Forecasting the Demand for Care of Individuals with Disabilities
for the Oregon Department of Human Services

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Abstract: We analyze demographic data available through different state departments to develop a forecasting model that will assist the Oregon Department of Human Services (DHS) in estimating the demand for services available for individuals with disabilities. Our results indicate that variation in DHS enrollment can largely be explained with the variation in county level data on population and age specific variables. Specific vital statistics, including births from mothers of different age categories, were also found to be significant in forecasting this demand.

Keyword: disability care; disability forecast; Oregon Department of Human Services

Approved: ____

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Introduction

The Oregon Department of Human Services (DHS) offers access to community services and long-term care support for individuals with developmental disabilities. Through specific programs available to Oregon residents and through community collaboration, DHS works to provide an environment where all Oregonians can become independent, healthy, and safe. According to the department's web site, DHS goals focus on helping low-income families achieve self-sufficiency, protecting residents from abuse and neglect, making health care readily available throughout Oregon, protecting public health, and providing resources to help seniors and people with disabilities live as independently as possible. However, the Staley v. Kitzhaber lawsuit and subsequent Staley agreement came as a result of the state of Oregon's inability to furnish long-term care services to eligible individuals.[1] The inability of the state to furnish these services violated both Federal Medicaid law and the Americans with Disabilities Act (ADA), which state that services will be provided with "reasonable promptness."[2] Though these services are guaranteed by the state, citizens were waitlisted, sometimes for years, before receiving aid. The Staley Agreement has since forced a restructuring of the disability care network to remedy these problems. Our research will aid DHS in the estimation of future resource needs to help alleviate the problem of wait listing.

Our work uses demographic data available through different state departments in conjunction with DHS disability service data to create explanatory models that help predict future long-term care needs demanded from DHS. Available demographic data includes population counts by age, income and poverty counts, healthcare, internal migration, and a variety of vital/pregnancy statistics. We use enrollment records in DHS services, broken up by

[1] Human Services Research Institute. (2006).
[2] The Arc of Oregon. (2005).

both disability and classification of entrants and exits, as our dependent variable and all other demographic information as independent variables.

Two models are considered in this paper; a prediction model that utilizes population data to explain variation in DHS net enrollments, and an explanatory model that considers 14 additional demographic variables that help to further explain variation the demand for DHS. In addition to constructing the two models, we also test the predictive power of both. To accomplish this, we compare the actual DHS records with the estimations from our models for years 2004 and 2005. Upon analyzing each model's results, we proceed with the estimations from our most effective model to predict future DHS enrollment through the year 2020. Ideally, these predictions will give DHS the opportunity to prepare for future demand, fund their programs accordingly, and eliminate excessive wait listing.

Background

The Seniors and People with Disabilities (SPD) section of DHS administers programs to both seniors and people with physical and developmental disabilities. The program's primary focus is to increase the independence of its service recipients by providing specialized services: housing and transportation; employment services; food and financial help; health/medical services; legal issues; care giving; and long-term care assistance, including nursing facilities, licensed community care facilities and in-home care programs.

The forecasting of these services at the state level is currently limited. It begins with the development of a Forecast Agreement that is created by a steering committee composed of representatives from DHS program and budget clusters, the Legislative Fiscal Office and the

Department of Administrative Services' Budget and Management Office.[3] Historical trend analysis is the primary method of current forecasting strategies. The committee stresses the mathematical relationship between the history of demanded services and the future. The current model, which was originally developed by Willamette University's Public Policy Research Institute to forecast Oregon's Medical Assistance Program caseloads, only considers three variables: current clients, new clients and transfer clients. The model, however, does not consider available demographic data that tracks differences in population trends. The consideration of the differences in population over time is what we propose to more effectively forecast accurate demands.

As previously mentioned, DHS currently forecasts the demands for its services by considering historical and current program enrollment. Unlike the United States forecasting efforts, the state of Oregon, to our knowledge, does not currently analyze the impact of independent variables such as age, income level, vital statistics, and pregnancy rates. The consideration of these variables will allow DHS to better forecast the variation among individuals entering and exiting its services.

Literature Review

There is limited literature that relates directly to our research topic. Available literature does, however, discuss topics that include the estimation of children in schools needing specific services, the transition from school to adult life for individuals with disabilities, and specific characteristics of individuals with developmental disabilities. Although the literature is limited on the topic of general disability care, literature has been completed on adult day health services

[3] Department of Human Services Finance & Policy Analysis Client Caseload Forecasting Team. (2005).

(ADHS). Pieces discussing ADHS can be used as references for modeling and forecasting procedures. Considering previous forecasting models, work on data analysis, disability research and related topics will better help us structure our model for estimating the changes in demand for specific DHS services.

