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2002

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Upjohn Institute Working Paper No. 02-84

#### **Published Version**

Essay in A Compilation of Selected Papers from the Employment and Training Administration's 2003 Biennial National Research Conference. December 2003, pp. 80-129

#### Citation

Eberts, Randall W., and Christopher J. O'Leary. 2002. "A Frontline Decision Support System for Georgia Career Centers." Upjohn Institute Working Paper No. 02-84. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research. http://research.upjohn.org/up\_workingpapers/84

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July 2002

JEL Classification Codes: J68, J65, J64, H49

This paper is based on work done for the Georgia Department of Labor by the W.E. Upjohn Institute for Employment Research under a grant from the U.S. Department of Labor. We thank Helen Parker of the Georgia Department of Labor, Stephen Wandner of the U.S. Department of Labor, and their staffs for technical guidance and constructive comments. Outstanding research assistance was provided by Ken Kline. Kim Kornokovich and Terry Durden of the Georgia Department of Labor coordinated implementation efforts. System programming was expertly done by Angela Simpson of the Georgia Department of Labor. Kelly DeRango, Wei-Jang Huang, Kristine Heffel, and Kris Kracker made substantive contributions. Clerical assistance was provided by Claire Black and Phyllis Molhoek. Opinions expressed are our own, and do not necessarily represent those of the W.E. Upjohn Institute for Employment Research. We accept responsibility for any errors.

### A Frontline Decision Support System for Georgia Career Centers

Randall W. Eberts and Christopher J. O'Leary

#### Abstract

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.

To help frontline staff in one-stop centers quickly assess customer needs and properly target services, the U.S. Department of Labor has funded development of a Frontline Decision Support System (FDSS). The FDSS is being pilot tested in the state of Georgia where one-stop centers are called Georgia Career Centers. Technical assistance on the project is being provided by the W.E. Upjohn Institute for Employment Research.

FDSS is comprised of two main parts: 1) the systematic job search module, and 2) the service referral module. The systematic job search module is a means to undertake a structured search of vacancy listings. The module provides information about a customer's prospects for returning to a job like their prior one, provides a realistic assessment of likely reemployment earnings, identifies occupations related to the prior one, and screens job vacancy listings by region, occupation, and earnings requirements. The service referral module identifies the sequence of activities that most often lead to successful employment for clients with similar background characteristics.

This paper documents the strategy and tools implemented to pilot test FDSS within the internetbased Georgia Workforce System. Pilot field operations in Georgia began in the Athens and Cobb-Cherokee Career Centers in July, 2002.

### A Frontline Decision Support System for Georgia Career Centers

#### BACKGROUND

The Workforce Investment Act (WIA) of 1998 emphasizes the integration and coordination of services to promote employment. This objective is fostered by the federal requirement that local areas receiving WIA funding must establish one-stop centers where providers of various employment services are assembled in one location.

WIA also broadens access to employment services by reducing eligibility requirements. As a consequence, a significant increase in customer volume is expected. Coupled with limited program resources, the challenges now facing the public employment system are to coordinate programs and streamline service delivery.

Meeting these challenges is hindered by the fact that prior experience of frontline staff is often specific to a single program, while customers of the new one-stop system will arrive with a broad variety of needs. An additional complication is the WIA emphasis on 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 being developed to help frontline staff in one-stop centers to quickly identify customer needs and choose appropriate services. FDSS includes new tools to promote effective job search and identify employment services most likely to be effective.

The U.S. Department of Labor commissioned the W.E. Upjohn Institute for Employment Research to design, develop, test, and implement FDSS in the state of Georgia. FDSS is being structured in a way that should permit other states to easily integrate the decision tools into their specific computer operating systems. After testing FDSS in Georgia, USDOL intends to offer the tools to other interested states.

The W.E. Upjohn Institute is in a unique position to undertake this project since the Institute both conducts employment-related research and administers state and federal employment programs for the local Workforce Investment Board. The Institute has been the administrator of state and federal employment-related programs for the Kalamazoo, Michigan area continuously 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). Over the past twenty years the Institute has also worked closely with employment security agencies in several states and countries to conduct applied employment policy research. This work has included a number of random trial field experiment evaluations of employment program innovations. Conducting employment research and operations within the same organization provides the Institute with valuable experience coordinating the type of analytical and administrative tasks required to develop and test FDSS within one-stop centers.

This paper provides an overview of FDSS and explains the analysis underlying the decision algorithms that form the backbone of FDSS tools. In the next section, we summarize the overall concept of FDSS and indicate where elements of FDSS could fit into the typical client flow through one-stop centers. Section 3 provides technical details of the statistical models behind the decision support tools in FDSS. Section 4 provides an example of a typical FDSS decision support session using prototype screens from the internet-based Georgia Workforce System. The final section of our paper provides a summary of FDSS and describes current plans for field testing and implementation in Georgia.

Pilot testing of FDSS in Georgia began in July of 2002. The examples provided in this paper are drawn from the prototype system pilot-tested in the Athens and Cobb-Cherokee Georgia Career Centers.

#### FRONT LINE DECISION SUPPORT WITHIN ONE-STOP CENTERS

To clarify the role of FDSS, we begin with a brief overview of one-stop centers, the services they provide, and the way in which staff members interact with customers. Since one-stop centers vary across states, we can provide only a stylized description. However, this summary will suffice for our purpose of describing how FDSS can be integrated into one-stop centers.

As mandated by WIA, one-stop centers are a central physical location for the provision of services by the following federal and state programs: Unemployment Insurance, Employment Service, Dislocated Worker and Youth Training, Welfare-to-Work, Veterans Employment and Training Programs, Adult Education, Post-secondary Vocational Education, Vocational Rehabilitation, Title V of the Older Americans Act, and Trade Adjustment Assistance. Other programs may also be included under a 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 those 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, and most states met that 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 require a greater level of staff involvement and, consequently, access is more limited 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 highest level of service intensity, are open to customers only through referrals. Typically, a list of approved organizations is set outside of one-stop centers to provide these services. Training services typically include adult basic skills education, on-the-job-training (OJT), work experience, and occupational skills training.

The first challenge for one-stop center operators is the expected large volume of customers. Nationally, nearly 50 million people are expected to use one-stop centers each year. 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. WIA does not provide additional resources for staffing or 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 to intensive 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.

To address the challenges of effectively operating one-stop centers, FDSS has two basic sets of tools or modules. Figure 2 shows how the two modules fit into the operation of the one-stop center. The first is the systematic job search module (SJSM). The SJSM is a set of tools to provide customized information about several aspects of the job search process. Initial job search activities are concentrated in the core services, and consequently this is where the systematic search module will be incorporated. The second module of FDSS is the service referral algorithm (SRM). The SRM is based on information about the characteristics of recent participants in services offered by one-stop centers. Statistical models of participant labor market success provide the basis for referral algorithms in the SRM, which will be available to support staff recommendations.

#### THE ANALYTIC FOUNDATION OF FDSS TOOLS

In this section we explain the analytic foundation for each of the tools in FDSS using examples drawn from the Atlanta region of the Georgia FDSS project. To review the tools, we sequentially consider the components of the SJSM and SRM.

#### **Systematic Job Search Module**

The SJSM contains tools which can be used to inform the customer about the: 1) probability of return to work in the prior industry, 2) expected job growth in the prior occupation, 3) likely reemployment earnings, 4) available suitable job vacancy listings, and 5) related occupations.

#### **Probability of Return to Work in the Prior Industry**

Most customers who use one-stop centers will not return to their prior employer, but instead will gain reemployment with a different employer. In our sample of Georgia UI clients, at most 19.1 percent returned to work with their prior employer.<sup>1</sup> Furthermore, the great majority of new jobs are in a different industry. A change in the industry of employment often means a loss in the value of industry specific skills, with an associated negative impact on reemployment earnings.<sup>2</sup> 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 and therefore return to work more quickly, FDSS provides an estimate of the probability of returning to employment in the prior industry.

Reliable data are available from UI wage records in Georgia to identify the industry in which the person was employed before and after displacement. 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 listed 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. However, only for two industry groups is the aggregate average probability of returning to work in the same industry greater than 50 percent: mining-construction and services. For all other industry groups there is a better than even chance of changing the industry of employment.

<sup>&</sup>lt;sup>1</sup>For UI clients in Georgia, return to the prior employer is judged using wage records for the five quarters immediately preceding the quarter of initial claim compared to the first quarter with earnings after the claim. Three contrasts were examined, each compared employers paying the greatest share of quarterly earnings. The definitions of prior employer (and rates of return) were: the employer paying the most wages in the quarter right before the UI claim (19.1%), the employer paying the most wages in any of the five quarters (16.0%), and the employer paying the most wages in the quarter with the highest total earnings among the five quarters (11.5%).

<sup>&</sup>lt;sup>2</sup>As suggested by Becker's (1964) theory of human capital.

Table 2 summarizes the gross average percentage change in quarterly earnings associated with the 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 associated with changing jobs. The vast majority of off-diagonal elements in Table 2 are negative. The greatest earnings losses are experienced by those who switch industries and move into either agriculture, retail trade, services, or public administration.

To provide individual estimates of the probability of getting reemployed in the prior industry, we estimated logit models for each industry transition. The logit model relates whether 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 indicator variables for prior occupation.<sup>3</sup> The logit model also includes variables to indicate whether an individual was a member of the following population groups: youth, veterans, currently employed, receiving public welfare assistance, and dislocated workers.<sup>4</sup> Because of eligibility conditions, UI beneficiaries include very few people currently enrolled in school, so that category was not included in the return to prior industry model.

Table 3 reports parameter estimates of the return to prior industry logit models computed on a combined sample of UI recipients and ES registered customers in the Atlanta region whose prior job was in the manufacturing industry. The model includes an indicator variable for UI recipients. To illustrate model sensitivity it is evaluated for three examples. Example 1 is a person aged 35, with a high school education, who earned \$30,000 per year in a sales or related occupation and became eligible for UI in the second calendar quarter.<sup>5</sup> The probability of return to the same industry was estimated to be 0.317 in the Atlanta region. Doubling prior earnings from \$30,000 to \$60,000 raised the chance of returning to manufacturing to 0.340 in the Atlanta area. The third example illustrates the effect of having a lower prior annual earnings of \$10,000; the direct correlation results in the probability of return to the prior industry falling to 0.205.

<sup>&</sup>lt;sup>3</sup>Age, gender, and race are prohibited variables in Worker Profiling and Reemployment Services (WPRS) models (Eberts and O'Leary 1996). However, unlike WPRS the FDSS system does not set criteria for program eligibility. The FDSS computer screens display age, gender, and race as customer background characteristics. However, among these only age is used in FDSS statistical models. Age is used to identify youth.

