothetical Workers 3
Log of Maximum Prior Earnings	0.465**	0.024	0.630**	0.020	0.632**	0.024	8.923	9.616	7.824
Age as of Reference Date	0.006	0.007	0.006	0.006	0.002	0.007	35	35	35
Age Squared	-9.1E-05	8.0E-05	-8.2E-05	6.9E-05	-5.0E-05	8.1E-05	1225	1225	1225
Education, Less than High School	-0.019	0.024	-0.019	0.020	-0.027	0.024	0	0	0
Education, More than High School	0.059**	0.022	0.056**	0.019	0.040*	0.022	0	1	0
Youth, Age 14-21	-0.061	0.053	-0.009	0.045	-0.037	0.054	0	0	0
Veteran	0.040	0.027	0.019	0.023	0.018	0.028	0	0	0
Welfare Recipient	-0.170**	0.044	-0.135**	0.039	-0.143**	0.047	0	0	0
Dislocated Worker	0.042	0.045	0.036	0.038	0.108**	0.046	0	0	0
Employed	0.084**	0.023	0.025	0.019	0.013	0.023	0	1	0
Union	0.115**	0.042	0.087**	0.036	0.097**	0.044	0	0	0
Economically Disadvantaged	-0.009	0.042	0.014	0.037	0.046	0.045	0	0	0
Reference Date in 2nd Quarter	-0.006	0.024	-0.003	0.021	-0.017	0.025	1	1	1
Reference Date in 3rd Quarter	0.020	0.023	0.018	0.020	0.051**	0.024	0	0	0
Reference Date in 4th Quarter	0.062	0.038	0.025	0.033	-0.004	0.039	0	0	0
Ref Date 3 Qtrs After Max Wage	0.023	0.023	-0.001	0.020	0.005	0.024	0	0	0
Ref Date 4 Qtrs After Max Wage	-0.050*	0.027	-0.053**	0.023	-0.061**	0.028	0	0	0
Ref Date 5 Qtrs After Max Wage	-0.010	0.026	-0.023	0.022	-0.003	0.027	0	0	0
Days Left in Current Quarter	4.9E-04	3.5E-04	4.7E-04	3.0E-04	-4.0E-04	3.6E-04	37	37	37
Weeks Benefits Drawn	-0.011**	0.001	-0.009**	0.001	-0.006**	0.001	1	1	1
Occupation: Clerical, Sales	-0.068*	0.038	-0.064**	0.032	-0.096**	0.039	1	1	1
Occupation: Services	-0.103*	0.056	-0.101**	0.047	-0.160**	0.057	0	0	0
Occupation: Ag, Forestry, Fishing	-0.057	0.068	-0.030	0.058	-0.106	0.070	0	0	0
Occupation: Processing	-0.120**	0.041	-0.129**	0.035	-0.073*	0.042	0	0	0
Occupation: Machine Trades	-0.094**	0.037	-0.065**	0.031	-0.103**	0.037	0	0	0
Occupation: Bench Work	-0.178**	0.038	-0.138**	0.031	-0.165**	0.037	0	0	0
Occupation: Structural Work	-0.084**	0.037	-0.022	0.032	-0.000	0.038	0	0	0
Occupation: Miscellaneous	-0.121**	0.035	-0.080**	0.029	-0.093**	0.035	0	0	0
Post Industry Same as Prior Industry	0.185**	0.019	0.168**	0.016	0.123**	0.020	0.346	0.532	0.114
Intercept	4.393**	0.238	3.163**	0.198	3.464**	0.238	1	1	1
Predicted 25th							5615	9249	3228
Predicted 50th							7164	12394	3450
Predicted 75th							8422	14081	4087

Example 1: Age 35, high school education, earning $30,000 per year in a clerical/sales occupation, entering in the 2nd quarter of the year.

Example 2: Age 35, post-high school education, earning $60,000 per year in a clerical/sales occupation, entering in the 2nd quarter of the year.

Example 3: Age 35, lest than high school education, earning $10,000 per year in a clerical/sales occupation, entering in the 2nd quarter of the year.

* Parameter significant at the 90 percent confidence level in a two-tailed test.