A team of researchers under the supervision of the Rutgers Center for State Health Policy (CSHP) and the New Jersey Department of Health and Senior Services (DHSS) reviewed literature relating specifically to adult day health services available to elderly and disabled populations. The paper was published in 2007.[4] Their research discovered that the majority of individuals seeking adult day health services are functionally dependent and are likely to have a high prevalence of disordered behaviors. Individuals diagnosed with a disability before the age of 22 and children who have unstable medical conditions are regularly dependent on these services, but to a lesser degree. It must be noted that the elderly population utilizes the ADHS more regularly than the disabled. The most commonly reported diagnoses among the users of ADHS include dementia, mental retardation/developmental disability, chronic mental illness, or some type of physical problem such as stroke, heart disease, or diabetes. Of these diagnoses, the population of mental retardation/developmental disability is the group most likely to transition into DHS services.

In a second piece of literature, Fiorentino (1998) studied three geographical districts to better determine outcomes of the transition process for young people with disabilities. The results of his work showed that young disabled people often experience a poor handover to adult services from high school if they had no statement of special educational need or if they

[4] Lucas, Judith A., et al. (2002).

continued education at the college level.[5] Although his research topic relates only minimally to our work, the methodology and data collection is worth considering.

Three hypothesis were formulated in the research: (1) that the arrangements for handover to adult services would differ between individual schools and types of schools; (2) that the experiences of the young disabled people would depend on the type, pattern, and severity of their disability; and (3) that the quality of the handover process itself would affect the perceptions of the people involved and the services that they subsequently received.

The population that was studied between 1993 and 1996 included more than one million people. However, only 519 names were obtained of individuals with possible physical disabilities. Of this group, only 258 people were identified as "probably having a physical disability." The number is greatly reduced because many of the individuals were found to have a learning disability when the study focused on physical disabilities. The data was sorted by different severity levels of the disabilities, and found that cerebral palsy and neural tube defects were the most frequent diagnoses among the students. Forty other disorders were also identified in the population. Similar to this study, DHS also identifies the severity of individuals' disabilities, which will allow for more accurate data analysis.

To determine whether or not the hypotheses were confirmed, the study interviewed individuals that had previously left school and were between the ages of 16 and 25 years of age. During the interviews, demographic details were recorded and specific disabilities were classified. Questions regarding the transfer process from pediatric medical services to school to adult services were the primary concern of all interviews. It was important to grasp individuals' opinions about the treatment they received since leaving school. Upon the completion of the

[5] Fiorentino, L., et al. (1998).

interviews, an ethnographic qualitative analysis of the interview material was completed to identify dominant themes in the experiences and opinions associated with the transition process.

Fiorentino's study confirmed the first and second hypotheses: the arrangements for handover were found to be different between individual schools and types of schools, and the experiences of the young disabled people appeared to depend on the type, pattern, and severity of their disability. The third hypothesis addressing perceptions of involved participants was not confirmed in the research.

Another piece of literature that relates to our work was completed in 1997. It attempted to improve estimates of children who are in need of special assistance in schools. The paper developed by Dennis P. Hogan, Ph.D. et al addresses population trends, socioeconomic factors, and disability characteristics in an attempt to validate measures that are appropriate for determining the number of children ages five to seventeen that identify as disabled or with functional limitation in mobility, self-care, communication or learning ability. Socioeconomic risk factors were considered. These factors include race/ethnicity, family structure, education of the guardian, and the measure of the family economic situation and isolation.

The research method was based on data collected in the 1994 National Health Interview Survey on Disability. The independent variables used to determine the likelihood of demand for special assistance in school (the dependent variable) included the different severity levels of specific disabilities. The sociodemographic factors described above were used as independent variables to better determine special needs. After assigning ordinal values to survey items in four functional areas, they were analyzed to produce scales with a 95 percent confidence level. Ordered logistic regressions models were used to measure the effects of functional limitations on disability and societal limitation. Ordered logistic regression models were used to predict severity and comorbidity among the socioeconomic differences.

The conclusions of the study found that future research on disabled populations should use multiple-item scales for distinct areas of functional limitations. Also stressed in the conclusion, was the correlation among socioeconomic status, family structure, and the demand for special services. Our model will be structured similarly. However, we will be addressing specific disabilities and sociodemographic factors in Oregon to determine aggregated demand for DHS, whereas Hogan's work considered individual level data.

Descriptive analysis of persons with developmental disabilities has also previously been completed. In 1990, the U.S. Department of Health and Human Services completed a study titled *An Estimate of the Number of Persons with Developmental Disabilities Receiving Supplemental Security Incomes Benefits and Their Characteristics.* The study was completed to assist with the national survey design project. Its primary focus was to determine specific estimates of persons receiving supplemental security income (SSI) due to a developmental disability. The committee sought to identify projection models with the potential to propose changes in Federal assistance programs, including Medicaid.