<sup>&</sup>lt;sup>4</sup>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.

<sup>&</sup>lt;sup>5</sup>Note that the earnings variables in the models are quarterly figures, not annual figures.

#### **Expected Job Growth in the Prior Occupation**

Data were available on the industry of both the previous and the new employer, making estimation of the probability of return to prior industry possible. However, no similar data are available by occupation. To provide some information on the chance of return to prior occupation, we simply present the estimated annual employment growth rate in the prior occupation based on the ten-year forecast produced using the U.S. Department of Labor methodology by the Workforce Information and Analysis Division of the Georgia Department of Labor.

This type of labor market information (LMI) is occasionally presented to customers to help them understand the market context of their job search. However, the data usually presented are aggregated over the labor market. By providing information specific to a customer's prior occupation and local labor market, the information is both customized and relevant to decisions during the job search process. The estimated employment growth rates may be positive, negative, or zero. Since the change may be small, the Georgia Workforce Information and Analysis Division reports growth with statistical significance to the one-hundredth of a percentage point. FDSS presents occupational employment growth estimates at the same level of precision.

Analysis of 786 occupations measured by the Georgia Department of Labor's Workforce Information and Analysis Division reveals that the median projected annual job growth rate is 1.62 percent over the next five years. This means half of the occupations will grow faster and half will either grow more slowly or decline. One-quarter of occupations are predicted to have growth rates above 2.78 percent and one quarter are predicted to grow less than 0.54 percent. Only computer scientists are forecast to have double-digit job growth. Employment will be steady or declining for about 20 percent, or approximately 157 occupations. The prototype FDSS informs a system user about the estimated growth in jobs by occupation for the local Workforce Investment Area.

#### **Likely 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."<sup>6</sup> 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 customer. By providing the customer with a

<sup>&</sup>lt;sup>6</sup>Section 133(d)(3)(i) and (ii), Workforce Investment Act (WIA), Public Law 105-220–August 7, 1998.

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 in 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, may expect to receive wages in their new jobs comparable to those in the job held prior to displacement. However, research suggests that displaced workers can expect a significant drop in earnings (Ashenfelter 1978). Most of the loss in earnings is due to a loss in the value of firm-specific skills (Jacobson, LaLonde, and Sullivan 1993).

It is important to point out that the FDSS earnings assessment is only suggestive. Customers 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 recent wage surveys and current labor market conditions.

A median regression model was used to estimate earnings. 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 customers to openings. The model assesses those factors in a systematic and consistent way, so that customers with similar needs and characteristics are treated similarly. We used a median regression model since FDSS will present a range of reemployment earnings estimates by giving quartiles of the reemployment earnings distribution. The median is the second quartile.

The earnings models were developed using quarterly earnings data from UI wage records. 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.<sup>7</sup>

We report the results from the median regression models for the manufacturing sector in metropolitan Atlanta, which is the same region and industry used in the "return-to-prior-industry"

<sup>&</sup>lt;sup>7</sup>Using data from the Current Population Survey for a comparable time period we computed an  $(8\times10)$  industryoccupation matrix of average hours worked using one digit industry and occupation groups. The matrix appears as Table 4 in this paper.

models discussed above. As shown in Table 5, 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 in the estimation process. Instead, when estimating the earnings for individuals, we use whether or not they actually returned to the same industry as data. When FDSS is used to predict a customer's earnings, however, we substitute the prediction of the probability the person will find a job in the same industry as the value for this variable in the earnings equation. Earnings models for Georgia also include age and age-squared terms 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, and current school enrollment status. The model also includes indicator 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 on the Atlanta data, as shown in Table 5, are broadly consistent with previous earnings research. Prior earnings, education, and age are positively correlated with future earnings. The variables indicating prior occupation are significant predictors of future earnings. In addition, returning to the industry of prior employment raises earnings by 15.7 percentage points and the coefficient estimate is highly statistically significant. Indicators for the various population groups are not statistically significant, except for veterans and the economically disadvantaged.

Coefficient estimates related to other special variables add further insight into the determinants of a worker's compensation. Possession of a driver's license increases reemployment earnings, and longer tenure on the previous job reduces reemployment earnings. This latter result is consistent with WPRS models that find increased prior job tenure associated with an increased chance of UI benefit exhaustion.

To compute median estimated earnings for a one-stop customer, 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 \$6,661 per quarter. 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 metropolitan Atlanta to \$11,705. 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 to \$3,070.

We attempted to estimate quartile earnings models (i.e., separate models for the 25<sup>th</sup>, 50<sup>th</sup>, and 75<sup>th</sup> percentiles of the earnings distribution). However, small sample sizes for some industries in some regions resulted in distributions of the prediction sampling errors of the quartile models, which greatly overlapped. This sometimes caused predicted reemployment earnings quartiles for an individual to appear to be out of order. Consequently, we adopted an alternative strategy for estimating the first and third quartiles.

Following the same sample structure as that used for earnings model estimation, we considered maximum quarterly reemployment earnings for each customer in the combined UI and ES sample by region of Georgia, occupation (10 SOC groups), and industry (8 groups), or youth or economically disadvantaged status. Within each cell we identified the first, second (median), and third quartiles. We then computed ratios of the quartiles. The ratio of the first quartile to the second yields a number between zero and one, and this ratio serves as the 25<sup>th</sup> percentile multiplier. The ratio of the third quartile to the second yields a number greater than one, and this serves as the 75<sup>th</sup> percentile multiplier. Table 6 lists the ratios for manufacturing in the Atlanta region. The earnings example in Table 5 for manufacturing in the Atlanta region assumes an occupation in the sales and related group. The ratios applied to this example are approximately 0.73 and 1.32.

#### **Available Suitable Job Vacancy Listings**

The heart of the SJSM is examination of job vacancy listings—called job orders by one-stop center staff—to identify the best available prospects for reemployment. The SJSM customizes this process by first reviewing the probability of returning to the prior industry, expected local job growth in the prior occupation, the quartile distribution of likely reemployment earnings, and the customer's reservation wage. The reservation wage is labeled as the "minimum salary desired." It is set by the customer when registering for services in response to the question: "What is your desired hourly wage at reemployment?"

With frontline staff assistance, customers may then view selected job orders available in the system screened by occupation, local area, and wage requirements. If no suitable openings are available, frontline staff may turn to the SRM to identify other core or intensive services which may be useful, or they may broaden the scan of job orders by considering listings for related occupation. The algorithm for identifying related occupations is the last part of the SJSM, and it is explained in the next sub-section.

#### **Related Occupations**

The FDSS algorithm for identifying related occupations provides frontline staff with a list of occupations that are related to the occupation that a customer most recently held. The purpose of the algorithm is to provide a customer who does not immediately find a suitable job match within existing job orders with a list of occupations that require similar skills and aptitudes, so that other relevant listed job orders may be considered. Displaced workers are paid less upon re-employment than those who change occupations voluntarily, in part because of the poor match between their current occupational skills and their new job skill requirements. 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 the employment growth rate 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. Successful job search could be promoted by identifying related occupations and providing clients with timely information on the prospects for work in those areas.

The related occupations algorithm is based on the O\*Net system. It identifies occupations that are closely related to the previously held occupation with respect to a person's qualifications, interests, work values, and previous work activities. O\*Net, developed by the U.S. Department of Labor, incorporates the expert opinions of human resource professionals and analysts about the characteristics 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 O\*Net related occupations 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. One of the major drawbacks of this methodology is that it does not consider the actual labor market

demand by employers for those skills embodied in the occupation. We investigated two alternatives to the O\*Net approach which embodied elements of labor demand as well as skill relations. One approach used Current Population Survey (CPS) data and the other used Georgia ES placement data. Because of required conversions across alternative occupational coding systems, neither approach yielded a sufficiently rich menu of related occupations in terms of the Standard Occupation Code (SOC), however, which is the standard for the Georgia Workforce System.

To illustrate the O\*Net approach which is used in the Georgia FDSS, we found occupations related to the occupation of cashier (O\*Net Occupation Code 41-2011.00).<sup>8</sup> As shown in Table 7, 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 task—elements which O\*Net focuses on in categorizing occupations. Since it is based on standard occupation codes (SOC), the FDSS for the Georgia Workforce System will provide related occupations for 674 SOC categories. Mapping all O\*Net occupations into SOC yields 824 SOC groups, but for 150 of these groups O\*Net does not identify a related occupation.

#### **Service Referral Module**

The SRM provides the frontline staff with two tools: 1) a ranking of the core and intensive services estimated to be most effective for clients with similar characteristics, and 2) a ranking of the effectiveness of job training types for clients with similar characteristics. To summarize client characteristics, we estimate employability models and group customers with similar scores. We first discuss employability estimates, and then turn to service referral and training effectiveness statistics.

#### **Employability Estimates**

The employability algorithm estimates the relationship between recent stable employment, personal characteristics, and local office indicators as a measure of local labor market conditions. The aim is to produce an "Employability Index" which summarizes characteristics influencing the likelihood of being employed. The model uses data on the experience of customers who have recently enrolled with the employment service or with other programs provided through one-stop centers. Since we are attempting to identify employability before receiving services, the dependent variable and all exogenous variables in the model are based on values before job search registration. 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 index will be used to create groups of customers having similar employability characteristics so as to examine the effectiveness of employment services for these different groups.

<sup>&</sup>lt;sup>8</sup>Occupation codes in O\*Net are not directly comparable to those used in the CPS and by the Georgia Department of Labor, complete matching was not possible in all cases (DeRango, et al. 2000).

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 (2002) 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 (2002), 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 employability model is similar to the earnings algorithm, except that a binary employment indicator is used as the dependent variable instead of earnings, and the model is estimated by logit. The sample includes both customers who have had steady work just prior to enrolling in one-stop programs, and those without recent steady work. Our model parameterizes the effects of measurable attributes on the likelihood of having or not having recent steady employment. The expectation is that those with recent work experience are more employable, even before they receive services.<sup>9</sup> The model is estimated using either UI or ES administrative data for each of four separate regions of Georgia (metropolitan Atlanta, Northern, Coastal, and Balance of the state) on a selected program population.

As an example, an employability model for UI recipients in metropolitan Atlanta is presented in Table 8. The explanatory variables in the model include the number of prior employment services used, age, age squared, educational attainment, whether the most recent prior UI claim exhausted benefits, months of tenure on prior job, tenure squared, number of prior employers in a recent prior quarter, prior industry, prior occupation, and the Georgia field service office where UI benefits were claimed. Most estimated coefficients in the model are statistically significant. Our measure of employability tends to be positively correlated with age, high school education, use of prior intensive services, the number of employers in a quarter before registration, and tenure on the prior job (positive but diminishing). Employability is negatively related to other than high school education, and not having a driver's license. Using an employability model of the type summarized in Table 8, the employability score for each customer using the FDSS in a Georgia Career Center is computed.