** Parameter significant at the 95 percent confidence level in a two-tailed test.

Table 9. Related Occupations for Bookkeeping, Accounting and Auditing Clerks (O*Net Occupation Code 43-3031.00)

O*Net SOC Title	O*Net SOC Code
Billing, Cost, and Rate Clerks	43-3021.02
Billing, Posting and Calculating Machine Operators	43-3021.03
Brokerage Clerks	43-4011.00
Loan Interviewers and Clerks	43-4131.00
Secretaries, Except Legal, Medical and Executive	43-6014.00
Office Clerks, General	43-9061.00

Source: O*Net Online (http://online.onetcenter.org)

Table 10. Placements According to JS200 Record and Concordance with JS300 Job Orders File From Occupation: (21) Computing and Account Recording

Placement Occupation (JS200)	Number of Placements by ES (JS200)	Proportion of Total Placements	Total of Past and Present Openings (JS300)	Total Placements (JS300)	Placements as a Percent of Openings	DOT Code
Packaging, Materials Handling	1435	13.7	88,542	82,710	93.4	92
Processing Food, Tobacco	1125	10.7	50,953	48,472	95.1	52
Miscellaneous Sales	948	9.0	23,656	21,397	90.5	29
Stenography, Typing, Filing	932	8.9	22,135	16,288	73.6	20
Food, Beverage Preparation, Services	904	8.6	25,578	24,053	94.0	31
Information and Message Distribution	508	4.8	9,890	8,515	86.1	23
Fabrication, Assembly, Repair of Metal Products	431	4.1	19,155	17,444	91.1	70
Miscellaneous Personal Services	260	2.5	7,800	6,381	81.8	35
Miscellaneous Clerical	259	2.5	6,802	5,291	77.8	24
Fabrication, Repair, Textile, Leather	243	2.3	7,787	7,499	96.3	78
Computing and Account Recording	3443	32.8	22,969	20,690	90.1	21

Table 11. Ten Most Frequent Occupation Changes from Bookkeepers, Accounting and Auditing Clerks (Census Code 337)

Title	Number of Observation	Census Code
Accountants and Auditors	22	23
Supervisors and Proprietors, Sales Occupations	13	243
Managers and Administrators, N.E.C.	11	22
Secretaries	12	313
General Office Clerks	7	379
Teachers, Elementary School	7	156
Payroll and Timekeeping Clerks	5	338
Cashiers	8	276
Receptionists	5	319
Administrative Support Occupations, N.E.C.	6	389
Bookkeepers, Accounting and Auditing Clerks	124	337

Table 12. Logit Estimates of Employability Model for Welfare Recipients in the State of Washington

Variable Description	Coefficient	Standard Error	Marginal/Discrete Effect
Unemployed in one of the four prior quarters	-0.849**	0.038	-0.136
Unemployed in two of the four prior quarters	-1.153**	0.041	-0.169
Unemployed in three of the four prior quarters	-1.205**	0.045	-0.174
Unemployed in all four prior quarters	-2.407**	0.045	-0.243
Maximum quarterly wage in the four prior quarters	4.7E-005**	1.0E-005	9.5E-006
Maximum quarterly wage squared	-2.1E-009**	5.8E-010	-4.1E-010
Education: Less than high school	-0.206**	0.026	-0.039
Education: GED	-0.018	0.042	-0.004
Education: Some college	0.063	0.047	0.013
Education: Associate degree	0.080	0.056	0.016
Education: Bachelor degree	0.147	0.096	0.030
Education: Advanced degree	0.495**	0.176	0.109
Willing to relocate	0.082*	0.044	0.017
Minimum required wage	0.018**	0.006	0.004
On food stamp	-0.038	0.106	-0.008
Not welfare recipient	0.334**	0.043	0.072
Economically disadvantaged	0.072	0.047	0.015
Language spoken at home: English	0.743**	0.053	0.169
Language spoken at home: Spanish	1.059**	0.079	0.248
Received deferrals	-0.739**	0.029	-0.122
Intercept	-0.002	0.080	-0.000

Note: Sample includes 46,732 individuals aged 14 and above, who had received some services from the Washington State Work First program.