Based on a 10 percent disability sample file, the study compared three populations: children under the age of 22 receiving SSI benefits, adult SSI recipients, and other individuals who are classified as "non-DD adults." Differences between age, race, sex, marital status, living arrangement, receipt of state supplementation payments, payment amounts and receipt of unearned income were compared across the three populations. Noteworthy findings include: (1) prevalence of developmental disabilities increases with age. The cause of this trend is likely linked to the difficulty associated with passing the Social Security disability test at a young age and the fact that some children do not develop their disabilities into later childhood. (2) Fifty percent of all SSI adults, during the time of this study, were between the ages of 22 and 30. (3) More men receive SSI than women. (This can be partly attributed to the fact that there is a higher incidence of mental retardation among males than females). (4) Over 90 percent of adults with developmental disabilities are not married. (5) Lastly, about 60 percent of adults with developmental disabilities on SSI also receive income from sources other than the SSI program.

The research completed in this study on specific age categories significantly relates to our study. In addition to the above findings, the study also states that less than four percent of the population receiving assistance is over the age of 65. However, generational trends and health care have drastically altered these statistics since 1990. Although we expect different results, we also consider the impact of specific age categories on DHS enrollment.

Hypothesis Development and Methodology

We consider two equations in our forecasting procedure. Both equations use ordinary least squares (OLS) to estimate new enrollments and exits of DHS programs. First, we construct a prediction model that utilizes population data to estimate future enrollments into the DHS system. We hypothesize population data to have high explanatory power in explaining the variation in DHS disability turnover. Thus, by solely utilizing population data we will yield a simple, but effective, estimate of future DHS enrollment. Next, we compare this total population model to a more specialized, age specific, model. This model considers different age categories to estimate DHS demand. Specifically, categories are defined by infants (ages 0-4), school-aged (ages 5-17), transitions (ages 18-24), adults (ages 25-64), and seniors (ages 65 and older). The estimated coefficients on the independent variables in our regression model provide evidence on how total population and population sub-categories contribute to the demand for DHS services.

After constructing a model that yields a high level of explanatory power, we test its predictive power. Using this model to estimate entrants, exits, and net change for the years 2004 and 2005 we compare our predicted values to the actual data from these years. Comparing predicted values to actual DHS records help confirm the predictive power of our model. This process provides us with an idea of how well we can expect the model to predict actual DHS entries, exits, and overall net changes for years into the future.

We then use Oregon population forecasts available through the Oregon Economic Bureau in conjunction with our statistical estimates to construct predictions of future DHS net enrollment. By inserting population projections we are able to estimate DHS entries, exits, and net changes across Oregon up to 35 years into the future. This straightforward approach yields a dependable and user-friendly model for predicting future DHS disability enrollment changes.

While population data will be the backbone of our project, it is clear that other factors may drive demand for DHS disability services. Thus, in a subsequent analysis we construct a fuller explanatory model to examine the additional demographic characteristics that affect DHS enrollments.

The second analysis provides as much explanatory power as we can get using observable data. However, the tradeoff is that we do not have forecasted data for the additional explanatory variables, as we do with the first analysis using only population data. By examining this second model, however, we are able to conclude how well our population based prediction model predicts relative to a model with a large number of diverse independent variables.

We consider a total of 17 variables in our models. The first variable in our prediction model is the annual estimation of total population for each county in Oregon. We expect not only a positive sign on this variable, but significant explanatory power as well. Overall, developmental disability rates are fairly constant over time for a given population. Given the coefficient on the population, we will be able to estimate the change in new DHS disability enrollments given a change in the total population, other things held constant.

The second variable we will include in our prediction model is the population-squared term. This variable is, quite simply, total population multiplied by total population. This variable captures the effect of larger populations, such as in a metropolitan area, on disability entrants. Given this, we expect a positive coefficient on this variable.

The trend variable captures additional explanatory power within our model that we have not explicitly accounted for with other dependent variables. An example of this effect may be additional explanatory power gained from the inclusion of an additional year of data. This variable would then show that each additional year, by itself, adds additional explanatory power to our model. To note this trend, a value ranging from zero to twelve will be assigned in our regression. The value comes from the data year less the first year of available data, which is 1993. For example, the value of the trend for the year 2000 is seven (2000 minus 1993). Combining the three previously mentioned variables allows us to create our prediction model:

Prediction Model:

$$\text{Net Entrants} = B_0 + B_1(\text{TotalPop}) + B_2(\text{TotalPop}^2) + B_3(\text{Trend})$$

In addition to the three previously mentioned variables and the constant term included in the prediction model above, we also consider fourteen additional variables in our more complex explanatory model. We expect each additional variable to increase the explanatory power of the model, but given the lack of available future forecasts for each, they will be used only to explain demographic factors that drive program enrollment. They will not be used in our prediction model.