Ordering employability scores from low to high, we divide the distribution of predicted employability by quintiles and present information about the effectiveness of alternative services for each of the five employability quintile groups. Table 9 shows the quintile employability scores. Each quintile group contains 20 percent of all observations. For UI clients in the Atlanta region, the quintiles are at employability scores of approximately 0.717, 0.846, 0.922, and 0.969. We decided to break the

<sup>&</sup>lt;sup>9</sup>In algebraic notation the model can be written as: e = a + B'X + u, where *e* is an indicator variable having a value of one if the customer had significant steady employment before registering for job search and zero otherwise, *X* is a matrix of personal and labor market explanatory variables, and *B* is a conformable vector of regression parameters. The error term, *u*, is assumed to have the logistic distribution and the model is estimated by the logit regression routine.

employability distribution into five groups for the purpose of examining patterns of service effectiveness, since that number clearly delineated the variation in service effectiveness across employability classes. There was more variation than represented by three classes, and variation diminished across neighboring classes when ten were used. Furthermore, several infrequently used services could not be meaningfully examined across more than five groups because of small sample size.

An indication of the power of the employability score to distinguish differences in customer characteristics is given in Table 10, which shows the mean values of descriptive characteristics for Atlanta UI claimants referred to the reemployment unit (REU). The low employability quintiles had lower values for prior earnings, educational attainment, age, and tenure on the prior job. The low quintiles also had higher values for number of prior employers in a recent quarter, the likelihood of a prior UI claim, the likelihood that a prior UI claim was exhausted, likelihood of being dislocated, and for those who are economically disadvantaged.

#### Service Referral

The service referral module algorithm identifies the set of activities that most often lead to successful employment for a customer in a particular employability quintile, in a particular UI or ES service subgroup, and a particular region of the state. Information about the characteristics and outcomes of individuals who have recently participated in services is used to estimate the relative impact of alternative services. 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.

To rank service effectiveness for customers grouped by employability score, impact estimates of alternative services were computed while correcting for selection bias. This was done using the least squares methodology with observable control variables. These estimates were validated using a propensity score 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).

Least squares estimates of relative service impacts were computed using data on only those who received services. Unfortunately, because of small sample sizes for some services, the resulting estimates of the relative effects of services were useful for reliably ranking only a few of the more than 20 available core and intensive services in Georgia Career Centers (Eberts, O'Leary, and DeRango 2002).<sup>10</sup> Fortunately, rankings based on these parametric estimates were nearly identical to rankings based on the simple gross outcome of interest–reemployment as measured by the proportion of customers with earnings of at least \$2,500 in each of two consecutive quarters in the four calendar

<sup>&</sup>lt;sup>10</sup>Of the 21 relative service impacts, 6 is the most estimated with precision among any of the five UI quintiles in Atlanta. Three of the five quintiles had only 4 out of 21 relative service impacts estimated with statistical significance (Eberts, O'Leary, and DeRango 2002, Table 8).

quarters immediately following registration for job search. Consequently, FDSS relies on a nonparametric approach and simply ranks service effectiveness by the proportion of an employability group achieving the reemployment criterion. Along with these rankings, information is provided on the number of customers in this employability quintile and region who used the service in a recent period.

Tables 11a to 11e separately provide full information for each of the five quintiles respectively on the gross effectiveness of alternative core and intensive services for UI clients sent to the reemployment unit in Atlanta region Career Centers. Rows in each table are sorted from most effective to least effective service as measured by the gross outcome "percentage of service users getting steady work." The display in these tables has the same layout as the service referral section of FDSS in the Georgia Workforce System. To put the gross outcome measure in context, the first column of numbers reports the total number of clients with similar employability characteristics and similar program orientation in the same geographic area of Georgia using the service recently. The second column of numbers shows the percentage of clients in that region/program group/quintile who used the service. The third column is the outcome measure of reemployment success. The far right column in each of these tables reports the relative effectiveness index.

As can be seen in Tables 11a to 11e, there is a bundle of five services which is most commonly received by UI claimants in the Atlanta profiling/REU/CAP group. These services include: service needs evaluation, orientation, eligibility review program (ERP), customer service plan, and counseling. For the first quintile group, Table 11a shows a common reemployment rate of 37.6 percent among customers receiving these services; however, the present summary provides service effectiveness information singly rather than in bundles. It is likely that patterns of service receipt under WIA will be different than that observed in these tables which are based on pre-WIA data.

There is not a common pattern of service effectiveness across quintiles. This can be seen in Table 12 which presents services ranked by effectiveness for quintile 1 and simply lists the rank of services for each of the other quintiles. Each quintile group has a different ranking of services, and for any particular service the ranking differs across quintile groups. For the UI profiling/REU/CAP clients in the Atlanta area, the bundle of five most common services tend to be most effective for the quintile five group, moderately ranked for the quintile one group, and ranked lower in effectiveness for the middle three groups. Job Referrals and call-ins (for job referral) are ranked as highly effective for the quintile five group who appear to be most job ready, but are very low on the list for quintile one. Service coordination is high on the list of effectiveness for quintile one, but ranked very low for all other quintiles.

#### **Training Statistics**

WIA organizes reemployment services into three classes: core, intensive, and training. To complement ranking of core and intensive services, FDSS provides similar information on four broad categories of training types which receive funding from the federal government. The four types of

training are: on-the-job (OJT), occupational skills, comprehensive assessment, and adult educationbasic skills-literacy. Small numbers of participants in these services mean that finer distinctions in service types are not possible. The bulk of training in Georgia is funded by the state lottery through Hope grants and Hope scholarships. Counts of these participants are not included in the FDSS tabulated statistics. The data in the pilot version of FDSS are from the federally funded job training program which preceded WIA—the Job Training Partnership Act (JTPA) program.

In FDSS, information on training effectiveness is presented as "training statistics," rather than suggesting a true ranking since only two training types had appreciable levels of activity: occupational skills training and comprehensive assessment. The other two types received little federal funding, and consequently had few participants counted in the JTPA data. Nonetheless, Table 13 shows differences in the ordering of occupational skills training and comprehensive assessment across the five employability quintile groups for UI in the Atlanta region. The lesser- used training types also appear to be more effective than the popular services for some quintiles. There are separate quintile rankings for UI and ES, and for each of the four Georgia regions.

#### A PROTOTYPE SYSTEM FOR GEORGIA

Appendix A to this paper presents prototype screens that have been integrated into the Georgia Workforce System (GWS) for pilot testing of FDSS in Athens and Cobb-Cherokee Career Centers. The GWS is the internet based combined intake and service referral record system for Georgia Career Centers. There are five screens in the prototype FDSS, which can be scrolled through once the FDSS internet web page is loaded for a particular client.

A frontline staff person conducting the FDSS session can quicky jump among the five screens without reloading the page by simply clicking on any of the titles which appear across the top of each screen. Each of the five screens lists the titles of the other four screens. The five screens are:

Customer Background Information Reemployment Probability and Estimated Earnings Related Occupations Service Referral Training Statistics

The **customer background information** screen is the starting point for an FDSS session. This page lists critical information needed to evaluate FDSS algorithms. The frontline staff person enters a customer's client ID number and then hits carriage return. This causes the entire FDSS web page to update and report information based on data about the client existing in the system. Much of this information is assembled from the most recent combined intake (UI/ES) registration, which may happen earlier on the same day of the first FDSS session.

One background variable merits special description. Special arrangements were made for the coding of prior occupation, since data from several different occupation coding systems are being used in FDSS. When the FDSS web page loads, the system identifies the prior occupation using the DOT (Dictionary of Occupational Titles) occupation code in the work history file. Since the related occupations algorithm is based on the O\*Net occupation coding system, known as SOC (Standard Occupation Code), a translation is required. Rules for the translation are presented in Table 14.

Occasionally, information in the GWS for a particular client may be incorrect or missing. The **customer background information** screen permits a frontline staff person to temporarily change some fields to values that the client claims to be appropriate for the current FDSS session. Temporary changes to these fields will not be recorded by the system; the values are only used in the currently active FDSS session. Values of variables which cannot be changed are listed above a line of demarcation, while changeable fields are below that line. Changeable fields include: education level, school enrollment status, employment status, geographic region of Georgia, and recent quarterly earnings. For each changeable field, a drop down menu is provided.

UI claimants find that it is often necessary to have missing wages added to their existing records to establish a claim. This procedure requires reliable documentation as evidence of the prior earnings. Unlike the UI eligibility process, the FDSS session requires no documentation to temporarily change values in these special fields. However, FDSS is not a means to correct erroneous wage records. Such information is provided only to produce recommendations from FDSS, and that advice is contingent on the accuracy of the data provided. Any values entered in these fields are not permanently recorded when the session is over.

After seeing FDSS results in other screens, a frontline staff person or client may wish to return to the **customer background information** screen later in an FDSS session in order to change values, and run "what if" scenarios. For example, what if the client enrolls in school?...or takes a part-time job?...or gets a driver's licence?...or locates in another region of Georgia? If the prior occupation is changed to a different one of ten SOC occupation groups, the SOC group is mapped into a DOT code based on the map presented as Table 15.

Clicking on the **reemployment and earnings estimates** title at the bottom of an FDSS screen jumps the view to that screen, evaluated at the most recent values given in the customer background information. Listed on this page are results of algorithms discussed in previous sections of this paper. The frontline staff person will see estimates for the client of the probability of returning to the prior industry, expected employment growth in the prior occupation, and a distribution of expected reemployment earnings. Also appearing on this screen is the customer's self-reported "minimum salary desired." Taken together, this information should help the frontline staff and customer identify reasonable reemployment goals, and then conduct a systematic search of vacancy listings (job orders). If the search of job orders fails to turn up any good job prospects, it may be useful to identify job openings in occupations related to that of the prior job. Frontline staff may identify **related occupations** by clicking on that title at the top of the screen. The **related occupations**\_screen lists up to five occupations identified by the O\*Net system as related to the prior occupation currently displayed on the **customer background information** screen. For each of the five occupations listed, the approximate starting hourly wage and the average annual job growth rate are provided for the local workforce area together with the O\*Net occupation code. Using the occupation codes, the frontline staff person may then identify appropriate job openings for the customer to consider.

If systematic job search yields no immediate candidates for job interviews, clicking on **service referral** at the top of any screen will jump the view to that screen. The result is an ordered list of core and intensive reemployment services ranked by effectiveness for clients with employability characteristics similar to those in the **customer background information** screen. For each service, the **service referral** screen displays information on the number of clients using the service, the percentage of clients using the service, the percentage of service users getting steady work, and the relative effectiveness index. The services are listed in order of the percentage of service users getting steady work, which is defined as the percentage having two consecutive quarters with earnings in each quarter exceeding \$2,500 in the four quarters after seeking services at a Georgia Career Center.