Table 13.   Selected Paths of Component Codes

A. FOLLOWING REFERRAL TO ESD (RI)

Path	Activity 1	Activity 2	Activity 3	Frequency	Percent
1	No Show (RN)			422	5.5
2	Referred back early (RB)			343	4.5
3	Working full-time - 30 or more hours/wk. (FT)			182	2.4
4	Working part-time - 29 or less hours/wk. (PT)			120	1.6
5	Initial job search (JI)			107	1.4
6	Sanction (SA)			102	1.3
7	Referred back early (RB)	Sanction (SA)		94	1.2
8	No show (RN)	Sanction (SA)		90	1.2
9	No show (RN)	Processing returned referral (PR)	Sanction (SA)	81	1.1
10	Job search workshop (JW)	Job search (JS)	Working full-time - 30 or more hours/wk (FT)	79	1.0
Total				7,642	

B. FOLLOWING NON-SUBSIDIZED EMPLOYMENT (PT OR FT)

Path	Activity 1	Activity 2	Activity 3	Frequency	Percent
1	WPLEX Contact (PS)			701	16.3
2	Employment Retention (RS)			321	7.4
3	Working full-time - 30 or more hours/wk (FT)			216	5.0
4	ESD (RI)			160	3.7
5	Working part-time - 29 or less hours/wk (PT)			120	2.8
6	Referred back early (RB)			57	1.3
7	Job search (JS)			54	1.3
8	Counseling/anger management; drug, alcohol or mental health treatment; temporary incapacity, medical treatment (XM)			51	1.2
9	ESD (RI)	No show (RN)		50	1.2
10	Other (RO)			50	1.2
Total				4,291	

Source: Washington WorkFirst activity file.

Table 14. Logit Estimates of Service Impact Model for Work First Participants in the State of Washington

	Coefficients	Standard Error	Marginal/ Discrete Effects
Unemployed in all four prior quarters	0.249**	0.083	0.053
Age as of reference date	0.008**	0.003	0.002
Dislocated worker	-0.888**	0.386	-0.141
Referred to ESD	-0.409**	0.086	-0.074
Job Search activity	-0.655**	0.105	-0.111
Job Search workshop	-0.040	0.174	-0.008
Attend HS or GED	-0.306*	0.183	-0.057
Training	-0.610**	0.257	-0.105
On the job training	-0.803**	0.206	-0.130
Pre-employment training	-1.087**	0.327	-0.162
Deferrals	-1.409**	0.110	-0.191
Other referrals (refer to)	-0.069	0.144	-0.014
Sanction	0.261*	0.158	0.055
Referrals (refer back)	0.138	0.087	0.028
Employment retention	0.302*	0.168	0.064
WPLEX	0.361**	0.150	0.078
Predicted employability (PE)	0.426**	0.180	0.085
Employment retention*PE	-0.088	0.382	-0.018
WPLEX*PE	0.551*	0.329	0.110
Intercept	0.161	0.129	

Note: Sample includes 9,009 individuals who have found either part-time or full-time employment after entering the Work First program. The dependent variable is 1 if the individual was off TANF after obtaining employment, and 0 if no record shows that he/she left TANF.

Figure 1. Use and Cost of One-Stop Career Center Services under the Workforce Investment Act