The first variable added to our model captures total births per county in Oregon. This variable is expected to have a positive coefficient. This expectation is substantiated with the data on the age of new entrants. As shown in Table 1 in the data section, nearly a quarter of the new entrants in the DHS system are between the ages of 0 and 4. This gives us strong reason to believe that the birth rate variable holds added explanatory power.

The variable on pregnancy of teenagers ages 15 to 19 is expected to have a positive coefficient, as teenage pregnancy correlates with a higher level of poverty and thus a lower level of prenatal care. Due to its high correlation with poverty and prenatal care, it may proxy for other factors as well.

Induced termination of pregnancy is expected to have a negative coefficient. We expect that the termination of unwanted births will decrease the number of DHS program enrollments because abortion will limit the number of total births in each county. It is also important to recognize that termination of pregnancy may be more prevalent among specific communities and poverty levels. Keeping this in mind, termination of pregnancy may simply be accounting for the difference in the pregnancy rate of each county. Thus, an increase in the pregnancy rate would lead to an increase in the number of abortions. In this case, the coefficient would be positive.

We expect the explanatory power of the internal migration variable to be limited as it accounts for population movement across counties within the state of Oregon and does not account for external migration. We expect the coefficient to be negative. This is expected because the disabled community may be more apt to stay in a location with familiar resources and services. Continual location changes would be difficult for this population as they would have to locate new services at each new location.

Inadequate prenatal care considers the health care received by mothers during pregnancy. We expect this variable to positively correlate to DHS enrollment because prenatal care should have a strong correlation with the health of the baby. Similarly, we expect the variables on births to unmarried mothers and low-weight births to both also have a positive coefficient.

Both variables on poverty, total population in poverty and youth ages 0 to 18 in poverty, are expected to have positive coefficients. This relationship is expected because we expect data on poverty to proxy for demographics such as health care and accessibility options. Similarly, the median household income variable is expected to have the opposite relationship.

The four 'payment of delivery' variables account for income levels and accessibility to health insurance. Given this explanation, we expect the coefficients on the 'delivery payment' variables, except 'paid by private insurance,' to be positive. We anticipate that these populations are less likely to afford health insurance.

When we combine all of the above variables, we obtain the following model:

Explanatory Model:

$$\text{Net Entrants} = B_0+B_1(\text{TotalPop})+B_2(\text{TotalPop}^2)+B_3(\text{Trend})+ B_4(\text{TotalBirths})+B_5(\text{TeenPreg})+ B_6(\text{InducedTermination})+ B_7(\text{InternalMigr})+ B_8(\text{InadPrenatal})+B_9(\text{BirthsUnmarried})+ B_{10}(\text{TotalPoverty})+ B_{11}(\text{YouthPoverty})+B_{12}(\text{LowWeightBirths})+ B_{13}(\text{PaidMedicaid})+B_{14}(\text{PaidPrivateIns})+ B_{15}(\text{PaidSelf})+ B_{16}(\text{PaidOther})+B_{17}(\text{MedianIncome})$$

It is important to note that the explanatory model will be used to explain as much of the variation in DHS enrollment as possible. Some variables may have more explanatory power than others, and some of the variables may even fail to significantly improve the model. However, in the interest of explaining all of the factors driving DHS demand, we are including as many variables as possible.

Data Description

All data used in this analysis are publicly available, with the exception of the DHS classifications of new entrants and exits from disability services program records. Data on both entrants and exits of DHS service recipients was used from 1996 through 2005. DHS tracks these numbers from July to July each year (its fiscal year). We identified each date by the closing year. As defined by DHS, entrants (also known as new enrollees) are clients enrolled in case management during a given fiscal year who had no record of entry in the previous year. Similarly, exits are recognized as those who were terminated from case management during the fiscal year. They are considered terminations if they are not found receiving developmental disability services in the succeeding year.[6]

Our explanatory model considers individual data from all 36 Oregon counties, with each new entrant or exit client tracked individually. We sorted this data into an aggregated data file to reflect the number of entrants and exits by county for each year. Once aggregated, the age trends found in Chart 1 and Table 1 were observed.

[6] Brown, Julia. (2007).