#### SUMMARY

The Workforce Investment Act of 1998 required creation of a national network of one-stop centers where intake and referral of customers to various programs are done in a coordinated fashion. Resource constraints dictate that each Workforce Development Area can serve only a fraction of the population that might benefit. Funding levels from state and federal sources affect 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 customers who will benefit the most, thereby maximizing the net social benefit of program expenditures.

The Frontline Decision Support System (FDSS) offers a set of tools that can help inform frontline 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 the chance of returning to work in the prior industry, reemployment earnings prospects, related occupations, and the likely outcomes of alternative reemployment services. The concept of FDSS is an extension of the Worker Profiling and Reemployment Services (WPRS) system, which all states have operated since 1994. The W.E. Upjohn Institute for Employment Research is working closely with the U.S. Department of Labor and the Georgia Department of Labor to design, pilot test, and implement FDSS in selected Georgia Career Centers. This paper documents the analytic foundation of each of the tools in FDSS using examples drawn from the Atlanta region of the Georgia FDSS that is currently being pilot tested in the Cobb-Cherokee Career Center. Pilot testing is also underway in the Atlanta Career Center based on algorithms for the Northern Georgia geographic region. To review the tools, we sequentially consider the elements of the systematic job search module (SJSM) and the service referral module (SRM).

The SJSM contains tools which can be used to inform the customer about the: 1) probability of returning to the prior industry, 2) likely employment growth in the prior occupation, 3) likely reemployment earnings, 4) available suitable job vacancy listings, and 5) occupations related to the prior one. The SRM provides the frontline staff with two tools: 1) a ranking of the core and intensive services estimated to be most effective for clients with similar characteristics, and 2) information about the effectiveness of alternative types of job training for clients with similar employability characteristics. To summarize client characteristics, we estimate employability models and group customers with similar scores.

Field testing of FDSS in the two Georgia pilot sites commenced in July, 2002. Based on the experience of field testing and using updated administrative data, the Georgia FDSS will be refined during the second half of 2002 with statewide implementation expected in early 2003.

An evaluation of FDSS is planned after the system is fully operational. The internet-based Georgia Workforce System will record frontline staff use of FDSS as a service in client records. This will provide a basis for future objective evaluations of FDSS effectiveness using administrative records.

#### References

Becker, Gary S. 1964. Human Capital. New York: National Bureau of Economic Research.

- DeRango, Kelly, Randall Eberts, Wei-Jang Huang, Kenneth Kline, Kris Kracker, and Christopher O'Leary. 2000. "Development of the Transferable Occupations Algorithm." A technical working paper. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.
- Eberts, Randall W. 2002. "Targeting for Welfare to Work." In *Targeting Employment Services*, Randall W. Eberts, Christopher J. O'Leary, and Stephen A. Wandner, eds. Kalamazoo, MI: W. E. Upjohn Institute for Employment Research.
- Eberts, Randall W., and Christopher J. O'Leary. 1996. "Design of the Worker Profiling and Reemployment Services System and Evaluation in Michigan." Staff working paper no. 96-41. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.
- Eberts, Randall W., Christopher J. O'Leary, and Wei-Jang Huang. 2000. "Elements of a Service Referral Algorithm for a Frontline Decision Support System for Washington Work First." A report to Washington State Employment Security Department and the U.S. Department of Labor. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research (November).
- Fallick, Bruce C. 1993. "The Industrial Mobility of Displaced Workers." *Journal of Labor Economics* 11(2): 302–323.
- Heckman, James J., Hidehiko Ichimura, Petra E. Todd. 1997. "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme." *Review of Economic Studies* 64(4): 605–654.
- Heckman, James J., Robert J. LaLonde, and Jeffrey A. Smith. 1999. "The Economics and Econometrics of Active Labor Market Programs." In *Handbook of Labor Economics*, *Volume 3A*, Orley Ashenfelter and David Card, eds. Amsterdam: Elsevier Science B.V., pp. 1865–2097.
- Heckman, James J., Jeffrey A. Smith, and Nancy Clements. 1997. "Making the Most Out of Programme Evaluations and Social Experiments: Accounting for Heterogeniety in Programme Impacts." *Review of Economic Studies* 64(4): 487–535.
- Jacobson, Louis S., Robert J. LaLonde, and Daniel G. Sullivan. 1993. "Earnings Losses of Displaced Workers." *American Economic Review* 83(4): 685–709.

- Markey, James P., and William Parks. 1989. "Occupational change: pursuing a different kind of work." *Monthly Labor Review* 112(9): 3–12.
- O'Leary, Christopher J., Paul T. Decker, and Stephen A. Wandner. 2002. "Targeting Reemployment Bonuses." In *Targeting Employment Services*, Randall W. Eberts, Christopher J. O'Leary, and Stephen A. Wandner, eds. Kalamazoo, MI: W. E. Upjohn Institute for Employment Research.
- Rosenbaum, P., and D. Rubin. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika* 70(1): 41–55.
- Smith, Jeffrey. 2000. "A Critical Survey of Empirical Methods for Evaluating Employment and Training Programs." Schweizerische Zeitschrift fuer Volkswirtschaft und Statistik (Swiss Journal of Economics and Statistics), 136(3): 247–268.
- Shaw, Kathryn L. 1987. "Occupational Change, Employer Change, and the Transferability of Skills." *Southern Economic Journal* 53(3): 702–719.
- U.S. Congress. 1998. Workforce Investment Act (WIA). Public Law 105-220 (August).

## Table 1Industry of Employment Transition Matrix; Percent of Unemployment Insurance<br/>Clients, Metropolitan Atlanta, Georgia

				Reemp	loyment In	dustry			
	Agriculture			Transpor- tation, Commu-	Whole-				
	Forestry	Mining	Manu-	nication,	sale	Retail	Finance		Public
Prior Industry	Fishery	Constr.	facturing	Utilities	Trade	Trade	Ins, RE	Services	Admin
Ag., For., Fish	26.3	10.1	10.9	4.9	10.5	11.7	3.2	20.6	1.6
Mine, Construct	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
WholesaleTrade	0.4	4.5	14.2	7.4	28.6	11.7	3.9	27.8	1.5
RetailTrade	0.3	2.4	6.2	5.5	7.3	45.5	4.7	26.6	1.5
Finance, Ins, RE	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 2Mean Percentage Change in Earnings for the Industry of Employment Transition<br/>Matrix, Metropolitan Atlanta, Georgia

		Reemployment Industry							
	Agriculture			Transpor- tation, Communi-	Whole-				
	Forestry	Mining	Manufac-	cation,	sale	Retail	Finance		Public
Prior Industry	Fishery	Const.	turing	Utilities	Trade	Trade	Ins, RE	Services	Admin
Ag., For., Fish	1.6	1.6	! 3.0	! 0.9	32.4	! 12.1	12.8	! 3.5	<b>!</b> 16.6
Mine, Construct	! 30.6	6.4	<b>!</b> 7.8	<b>!</b> 0.9	! 2.1	<b>!</b> 25.4	3.3	<b>!</b> 9.9	<b>!</b> 25.5
Manufacturing	! 34.3	<b>!</b> 14.3	6.6	! 0.5	! 2.1	<b>!</b> 29.4	<b>!</b> 9.0	! 15.7	<b>!</b> 21.4
Trans,Comm,Util	! 25.8	0.1	<b>!</b> 2.1	6.2	<b>!</b> 4.3	<b>!</b> 25.2	<b>!</b> 9.3	! 15.8	! 19.0
WholesaleTrade	! 28.3	! 2.0	! 2.0	1.3	7.1	<b>!</b> 21.4	<b>!</b> 0.7	<b>!</b> 7.4	<b>!</b> 26.8
RetailTrade	! 12.1	0.8	9.0	6.0	10.1	1.9	10.2	! 3.1	<b>!</b> 9.7
Finance, Ins, RE	! 28.3	<b>!</b> 9.9	<b>!</b> 6.6	<b>!</b> 10.1	1.4	<b>!</b> 26.4	8.6	! 11.2	<b>!</b> 23.4
Services	! 20.3	6.3	8.7	9.3	14.4	<b>!</b> 20.0	6.7	3.9	<b>!</b> 8.4
Public Admin.	! 22.7	<b>!</b> 7.7	1.7	2.2	12.2	<b>!</b> 21.5	<b>!</b> 8.6	<b>!</b> 2.4	<b>!</b> 4.2

	Parameter	Standard	Marginal	Hypothetical Workers		
Variable Description	Estimate	Error	Effect	1	2	3
Log of Maximum Prior Earnings	0.723**	0.061	0.180	8.923	9.616	7.824
UI Client	<b>!</b> 0.663**	0.058	<b>!</b> 0.157	1.000	1.000	1.000
Age as of Reference Date	0.042**	0.017	0.011	35.000	35.000	35.000
Age Squared	! 0.000*	0.000	<b>!</b> 0.000	1225.000	1225.000	1225.000
Education, Less than High School	0.208*	0.086	0.052	0.000	0.000	1.000
Education, GED	<b>!</b> 0.006	0.119	<b>!</b> 0.001	0.000	0.000	0.000
Education, Some College	<b>!</b> 0.244**	0.060	<b>!</b> 0.060	0.000	0.000	0.000
Education, Bachelor Degree	! 0.399**	0.085	<b>!</b> 0.097	0.000	1.000	0.000
Education, Advanced	<b>!</b> 0.527**	0.177	<b>!</b> 0.127	0.000	0.000	0.000
Veteran	<b>!</b> 0.129**	0.065	! 0.032	0.000	0.000	0.000
Dislocated Worker	! 0.205**	0.057	<b>!</b> 0.051	0.000	0.000	0.000
Employed	0.386**	0.077	0.096	0.000	0.000	0.000
Reference Date in 2nd Quarter	<b>!</b> 0.071	0.059	<b>!</b> 0.018	1.000	1.000	1.000
Reference Date in 3rd Quarter	<b>!</b> 0.153**	0.065	<b>!</b> 0.038	0.000	0.000	0.000
Reference Date in 4th Quarter	! 0.218**	0.070	<b>!</b> 0.054	0.000	0.000	0.000
Prior Occ: Mgmt, Business, Finance	! 0.822**	0.101	! 0.191	0.000	0.000	0.000
Prior Occ: Professional and Related	! 0.822**	0.088	! 0.191	0.000	0.000	0.000
Prior Occ: Services	<b>!</b> 0.662**	0.132	<b>!</b> 0.157	0.000	0.000	0.000
Prior Occ: Sales and Related	<b>!</b> 1.097**	0.118	! 0.243	1.000	1.000	1.000
Prior Occ: Office and Admin Support	<b>!</b> 0.934**	0.078	! 0.213	0.000	0.000	0.000
Prior Occ: Farming, Fishing, Forestry	0.158	0.550	0.039	0.000	0.000	0.000
Prior Occ: Construction, Extraction	<b>!</b> 0.565**	0.169	<b>!</b> 0.136	0.000	0.000	0.000
Prior Occ: Install, Maintenance, Repair	<b>!</b> 0.409**	0.118	<b>!</b> 0.100	0.000	0.000	0.000
Prior Occ: Transp, Material Moving	<b>!</b> 0.414**	0.066	<b>!</b> 0.100	0.000	0.000	0.000
Intercept	<b>!</b> 6.461**	0.564	<b>!</b> 0.475	1.000	1.000	1.000
Return to Same Industry Probability	:			0.317	0.340	0.205

## Table 3Logistic Model for the Probability of Returning to the Same Industry<br/>(UI and ES Clients in Atlanta whose Prior Industry was Manufacturing)

Example 1: Age: 35, Educ: HS grad, Annual income: \$30,000, Occupation: sales, Months tenure: 24.