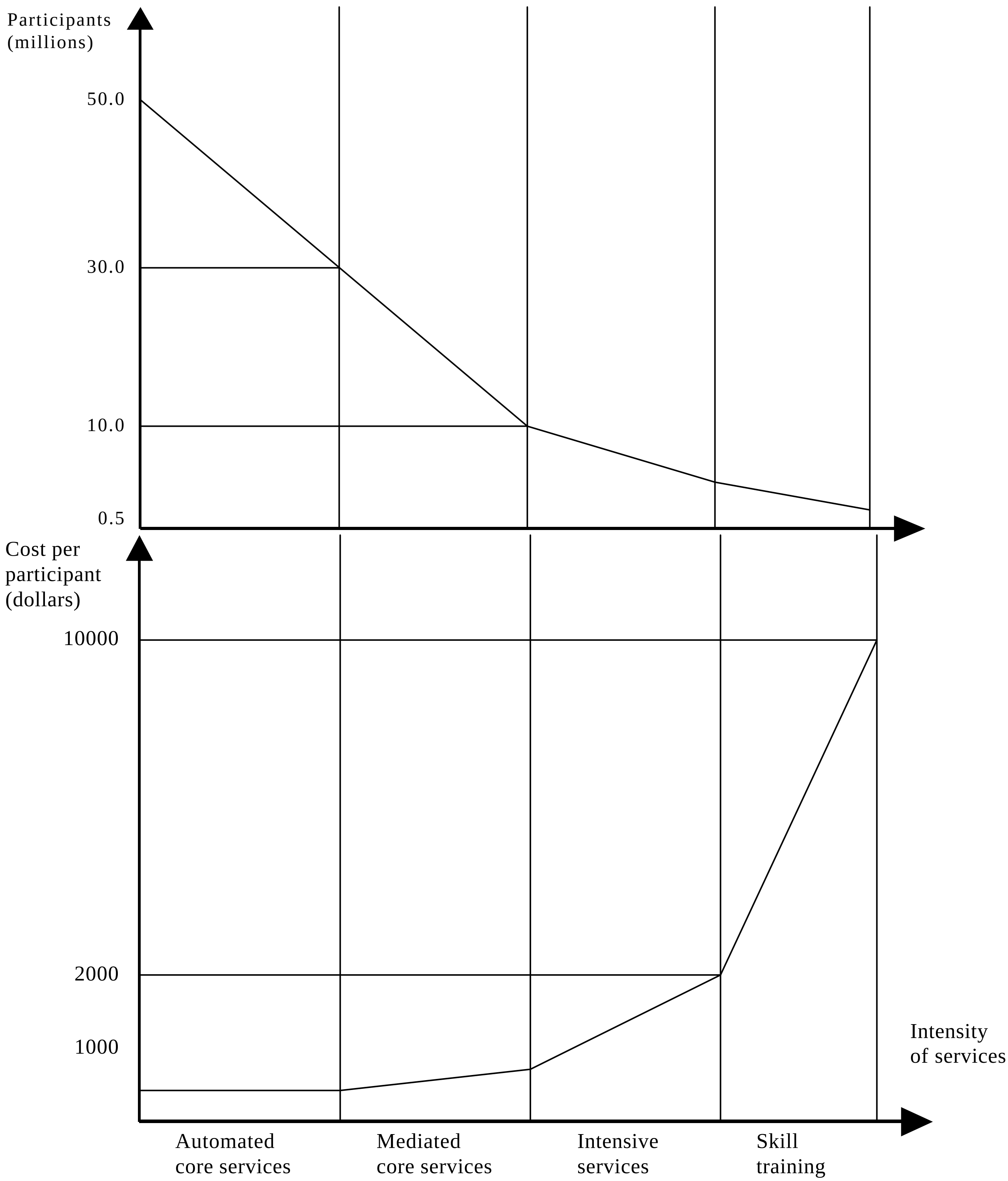
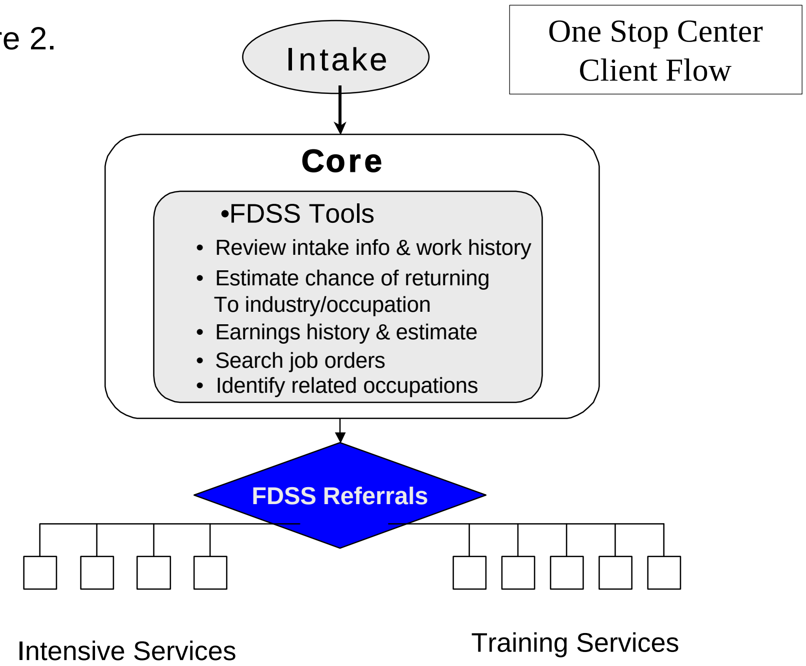


Figure 2.


One Stop Center
Client Flow
Intake
Core
•FDSS Tools
• Review intake info & work history
• Estimate chance of returning To industry/occupation
• Earnings history & estimate
• Search job orders
• Identify related occupations
FDSS Referrals
Intensive Services
Training Services