Chart 1: Age of New Entrants

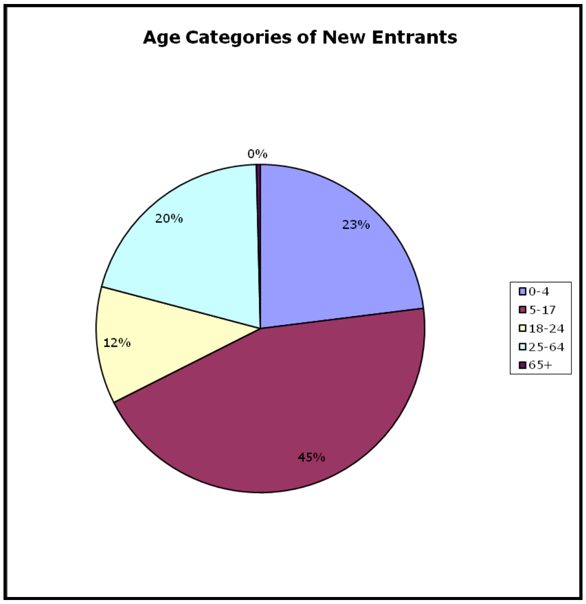


Table 1: Age of New Entrants

Age	Percent	Cumulative
0-4	23.03	23.03
5-17	44.53	67.55
18-24	11.56	79.12
25-64	20.49	99.61
65+	0.39	100

It is important to note that the majority of entrants begin their services with DHS between the age of 5 and 17. Age groups, 0 to 4 and 25 to 65, both also play a significant role as transition periods for new DHS entrants. The elderly population, however, makes up less than a percent of all entrants.

We similarly analyzed DHS exits by age categories. The results for exits looked similar to the results for entrants, as the infant category was still most significant. Further descriptive statistics on exits are available on the next page in Chart 2 and Table 2.

Chart 2: Age of Exits

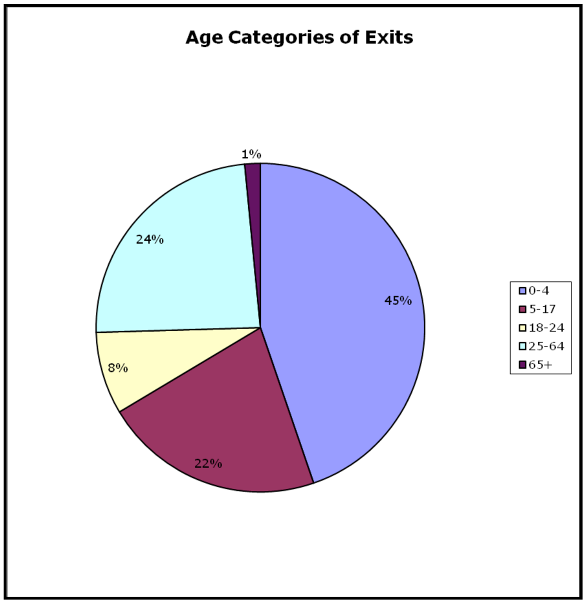


Table 2: Age of Exits

Age	Percent	Cumulative
0-4	44.75	44.75
5-17	21.68	66.43
18-24	8.11	74.54
25-64	23.93	98.47
65+	1.53	100

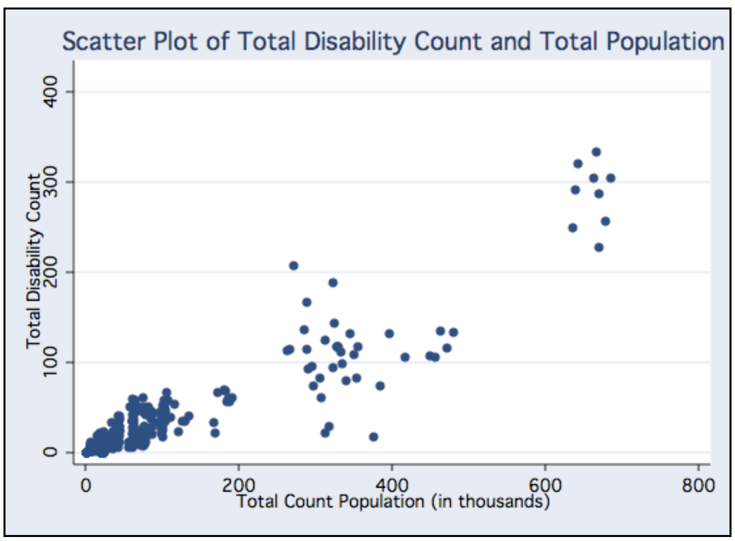
The data used to construct our independent variables were collected from a variety of public institutions with access to county level data. The data on the total population by county from 1993 to 2005 were obtained through the Portland State University Population Research Center. The Census Bureau provided data on migration within the state of Oregon. Internal migration records were available from 1990 to 2005. The DHS Vital Statistics County Data Book provided data on teenage pregnancies, prenatal care, pregnancy terminations, household income, and delivery payment types. Specific data regarding these categories was used from 1993 through 2004. In some cases, some counties failed to provide statistics for given years.

As we progressed in our research we discovered that the change in demand for DHS services is explained most by three population variables: total population, total population squared, and trend variation that accounts for year-to-year trends. The summary of these variables by county can be viewed in Table 3.