Example 2: Age: 35, Educ: post-HS (Bachelors), Annual income: \$60,000, Occupation: sales, Months tenure: 48. Example 3: Age: 35, Educ: less than HS, Annual income: \$10,000, Occupation: sales, Months tenure: 8.

\* 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.

				Standard Occ	cupation Code	e (SOC) Occuj	pation Group			
	11–13	15–29	31–39	41	43	45	47	49	51	53
Industry Group										
Ag, forest, fish	521.5	515.9	444.4	559.9	346.8	459.9	416.7	629.4	376.0	350.8
Mining, Constr	564.1	539.0	405.0	601.9	411.1	518.6	403.9	322.7	511.2	471.4
Manufacturing	578.3	537.8	456.8	560.9	492.0	483.3	492.8	509.8	543.4	497.0
Trans, Comm, Util	570.8	530.7	423.5	550.0	483.0	500.9	478.8	520.0	536.7	478.3
Wholesale Trade	545.5	518.6	425.4	587.2	513.3	429.6	417.7	650.0	473.1	445.5
Retail Trade	566.6	507.5	323.9	559.2	334.5	417.7	482.2	514.3	511.3	410.3
Finance, Ins, RE	533.0	519.1	416.0	572.2	481.2	475.8	337.9	440.0	437.6	444.1
Services	508.3	480.3	392.1	462.4	382.4	413.1	323.0	333.0	478.0	381.5
Public Admin	517.7	517.4	541.6	545.3	472.0	467.4	383.9	520.0	471.2	478.6

Table 4Industry-Occupation Matrix of Usual Quarterly Hours Worked based on 1996 to 199 CPS March Survey Data

	Medi	an	Нур	othetical Wo	rkers
	Parameter	Standard			
Variable Description	Estimate	Error	1	2	3
Log of Maximum Prior Earnings	0.656**	0.011	8.923	9.616	7.824
UI Client	! 0.058**	0.011	1	1	1
Age as of Reference Date	! 0.001	0.003	35	35	35
Age Squared	! 0.000	0.000	1225	1225	1225
Education, Less than High School	! 0.055**	0.015	0	0	1
Education, GED	<b>!</b> 0.048**	0.020	0	0	0
Education, Some College	0.041**	0.011	0	0	0
Education, Bachelors Degree	0.131**	0.015	0	1	0
Education, Advanced	0.174**	0.031	0	0	0
Veteran	0.027**	0.012	0	0	0
Dislocated Worker	! 0.002	0.010	0	0	0
Education Status	! 0.020	0.027	0	0	0
Employed	0.035**	0.014	0	0	0
Exhausted Prior UI Claim	! 0.082**	0.042	0	0	0
Weeks of UI Collected Prior Claim	0.005**	0.002	0	0	0
Does Not Have Driver's License	! 0.068**	0.019	0	0	0
Available for Rotating Shifts	0.023**	0.011	0	0	0
Months of Tenure, Most Recent Job	! 0.001**	0.000	24	48	8
Months of Tenure Squared	0.000**	0.000	576	2304	64
Reference Date in 2nd Qtr	0.002	0.010	1	1	1
Reference Date in 3rd Qtr	! 0.006	0.012	0	0	0
Reference Date in 4th Qtr	! 0.007	0.013	0	0	0
Ref Date 3 Qtrs After Max Wage	! 0.003	0.010	1	1	1
Ref Date 4 Qtrs After Max Wage	0.002	0.012	0	0	0
Ref Date 5 Qtrs After Max Wage	! 0.004	0.011	0	0	0
Days Left in Current Quarter	0.000	0.000	54	54	54
Unemployment Rate, t! 3	0.189	0.526	0.040	0.040	0.040
Employ Yr-Over-Yr Pct. Chg., t! 3	0.070	0.253	0.060	0.060	0.060
Post Industry Same as Prior Industry	0.156**	0.009	0.292	0.325	0.171
Occup: Mgmt, Business, Finance	0.045**	0.018	0	0	0
Occup: Professional and Related	0.074**	0.016	0	0	0
Occup: Services	! 0.012	0.024	0	0	0
Occup: Sales and Related	0.042**	0.020	1	1	1
Occup: Office and Admin Support	! 0.005	0.014	0	0	0
Occup: Farming, Fishing, Forestry	! 0.158	0.097	0	0	0
Occup: Construction, Extraction	! 0.017	0.031	0	0	0
Occup: Installation, Maintenance	0.101**	0.021	0	0	0
Occup: Transportation, Material Move	! 0.023**	0.012	0	0	0
Intercept	3.029**	0.114	1	1	1
Predicted 25 <sup>th</sup>			4871	8559	2245
Predicted 50 <sup>th</sup>			6661	11705	3070
Predicted 75 <sup>th</sup>			8799	15462	4055

# Table 5Median Regression Coefficient Estimate and Examples of Predicted Earnings for<br/>Recent Manufacturing Employees Among UI Recipients in Metropolitan Atlanta,<br/>Georgia

Example 1: Age: 35, Educ: HS grad, Annual income: \$30,000, Occupation: sales, Months tenure: 24.

Example 2: Age: 35, Educ: Bachelors degree, Annual income: \$60,000, Occupation: sales, Months tenure: 48.

Example 3: Age: 35, Educ: less than HS, Annual income: \$10,000, Occupation: sales, Months tenure: 8.

\* (\*\*) Parameter significant at the 90 (95) percent confidence level in a two-tailed test.

		Ratio for	Ratio for
Occupation Code	Description	25th Percentile	75th Percentile
soc1113	Management, Business, Financial	0.716465824	1.334754150
soc1529	Professional and Related	0.750614349	1.364359733
soc3139	Services	0.796787908	1.413971832
soc41	Sales and Related Occupations	0.731179242	1.320901332
soc43	Office and Administrative Support	0.772121670	1.310724935
soc45	Farming, Fishing, Forestry	0.702977445	1.317053626
soc47	Construction and Extraction	0.757809558	1.327728492
soc49	Installation, Maintenance and Repair	0.736310733	1.370156660
soc51	Production	0.728655695	1.409237099
soc53	Transportation and Material Moving	0.729236288	1.344032112

## Table 6Atlanta Metro Area - Manufacturing Industry Ratios to Calculate 25th and 75th<br/>Earnings Percentiles

SOC: Standard Occupation Code.

O*Net SOC Title	O*Net SOC
Food preparation and serving	35-3021
Counter and retail clerks	41-2021
Parts sales persons	41-2022
Insurance sales agents	41-3021
Receptionists	43-4171

 Table 7
 Occupations Related to Cashier (O\*Net SOC 41-2011)

SOC: Standard Occupation Code.

	Parameter		-	Hypothetical Workers		
Variable	Estimate	Error	Effect	1	2	3
Intercept	! 0.092	0.126	<b>!</b> 0.016	1	1	1
Months Tenure on Prior Job	0.012**	0.001	0.002	24	48	8
Months Tenure Squared	! 0.000**	0.000	! 0.000	576	2,304	64
Number of Employers, Qtr T! 5	! 0.032**	0.015	! 0.005	1	1	1
Prior Wages, 5 Qtrs Before Ref Date	0.000**	0.000	0.000	7,500	15,000	2,500
Age as of Reference Date	0.059**	0.006	0.010	35	35	35
Age Squared	! 0.000**	0.000	! 0.000	1,225	1,225	1,225
Education, Less than High School	! 0.225**	0.034	! 0.040	0	0	1
Education, GED	! 0.093*	0.049	! 0.016	0	0	0
Education, Some College	0.069**	0.025	0.011	0	0	0
Education, Bachelor Degree	0.226**	0.038	0.035	0	1	0
Education, Advanced	0.233**	0.076	0.036	0	0	0
Youth, Ages 14 through 21	! 0.665**	0.051	<b>!</b> 0.131	0	0	0
Veteran	! 0.021	0.033	! 0.004	0	0	0
Dislocated Worker	0.138**	0.024	0.022	0	0	0
Welfare Recipient	<b>!</b> 0.632**	0.052	! 0.123	0	0	0
Economically Disadvantaged	<b>!</b> 0.656**	0.022	! 0.129	0	0	0
Exhausted Prior UI Claim	! 1.053**	0.045	! 0.222	0	0	0
Has No Drivers' License	! 0.356**	0.029	! 0.065	0	0	0
Available for Rotating Shifts	<b>!</b> 0.045	0.031	! 0.008	0	0	0
Reference Date in 2nd Quarter	0.147**	0.025	0.023	1	1	1
Reference Date in 3rd Quarter	0.411**	0.029	0.060	0	0	0
Reference Date in 4th Quarter	0.285**	0.030	0.043	0	0	0
Prior Industry: Ag, Forestry, Fish	<b>!</b> 0.277*	0.157	! 0.050	0	0	0
Prior Industry: Mining and Construction	! 0.252**	0.061	! 0.045	0	0	0
Prior Industry: Trans, Comm, Utilities	0.043	0.059	0.007	0	0	0
Prior Industry: Wholesale Trade	0.052	0.056	0.008	0	0	0
Prior Industry: Retail Trade	! 0.401**	0.034	<b>!</b> 0.074	0	0	0
Prior Industry: FIRE	0.213**	0.064	0.033	0	0	0
Prior Industry: Services	<b>!</b> 0.159**	0.032	! 0.028	0	0	0
Prior Industry: Public Admin	<b>!</b> 0.156**	0.073	! 0.027	0	0	0
Prior Occupation: Management, Business, Financial	0.072	0.057	0.012	0	0	0
Prior Occupation: Professional and Related	! 0.068	0.051	<b>!</b> 0.011	0	0	0
Prior Occupation: Services	<b>!</b> 0.655**	0.046	! 0.128	0	0	0
Prior Occupation: Sales and Related Occupations	! 0.303**	0.053	! 0.055	1	1	1
Prior Occupation: Office and Administrative Support	! 0.301**	0.044	<b>!</b> 0.054	0	0	0
Prior Occupation: Farming, Fishing and Forestry	<b>!</b> 0.135	0.125	! 0.023	0	0	0
Prior Occupation: Construction and Extraction	<b>!</b> 0.046	0.063	! 0.008	0	0	0
Prior Occupation: Install, Maintenance and Repair	0.037	0.074	! 0.006	0	0	0
Prior Occupation: Transport and Material Moving	<b>!</b> 0.189**	0.047	<b>!</b> 0.033	0	0	0
Field Service Office: DeKalb	<b>!</b> 0.034	0.034	<b>!</b> 0.006	1	1	1
Field Service Office: Gwinnett	0.184**	0.043	0.029	0	0	0
Field Service Office: North Metro	0.007	0.038	0.001	0	0	0
Field Service Office: South Metro	<b>!</b> 0.156**	0.033	<b>!</b> 0.027	0	0	0
Field Service Office: Cobb/Cherokee	! 0.006	0.038	<b>!</b> 0.001	0	0	0
Employability Score:				0.953	0.996	0.786

#### Table 8 Employability Model: Atlanta Metro, UI Sample

Example 1: Age: 35, Educ: HS grad, Annual income: \$30,000, Occupation: sales, Months tenure: 24.