Table 3: Descriptive Statistics on County Populations (in thousands)

Variable	Num of Obs.	Mean	St. Dev.	Min	Max
Total Population	468	92.40266	138.7981	1.5	692.823
Total Population²	468	27762	78342.37	2.25	480003.7
Trend	468	5	3.745661	0	12

Graphing the total population over the total disability counts for each respective county produces recognized positive correlation. As the county population increases, so does the number of disabled individuals who are identified from DHS. The scatter plot graph below helps show the positive correlation between the number of disabled individuals and total population.



In addition to the three population variables uses in both the prediction model and the explanatory model, we also consider the significance of 14 other independent variables. The descriptive statistics are available on the following page in Table 4.

Table 4: Descriptive Statistics on Variables Used in Explanatory Model

Variable	Obs	Mean	Std. Dev.	Min	Max
Births	468	1224.083	1975.378	6	9478
Internal Migration	468	606.8718	1529.514	-13636	6628
Induced Preg. Term.	430	331.3279	758.4901	0	4590
Births to Unmarried Mothers	432	369.5972	600.4437	1	3191
Teen Preg. (age 15-19)	411	198.2044	305.064	0	1888
Inadequate Prenatal Care	428	67.1215	110.966	0	592
Low Weight Births	428	69.30607	116.7276	0	646
Delivery Paid by Priv. Ins.	432	717.213	1289.819	2	5996
Delivery Paid by Self	430	61.07674	94.76179	0	569
Delivery Paid by Medicaid/OHP	432	422.9491	641.2338	1	3623
Delivery Paid by Other	432	5.083333	9.435457	0	89
Median Household Income	360	35125.27	6375.563	21077	55933
All Ages in Living Poverty	360	11088.7	15999.57	119	93871
Ages 0-18 Living in Poverty	360	3790.478	5362.691	39	31320

The descriptive statistics in Table 5 are on our dependent variables, DHS net enrollments. In addition to net change in DHS services, we also broke up the data summary by entrants and exits. As shown in this table, the mean number of entrants is greater than the mean exits, upholding evidence for the trend of increasing enrollment over time.

Table 5: Descriptive Statistics on Net DHS Entrants

Variable	Num of Obs.	Mean	St. Dev.	Min	Max
Total Entrants	308	38.98052	57.37402	0	422
Total Exits	308	21.51299	34.23377	0	212
Net Entrants	308	17.46753	35.04463	-125	233

Econometric Results: Prediction Model

We used OLS to estimate the number of new entrants, exits and net change in the disability services program offered by DHS. For each of the three categories, we created a prediction model that helps estimate the change in demand for DHS.

For entrants, we expected all considered variables to be positively signed. Thus, for an increase in total population we would observe an increase in the number of people entering DHS services. A total population squared variable was also used to account for the fact that larger metropolitan areas with higher population may have a greater impact on our results. A trend variable was included to capture any additional explanatory power that we had not explicitly accounted for through other variables. Table 6 shows our regression results. It is important to see that our R-squared continues to increase as our model is expanded to include additional explanatory terms. An increase in R-squared confirms that our model continues to explain more variation in demand, and increases the quality of our model.

Table 6: Total Entrant Regression (coefficients represent change per thousand)

Variable	**Model 1**	**Model 2**	**Model 3**
Total Population	0.3660111*	0.1819485*	0.1826355*
	(0.0094202)	(0.0250744)	(0.0250433)
Total Population²		0.0003438*	0.000341*
		(0.000044)	(0.000044)
Trend			0.5895122
			(0.4300365)
Constant	0.358293	8.951764	5.118657
	(1.671899)	(1.882868)	(3.369505)
Number of Obs.	308	308	308
R-Squared	**0.8315**	**0.8596**	**0.8605**
F-Statistic	F(1, 306) = 1509.63	F(2, 305) = 933.59	F(3, 304) = 624.82

*: Statistically Significant at the 1 percent level

As seen in Table 6, the coefficients on the variables are positive, as predicted. Our R-squared in Model 3 shows that 86 percent of the variation in disability enrollments can be explained by the variation in the three considered variables. This specification of the model shows that for a 1,000 person increase in the total population, 0.523 new DHS program entries will occur. This increase considers coefficients on the population variable and the population squared variable. Using the coefficients from Model 3, the prediction model for new DHS entrants reads as follows:

Prediction Model:

Entrants = 5.118657 + 0.1826355Totalpop + 0.000341TotalPop^2 + 0.5895122Trend

The regression on DHS program exits is below in Table 7. The R-squared values for the exit model are far less than that of the entrant model. Therefore, population data explains more variation in program entrants than it does for exits.