Example 2: Age: 35, Educ: Bachelors degree, Annual income: \$60,000, Occupation: sales, Months tenure: 48.

Example 3: Age: 35, Educ: less than HS, Annual income: \$10,000, Occupation: sales, Months tenure: 8.

\* (\*\*) Parameter significant at the 90 (95) percent confidence level in a two-tailed test.

Region	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
	Georgi	a - UI Profiling	g/REU/CAP C	lients	
Atlanta	0.717	0.846	0.922	0.969	1.000
Northern	0.649	0.809	0.899	0.958	1.000
Coastal	0.470	0.664	0.829	0.939	1.000
Balance	0.467	0.654	0.809	0.920	1.000
	Georgia -	UI NON-Profi	ling/REU/CA	P Clients	
Atlanta	0.610	0.761	0.860	0.940	1.000
Northern	0.510	0.680	0.818	0.917	1.000
Coastal	0.356	0.540	0.719	0.883	1.000
Balance	0.367	0.542	0.701	0.856	1.000
		Georgia Train	ing Referrals		
		on UI Employ	0	Model	
Atlanta	0.756	0.878	0.935	0.970	1.000
Northern	0.685	0.841	0.911	0.960	1.000
Coastal	0.500	0.694	0.825	0.928	1.000
Balance	0.480	0.700	0.833	0.923	1.000

## Table 9 Employability Score Quintiles

Description	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Prior Wages, 5 Qtrs Before Ref Date	1,969	3,074	4,491	6,279	11,268
Number of Employers, Qtr T-5	1.39	1.33	1.26	1.18	1.12
Had Prior UI Claim	0.167	0.086	0.072	0.052	0.037
Exhausted Prior UI Claim	0.086	0.011	0.010	0.004	0.003
Age as of Reference Date	37	38	39	40	42
Months Tenure on Prior Job	19	24	35	49	70
Educ, LT High School	0.174	0.082	0.069	0.049	0.017
Educ, GED	0.051	0.038	0.032	0.023	0.014
Educ, HS Grad	0.495	0.430	0.409	0.360	0.225
Educ, Some College	0.229	0.294	0.297	0.301	0.255
Educ, Bachelor	0.042	0.122	0.163	0.224	0.379
Educ, Advanced	0.008	0.033	0.030	0.042	0.109
Education Status, 1=In School	0.017	0.018	0.016	0.013	0.011
Youth, Ages 14 through 21	0.089	0.010	0.002	0.000	0.000
Veteran	0.084	0.119	0.114	0.100	0.122
Dislocated Worker	0.623	0.608	0.598	0.608	0.576
Welfare Recipient	0.081	0.005	0.003	0.001	0.000
Economically Disadvantaged	0.740	0.331	0.209	0.091	0.031
Employment Status, 1=Employed	0.039	0.028	0.025	0.019	0.011
Has No Drivers License	0.247	0.090	0.052	0.023	0.007
Available for Rotating Shifts	0.113	0.113	0.106	0.106	0.103

## Table 10 Characteristics of Employability Quintile Groups Atlanta UI Profiling/REU/CAP Clients

				Percentage of	
		Number of	Percentage	Service Users	Relative
		Clients Using	of Clients	Getting Steady	Effectiveness
Rank	Description	Service	Using Service	Work	Index (*1)
1	Job Finding Club	1	0.0	100.0	2.66
2	Testing	1	0.0	100.0	2.66
3	Service Coordination	10	0.0	60.0	1.59
4	Job Referrals	1,356	28.0	42.1	1.12
5	Resume Preparation	1,550	3.2	40.8	1.08
6	Order Search	1,279	26.4	40.0	1.06
7	Specific LMI	640	13.2	39.7	1.05
8	Service Needs Evaluation	4,698	97.1	37.6	1.00
9	Orientation	4,696	97.0	37.6	1.00
10	ERP	4,726	97.6	37.6	1.00
11	Job Search Assistance	542	11.2	37.6	1.00
12	Customer Service Plan	4,705	97.2	37.6	1.00
13	Counseling	4,709	97.3	37.6	1.00
14	Workshops	3,139	64.9	36.6	0.97
15	Job Search Planning	837	17.3	34.1	0.91
16	Referred to Support Services	44	0.9	34.1	0.91
17	Job Development	115	2.4	33.9	0.90
18	Call-In	495	10.2	33.5	0.89
19	Referred to Training	138	2.9	31.2	0.83
20	Expanded Workshop	8	0.2	25.0	0.66
21	Bonding Assistance	3	0.1	0.0	0.00

## Table 11a Service Referral Rankings for Quintile 1; Atlanta UI Profiling/REU/CAP Clients

				Percentage of	
		Number of	Percentage	Service Users	Relative
		Clients Using	of Clients	Getting Steady	Effectiveness
Rank	Description	Service	Using Service	Work	Index (*1)
1		1	0.0	100.0	2.02
1	Testing	1	0.0	100.0	2.02
2	Job Referrals	1,212	25.0	55.6	1.12
3	Job Search Assistance	513	10.6	51.9	1.05
4	Referred to Support Services	45	0.9	51.1	1.03
5	Specific LMI	699	14.4	50.9	1.03
6	Order Search	1,629	33.7	50.8	1.02
7	Call-In	413	8.5	50.1	1.01
8	Expanded Workshop	2	0.0	50.0	1.01
9	Orientation	4,744	98.0	49.4	1.00
10	ERP	4,763	98.4	49.4	1.00
11	Service Needs Evaluation	4,742	98.0	49.3	0.99
12	Customer Service Plan	4,754	98.2	49.3	0.99
13	Counseling	4,754	98.2	49.3	0.99
14	Workshops	3,287	67.9	48.8	0.98
15	Job Development	115	2.4	47.8	0.96
16	Resume Preparation	166	3.4	47.0	0.95
17	Service Coordination	15	0.3	46.7	0.94
18	Job Search Planning	457	9.4	46.0	0.93
19	Referred to Training	81	1.7	43.2	0.87
20	Bonding Assistance	3	0.1	33.3	0.67
21	Job Finding Club	1	0.0	0.0	0.00

## Table 11b Service Referral Rankings for Quintile 2 Atlanta UI Profiling/REU/CAP Clients

		Percentage of				
		Number of	Percentage	Service Users	Relative	
		Clients Using	of Clients	Getting Steady	Effectiveness	
Rank	Description	Service	Using Service	Work	Index (*1)	
1	Joh Finding Club	2	0.0	100.0	1.85	
2	Job Finding Club	1	0.0	100.0	1.85	
	Testing	4	0.0	75.0		
3	Expanded Workshop	-	0.1-		1.39	
4	Job Development	125	2.6	63.2	1.17	
5	Job Referrals	1,045	21.6	61.8	1.15	
6	Resume Preparation	152	3.1	61.8	1.15	
7	Referred to Training	72	1.5	61.1	1.13	
8	Referred to Support Services	46	1.0	58.7	1.09	
9	Call-In	365	7.5	55.6	1.03	
10	Job Search Assistance	479	9.9	55.5	1.03	
11	Order Search	1,698	35.1	54.2	1.00	
12	Service Needs Evaluation	4,760	98.3	53.6	0.99	
13	Orientation	4,762	98.4	53.6	0.99	
14	ERP	4,776	98.7	53.6	0.99	
15	Customer Service Plan	4,768	98.5	53.6	0.99	
16	Counseling	4,774	98.6	53.6	0.99	
17	Specific LMI	634	13.1	53.0	0.98	
18	Workshops	3,421	70.7	52.9	0.98	
19	Job Search Planning	283	5.8	51.2	0.95	
20	Service Coordination	7	0.1	42.9	0.80	
20	Bonding Assistance	5	0.1	40.0	0.74	

## Table 11c Service Referral Rankings for Quintile 3 Atlanta UI Profiling/REU/CAP Clients

		Percentage of				
		Number of	Percentage	Service Users	Relative	
		Clients Using	of Clients	Getting Steady	Effectivenes	
Rank	Description	Service	Using Service	Work	Index (*1)	
1	Testing	1	0.0	100.0	1.71	
2	Bonding Assistance	1	0.0	100.0	1.71	
3	Job Referrals	954	19.7	67.8	1.16	
4	Resume Preparation	162	3.3	63.0	1.08	
5	Job Development	124	2.6	61.3	1.05	
6	Order Search	1,838	38.0	60.8	1.04	
7	Job Search Assistance	440	9.1	58.9	1.01	
8	Specific LMI	671	13.9	58.7	1.00	
9	Service Needs Evaluation	4,785	98.9	58.3	1.00	
10	Orientation	4,784	98.8	58.3	1.00	
11	ERP	4,788	98.9	58.3	1.00	
12	Customer Service Plan	4,787	98.9	58.3	1.00	
13	Counseling	4,793	99.0	58.3	1.00	
14	Workshops	3,434	71.0	57.3	0.98	
15	Call-In	298	6.2	54.4	0.93	
16	Referred to Support Services	43	0.9	53.5	0.91	
17	Job Search Planning	239	4.9	52.7	0.90	
18	Referred to Training	60	1.2	51.7	0.88	
19	Service Coordination	8	0.2	50.0	0.85	
20	Job Finding Club	0	0.0	na	na	
21	Expanded Workshop	0	0.0	na	na	

## Table 11d Service Referral Rankings for Quintile 4 Atlanta UI Profiling/REU/CAP Clients

			Percentage of			
		Number of	Percentage	Service Users	Relative	
		Clients Using	of Clients	Getting Steady	Effectiveness	
Rank	Description	Service	Using Service	Work	Index (*1)	
1	Job Referrals	635	13.1	64.9	1.15	
2	Job Development	90	1.9	58.9	1.04	
3	Call-In	247	5.1	58.7	1.04	
4	Service Needs Evaluation	4,792	99.0	56.6	1.00	
5	Orientation	4,793	99.0	56.6	1.00	
6	ERP	4,797	99.1	56.6	1.00	
7	Customer Service Plan	4,795	99.1	56.6	1.00	
8	Counseling	4,797	99.1	56.6	1.00	
9	Order Search	1,897	39.2	56.2	1.00	
10	Job Search Assistance	362	7.5	55.5	0.98	
11	Specific LMI	515	10.6	55.1	0.98	
12	Workshops	3,372	69.7	54.5	0.97	
13	Job Search Planning	107	2.2	53.3	0.94	
14	Resume Preparation	106	2.2	51.9	0.92	
15	Referred to Support Services	29	0.6	51.7	0.92	
16	Service Coordination	8	0.2	50.0	0.89	
17	Referred to Training	30	0.6	40.0	0.71	
18	Bonding Assistance	3	0.1	33.3	0.59	
19	Job Finding Club	1	0.0	0.0	0.00	
20	Testing	2	0.0	0.0	0.00	
21	Expanded Workshop	0	0.0	na	na	

# Table 11e Service Referral Rankings for Quintile 5 Atlanta UI Profiling/REU/CAP Clients

Description	1	2	3	4	5
Job Finding Club	1	21	1	na	19
Testing	1	1	1	1	20
Service Coordination	3	17	20	19	16
Job Referrals	4	2	5	3	1
Resume Preparation	5	16	6	4	14
Order Search	6	6	11	6	9
Specific LMI	7	5	17	8	11
Service Needs Evaluation	8	11	12	9	4
Orientation	8	9	12	9	4
ERP	8	9	12	9	4
Workshops	8	14	18	14	12
Job Search Assistance	8	3	10	7	10
Customer Service Plan	8	12	12	12	4
Counseling	8	12	12	13	4
Referred to Support Services	15	4	8	16	15
Job Search Planning	16	18	19	17	13
Job Development	17	15	4	5	2
Call-In	18	7	9	15	3
Referred to Training	19	19	7	18	17
Expanded Workshop	20	8	3	na	na
Bonding Assistance	21	20	21	1	18

# Table 12A Ranking of Service Effectiveness by Quintile Group Atlanta UI<br/>Profiling/REU/CAP Clients

Rank	Service Variable	Description	Number of Clients Using Service	Percentage of Clients Using Service	Percentage of Service Users Steadily Working	Relative Effectiveness Index
		The second se			6	
	. 10		Quintile 1	2.0	40.2	1.26
1	jtpa40	On-the-Job Training	29	2.0	48.3	1.36
2	jtpa41	Occupational Skills Training	532	37.3	37.8	1.06
3	jtpa5	Comprehensive Assessment	837	58.7	33.9	0.95
4	jtpa39	Adult Ed, Basic Skills, Literacy	38	2.7	28.9	0.81
			Quintile 2			
1	jtpa5	Comprehensive Assessment	312	55.1	53.2	1.03
2	jtpa39	Adult Ed, Basic Skills, Literacy	2	0.4	50.0	0.97
3	jtpa41	Occupational Skills Training	248	43.8	49.2	0.96
4	jtpa40	On-the-Job Training	5	0.9	40.0	0.78
			Quintile 3			
1	jtpa39	Adult Ed, Basic Skills, Literacy	9	1.7	66.7	1.21
2	jtpa5	Comprehensive Assessment	257	47.3	56.0	1.02
3	jtpa41	Occupational Skills Training	283	52.1	54.4	0.99
4	jtpa40	On-the-Job Training	2	0.4	50.0	0.91
			Quintile 4			
1	jtpa39	Adult Ed, Basic Skills, Literacy	3	0.5	66.7	1.12
2	jtpa41	Occupational Skills Training	301	53.7	60.8	1.02
3	jtpa5	Comprehensive Assessment	259	46.2	57.9	0.98
4	jtpa40	On-the-Job Training	0	0.0	na	na
			Quintile 5			
1	jtpa40	On-the-Job Training	1	0.1	100.0	1.59
2	jtpa39	Adult Ed, Basic Skills, Literacy	4	0.6	75.0	1.19
3	jtpa5	Comprehensive Assessment	255	38.1	66.3	1.06
4	jtpa41	Occupational Skills Training	412	61.6	60.4	0.96

# Table 13 Atlanta Training Referral Based on UI Employability Model

SOC name	SOC number	DOT range of codes
Management, business and financial	11-0000 to 13-0000	161-168
Professional and related occupations	15-0000 to 29-0000	00-05, 07, 09-16, 19, 96-97 but excluding 161-168
Services including military	31-0000 to 39-0000	30-38
Sales and related occupations	41-0000	25-27, 29
Office and administrative support	43-0000	20-24
Farming, fishing and forestry	45-0000	40-46
Construction and extraction	47-0000	85, 86, 89, 93
Installation, maintenance and repair	49-0000	62, 63, 82
Production	51-0000	50-61, 64-81, 84, 95
Transportation and material moving	53-0000	90-92

## Table 14 Mapping from DOT to SOC Occupation Codes

SOC: Standard Occupation Code.

DOT: Dictionary of Occupational Titles.

## Table 15Mapping from an SOC Group to a DOT Code

SOC name	SOC number	DOT number	DOT name
Management, business and financial	11-0000 to 13-0000	162157018	Buyer
Professional and related occupations	15-0000 to 29-0000	091227010	Teacher, secondary school
Services including military	31-0000 to 39-0000	352367010	Airline Flight Attendant
Sales and related occupations	41-0000	003151010	Sales Engineer, electrical products
Office and administrative support	43-0000	201362030	Secretary
Farming, fishing and forestry	45-0000	401137010	Area Supervisor
Construction and extraction	47-0000	824137010	Chief Electrician
Installation, maintenance and repair	49-0000	184167050	Maintenance Supervisor
Production	51-0000	641562010	Corrugator Operator
Transportation and material moving	53-0000	168167082	Transportation Inspector

SOC: Standard Occupation Code

DOT: Dictionary of Occupational Titles.

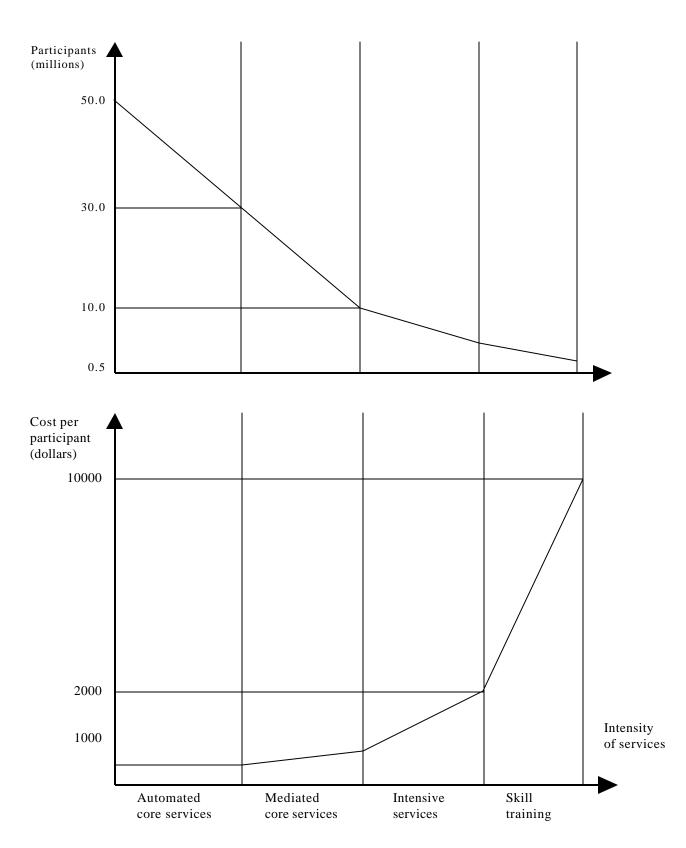
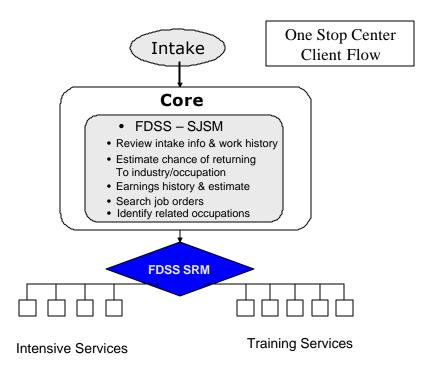


Figure 1 Use and Cost of One-Stop Career Center Services under the Workforce Investment Act

Figure 2 One-Stop Center Client Flow



Appendix A

The Frontline Decision Support System: Prototype Screens for the Georgia Workforce System

## FRONTLINE DECISION SUPPORT SYSTEM

## **Customer Background Information**

Wednesday May 08, 2002 at 09:13:07 ET.

Reemployment and Earning Estimates | Related Occupations | Service Referral | Training Statistics

SSN: 123456789

#### Name - JOHN SMITH

Current Age: 35 Gender/Race: WHITE Hispanic Origin: No Veteran Status: No Recently Separated: Disability: Citizenship: Yes Economically disadvantaged: No Disability: No Exhausted previous UI claim: No Resides in: COBB COUNTY Claimant: YES Last Chk: 05/05/02 Wks paid: 2 BYE: 04/01/03 POTENTIAL Dislocated Worker: No TANF: No Employment Status: Not Employed Currently in school: No Prior Industry: MANUFACTURING

County of Employment: COBB Education Level: HS GRADUATE High School Graduate: YES GED: NO Driver's license: YES Available for all shifts: NO

Prior Occupation: SALES Months Experience in Prior Occupation: 24 Prior Hourly Wage Rate: \$15.00 Minimum Salary Desired: \$10.00 Per: HOUR

#### Wage Information:

Qtr	Year	Wages
4	2001	\$ 6,000
3	2001	\$ 7,000
2	2001	\$ 8,000
1	2001	\$ 9,000

#### **RECALCULATE VALUES**

#### **RESET ORIGINAL VALUES**

## **Reemployment Probability and Estimated Earnings**

Customer Background Information | Related Occupations | Service Referral | Training Statistics

SSN: 123456789 Name: JOHN SMITH

Probability of Return to Work in Your Prior Industry:

The chance of returning to the <u>MANUFACTURING</u> industry in <u>COBB</u> county is 61%.