Table 7: Total Exit Regression (coefficients represent change per thousand)

Variable	**Model 1**	**Model 2**	**Model 3**
Total Population	0.1933646*	0.1933646*	0.0755082*
	(0.0080789)	(0.0080789)	(0.0224588)
Total Population²		1.108765*	0.000221*
		(1.433845)	(0.0000394)
Trend			-0.3310447
			(0.3856555)
Constant	1.108765	6.593203	8.74571
	(1.433845)	(1.685395)	(3.021762)
Number of Obs.	308	308	308
R-Squared	**0.6518**	**0.6840**	**0.6848**
F-Statistic	F(1, 306) = 572.86	F(2, 305) = 330.09	F(3, 304) = 220.12

*: Statistically Significant at the 1 percent level

Prediction Model:

Exits = 8.74571 + 0.0755082Totalpop + 0.000221TotalPop^2 - 0.3310447Trend

Our forecasting goes beyond explaining the variation in DHS entrants and exits on a year-to-year basis. We are able to forecast net change in program demand when we consider both the entrants and exits into the DHS programs for specific years. Before looking at the regression results for the net change in services, it is important to note that the consideration of program exits reduces the explanatory power of our model. The regression on the net change in demand for DHS services reads as follows:

Table 8: Total Net Change Regression (coefficients represent change per thousand)

Variable	**Model 1**	**Model 2**	**Model 3**
Total Population	0.1726465*	0.1060545*	0.1071273*
	(0.0099516)	(0.0287355)	(0.0286238)
Total Population²		0.0001244*	0.0001201*
		(0.0000504)	(0.0000503)
Trend			0.9205569
			(0.4915198)
Constant	-0.7504719	2.358561	-3.627053
	(1.766222)	(2.157787)	(3.851251)
Number of Obs.	308	308	308
R-Squared	**0.4959**	**0.5057**	**0.5114**
F-Statistic	F(1, 306) = 300.97	F(2, 305) = 156.03	F(3, 304) = 106.05

*: Statistically Significant at the 1 percent level

Prediction Model:

Net Entrants = -3.627053 + 0.1071273Totalpop + 0.0001201TotalPop^2 + 0.9205569Trend

We wanted to verify that we had built the best prediction model possible given the population data that we had available. As described in our data section, the population data was broken down into age specific categories broken into five year intervals. We decided to construct an alternate prediction model utilizing the population by age categories to tease out any additional explanatory power garnered by examining these population subsets. We ran the following regression, observed in Table 9, on net DHS entrants to examine the explanatory power yielded by looking at specific age intervals.

Table 9: Total Net Regression Results

Variable	**Model**
Total Population	0.6851904
	(0.2578751)
Total Population²	0.0001039
	(0.0000707)
Trend	-2.208659
	(0.6214546)
Ages 0-4	-2.837044
	(1.281172)
Ages 5-17	-0.2724716
	(0.515068)
Ages 18-24	-0.0437238
	(0.235468)
Ages 25-64	-0.789586
	(0.6235799)
Ages 65+	0.6531714
	(0.5039106)
Constant	-2.025587
	(3.989668)
Number of Obs.	308
R-Squared	**0.5342**
F-Statistic	F(8, 299) = 42.87

The table above shows that the R-squared from our age specific prediction model on net entrants is 0.5342. Recall from Table 8 that our initial prediction model using total population, population squared, and a trend term alone yields a 0.5114 R-squared. Though the age-specific explanatory model explains more of the variation in DHS demand, the amount is minimal. Due to the limited additional explanatory power, we decided to use our more straightforward initial model to forecast future changes in DHS enrollment.

Econometric Results: Testing Our Prediction Model

We used our prediction model to forecast net changes in DHS disability services. This model incorporates only total population, total population-squared, and a trend variable. Regression results are available in Model 3 of Table 8. We believe that this is the most useful model for DHS to consider as it combines the high explanatory power of the three selected variables with available population data. The use of this population data allows us to forecast net change projections years into the future.

Before concluding the accuracy of our model, we decided to test its accuracy in forecasting the demand for DHS services. To do this, we removed the last two years of data from our regression and used the remaining years of available data to obtain our coefficient estimates. We thus used this prediction model to forecast demand for years 2004 and 2005, for which we already have recorded values. Next, we compared the predicted values with actual values available from DHS. We completed this process for all three categories: entrants, exits and net.

When the results are examined county-by-county there is some disparity between the predictions and the actual data. The results of the statewide total, however, work out to be very close to the actual recorded values. For example, our model predicted 1377 new entrants for 2004 and the actual number of new entrants for this year was recorded at 1343. This gives us a difference of only 34, a 2.5 percent error. The estimations for all three categories for years 2004 and 2005 are available in the appendix (AP 1.1 – AP 1.3). Please note that predictions from Gilliam, Hood River, Wasco, and Wheeler counties have been omitted to allow for an accurate comparison to DHS records. These counties were omitted from our model due to their grouped classification, thus making it difficult to get accurate population estimates. These geographic regions contain both entrant and exit categories. We account for this later, but exclude them in this step to allow for a correct comparison of the state totals.