Expected Job Growth in Prior Occupation:

Over the next 5 years, employment in the <u>SALES</u> occupation is expected to grow by +2.25% per year in <u>COBB</u> county.

Likely Reemployment Earnings:

Individuals with a similar background had the following estimated reemployment earnings:

25% had earnings less than \$8.10 per hour 50% had earnings less than \$9.05 per hour 75% had earnings less than \$10.20 per hour

Minimum Salary desired \$10.00 per hour

## **Related Occupations**

Customer Background Information | Reemployment Probability and Estimated Earnings | Service Referral | Training Statistics

The following occupations are related to <u>Cashiers</u>. For each related occupation listed, the approximate starting hourly wage and the average annual job growth rate in the <u>Cobb County</u> Workforce area are given.

Related Occupations	Approximate Starting Hourly Wage	Average Annual Job Growth Rate	O*Net Code
Food preparation and serving	\$5.93	1.02%	35-3021
Counter and retail clerks	\$6.29	4.29%	41-2021
Parts sales persons	\$6.29	2.29%	41-2022
Insurance sales agents	\$8.69	3.52%	41-3021
Receptionists	\$7.20	5.67%	43-4171

### SSN: 123456789 Name: JOHN SMITH

# Service Referral

Customer Background Information | Reemployment Probability and Estimated Earnings | Related Occupations | Training Statistics

The following is a list of services ranked in order of effectiveness for recent clients in the <u>ATLANTA</u> <u>METRO</u> region with characteristics similar to those in the Customer Background Information screen.

Service	Number of Clients Using Service	Percentage of Clients Using Service	Percentage of Service Users Getting Steady Work	Relative Effectiveness Index (*1)
Job Finding Club	2	0.0	100.0	1.85
Testing	1	0.0	100.0	1.85
Expanded Workshop	4	0.1	75.0	1.39
Job Development	125	2.6	63.2	1.17
Job Referrals	1045	21.6	61.8	1.15
Resume Preparation	152	3.1	61.8	1.15
Referred to Training	72	1.5	61.1	1.13
Referred to Support Services	46	1.0	58.7	1.09
Call-In	365	7.5	55.6	1.03
Job Search Assistance	479	9.9	55.5	1.03
Order Search	1698	35.1	54.2	1.00
Service Needs Evaluation	4760	98.3	53.6	0.99
Orientation	4762	98.4	53.6	0.99
ERP	4776	98.7	53.6	0.99
Customer Service Plan	4768	98.5	53.6	0.99
Counseling	4774	98.6	53.6	0.99
Specific LMI	634	13.1	53.0	0.98
Workshops	3421	70.7	52.9	0.98
Job Search Planning	283	5.8	51.2	0.95
Service Coordination	7	0.1	42.9	0.80
Bonding Assistance	5	0.1	40.0	0.74

SSN: 123456789 Name: JOHN SMITH

## **Training Statistics**

Customer Background Information | Reemployment Probability and Estimated Earnings | Related Occupations | Service Referral

The following is information about the recent use of the four general types of adult training by clients in the <u>ATLANTA METRO</u> region with characteristics similar to those in the Customer Background Information screen.

## SSN: 123456789 Name: JOHN SMITH

Service	Number of Clients Using Service	Percentage of Clients Using Service	Percentage of Service Users Getting Steady Work	Relative Effectiveness Index (*1)
Adult Ed, Basic Skills, Literacy	9	1.7	66.7	1.21
Comprehensive Assessment	257	47.3	56.0	1.02
Occupational Skills Training	283	52.1	54.4	0.99
On-the-Job Training	2	0.4	50.0	0.91

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Appendix B

An Accounting of Samples and Models Underlying the FDSS for the Georgia Workforce System

## Appendix B An Accounting of Samples and Models Underlying the FDSS for the Georgia Workforce System

This paper presents examples of algorithms for the FDSS prototype being used in the internetbased Georgia Workforce System (GWS) at two pilot one-stops in Georgia: Athens Career Center and Cobb-Cherokee Career Center. All the examples provided in this paper are for the Atlanta metropolitan area of Georgia which includes Cobb-Cherokee. This appendix provides a quick accounting of the samples used and the models estimated for the full set of 88 models, plus 60 service referral summaries and 40 training type rankings which form the basis for decision support algorithms in FDSS statewide.

#### Systematic Job Search Module (SJSM)

Models predicting return to prior industry and likely reemployment earnings in the SJSM are estimated on data combined from both the unemployment insurance (UI) and employment service (ES) programs with an indicator variable for UI included in each model. While UI beneficiaries who are not job-attached (awaiting employer recall or union hiring hall members) are required to register for job search with the ES, only one observation for each client identity number is retained in the pooled data. In the combined data sample, three separate sub-samples are used for estimation: 1) youth (clients aged 14 to 21 who are not welfare recipients or economically disadvantaged), 2) economically disadvantaged and welfare recipients, and 3) others. Models for the first two sub-groups—youth and economically disadvantaged and welfare recipients—are estimated on data pooled across all prior industries. Models for the third subgroup—other—are estimated separately for each of eight industry groups (agriculture, mining, and construction were combined because of small sample sizes in some regions, and an indicator variable was included in those equations for agriculture).

Since the earnings models are intended to predict full time earnings, for the eight industry specific models a sample inclusion restriction was imposed that quarterly earnings must equal or exceed \$2,500 in at least one of the four quarters between two and five quarters before registration. However, no such prior earnings restriction was imposed on the youth and welfare recipients or economically disadvantaged samples. Models are estimated for four separate regions of Georgia: Atlanta metropolitan, northern, coastal, and balance of the state. Considering the return to prior industry plus the median earnings models to be a group, then 10 groups of models are estimated for each of four regions in Georgia for a total of 80 models—40 return to prior industry models and 40 earnings models.

### Service Referral Module (SRM)

Service referral rankings are compiled for groups formed using an employability score. The employability score summarizes characteristics related to prior employment stability. For the full FDSS

system, employability models are estimated for two program data samples, UI and ES, on data for each of the four geographic regions of Georgia. These eight employability models are used to set up the quintile groups for the service referral algorithm. That is, based on each model, the ordered distribution of employability scores is divided into five equal parts.

Within the UI sample, rankings of service effectiveness are prepared for two programmatically distinct subgroups. The first group is those who are sent directly to the reemployment unit (REU) for a special work search orientation workshop and a scheduled series of eligibility review interviews and workshops. The REU handles clients who are either profiled and referred by the state worker profiling and reemployment services (WPRS) system, or referred by the Georgia claimant assistance project (CAP). CAP refers to the REU all UI beneficiaries who qualify based on earnings only in the state of Georgia and are entitled to at least 14 weeks of benefits. For FDSS service referral, the non-REU UI beneficiaries are collected into a second UI group. ES clients who are not UI eligible form the third group for service referral ranking.

For each of the three program groups, service referral rankings were prepared for distinct quintile groups within each of the four geographic regions of Georgia. That is, service referral quintiles (5), for two UI groups and one ES group (3), in four regions (4), for a total of 60 service rankings ( $5 \times 3 \times 4$ ). Also, training statistics are summarized separately for UI and ES in four regions with five quintile groups each for a total of 40 training type rankings.

A one page summary of this information which identifies the sample sizes used for all computations of FDSS models and service referral rankings for the prototype system is provided as appendix Table B.1. The following notes apply to the summary given in Table B.1.

1. In the service referral section, for the REU/Profiling/CAP rows, the total for REU/Profiling/CAP is the same as the total for those REU/Profiling/CAP people who used services since all persons in that sample received some services.

2. The sum of persons used for service referral is slightly less than the total sample for the employability score models. For example, for UI clients across all four regions, 204,771 persons were used in the UI employability score regression. The sum of the UI categories is 202,346 (52,112 REU/Profiling/CAP + 150,234 Other UI). The shortfall is due to the identification of the 15-day period in which the use of services was totaled. The end of that 15-day period had to have occurred during or before the fourth quarter of 1998 (98:4). This constraint was applied so that for all persons we had at least 4 quarters of wages to observe successful outcomes.

3. Across all four regions, there were 150,234 persons who were in the Other UI category (non-REU/Profiling/CAP). Of those, 107,178 used services. The drop off comes from two sources: A) Persons who did not receive any services, and B) Persons who received some services but their 15-day period of most services received was more than one year after the reference date. For example,

for the UI people, if the service activity used to identify the 15-day period occurred more than one year after their benefit year begin date, the flurry of activity does not apply to that benefit year. The same one year constraint was also applied to those in the ES sample.

# Table B.1 Sample Sizes for Estimating FDSS Algorithms

Sample Size Summary	for Return to Prior Industr	y and Earnings	Median Model	ls		Count of Equations
	Atlanta Metro	Northern	Coastal	Balance of	Total	Total Number of
Group	Area	Georgia	Georgia	State	Sample Size	Models = 88
Youth (UI and ES samples combined)	7875	9826	4623	8010	30334	4  ret. + 4  earn. = 8
Economically Disadvantaged (UI and ES)	38154	26378	16780	45983	127295	4  ret. + 4  earn. = 8
Other (UI and ES combined):						
Agriculture, Mining, Construction	3317	3733	2066	4636	13752	4 return to industry +
Manufacturing	8256	19859	5320	13907	47342	4 earnings
Transportation, Communication, Utilities	4795	2019	1241	2047	10102	= 8
Wholesale Trade	5642	3217	1138	2611	12608	
Retail Trade	8585	5536	3440	5939	23500	For 8
Finance, Insurance, Real Estate	4087	1362	557	1450	7456	industries
Services	18460	8370	4724	8971	40525	
Public Administration	1764	1499	862	2711	6836	= 64
Total Other	54906	45595	19348	42272	162121	
	Sample Size Summary	for Employabilit	y Score Model	ls		
UI	75055	45513	27514	56689	204771	4
ES	63584	54046	34969	68554	221153	2
	Sample Size Summary	for Service Refe	rral Summaries	S		
UI REU (Profiling/CAP)	24200	10180	6721	11011	52112	5 quintiles x
Used Services	24200	10180	6721	11011	52112	2 groups x
						4 regions = $40$
Other UI (Non-Profiling/CAP)	50105	34772	20543	44814	150234	
Used Services	30763	26897	15314	34204	107178	
ES Total	62779	53495	34607	67918	218799	5 quintiles x
Used Services	49795	49526	31970	61890	193181	1 groups x 4 regions = $20$
JTPA Total	9563	7800	4104	9199	30666	5 quintiles x
Used Services	3781	2791	1194	3959	11725	2 groups x 4 regions = $40$