Econometric Results: Predicting Future Changes

We were able to forecast future demand for DHS services with the use of population estimates available through the Oregon Economic Bureau. Plugging the population estimates into our prediction model allowed us to estimate future demand, holding all else constant. We were able to estimate new DHS program entrants for years 2006 through 2010, as well as for years 2015 and 2020. The results are available in Table 10.

We used the results from our 2005 prediction model as the base for our future predictions. This may at first seem counterintuitive as there are DHS records for year 2005. However, due to the grouping of some geographic regions, we were unable to observe the true relationship between the population and changes in the DHS disability services. Therefore, we used the 2005 estimates on net change to obtain predictions on future years for all counties across Oregon. These results estimated remarkably close to the recorded values at only a 4.2 percent error. This procedure yields an accurate total of disability enrollments for the entire state, having provided for the count of every person in every county in Oregon.

Table 10: Predictions Using 2005 Predicted Net (Allows for estimation in all counties)

County	2005	2006	2007	2008	2009	2010	2015	2020
Baker	10	11	11	12	13	13	22	29
Benton	18	19	20	21	22	23	33	40
Clackamas	57	59	62	65	69	72	90	103
Clatsop	13	13	14	15	16	16	26	32
Columbia	15	16	17	17	18	19	28	34
Coos	16	17	17	18	19	20	30	36
Crook	12	12	13	13	14	15	24	31
Curry	11	11	12	13	13	14	23	30
Deschutes	27	29	30	32	33	35	48	57
Douglas	21	23	24	25	26	27	37	44
Gilliam	9	9	10	10	11	11	20	27
Grant	9	10	10	11	11	12	21	28
Harney	10	10	11	11	12	12	21	28
Hood River	12	13	13	14	15	15	23	30
Jackson	34	36	37	39	41	43	55	64
Jefferson	12	13	14	14	15	16	24	30
Josephine	18	19	20	21	22	23	33	41
Klamath	18	19	20	21	22	23	30	37
Lake	10	10	11	11	12	12	21	28
Lane	53	56	58	61	64	67	79	90
Lincoln	14	14	15	16	16	17	27	34
Linn	24	26	27	28	30	31	37	45
Malheur	14	15	16	16	17	18	25	32
Marion	61	65	68	71	75	78	76	86
Morrow	11	11	12	13	13	14	22	29
Multnomah	120	126	132	138	145	152	151	162
Polk	18	19	19	20	21	22	33	41
Sherman	9	9	10	10	11	11	20	27
Tillamook	12	12	13	13	14	15	24	31
Umatilla	21	23	24	25	26	27	32	39
Union	12	13	14	14	15	16	24	31
Wallowa	10	10	11	11	12	12	21	28
Wasco	12	13	13	14	15	15	24	30
Washington	94	98	103	108	114	119	124	142
Wheeler	9	9	10	10	11	11	20	27
Yamhill	22	23	24	25	26	28	36	45
State Total	**848**	**889**	**933**	**979**	**1028**	**1078**	**1386**	**1665**

Table 10 summarizes our prediction of the net change in demand for DHS disability services for years up to 2020. Recall that we defined the net enrollment for services as entrants minus exits. Given this definition, we expect that net enrollment, and thus total demand for DHS disability services, to be growing at a rate of 4.82 percent a year. We predict this rate to be consistent over the next five years. We also made predictions on the years 2015 and 2020. These predicted values give insight into the growth that DHS can expect in future years, but should be reevaluated as more timely population projections become available.

Explanatory Model

In addition to creating a solid prediction model we also wanted to examine all factors driving DHS net enrollment. To accomplish this task we started with our basic prediction model and then began to add variables. Each additional variable added explanatory power. The regression results of this process are available in the Appendix (AP 2.1 — AP 2.3).

In our 17th and final model we had R-squared values of 0.9389 for the entrant model, 0.8014 for our exit model and 0.6238 for our net model. When compared to the original R-squared values of our prediction model, this amounts to an increase of 0.0784 in the entrant model, 0.1166 in the exit model and 0.1124 in our net model.

Predicting using the Explanatory Model

Similar to what we did with our prediction model, we used our explanatory model to predict future DHS enrollment. However, there were a number of problems that we encountered when trying to predict with our explanatory model. We first wanted to compare the 2004 and 2005 values from our prediction model, explanatory model and DHS records, but found that such a comparison could not be made due to missing 2005 data on several of the explanatory variables. Next, we attempted to compare the 2004 values from our records, but found that we had to drop both the teen pregnancy and the induced termination of pregnancy variables to get a usable result. Data for these variables were not available in all counties for all years. With the 15 remaining variables we ran our regression and estimated our predicted values. The values are available in Table 11.

Table 11: Comparison of Prediction, Explanatory and Actual 2004 Net Values

County	Prediction	Explanatory	Actual
Baker	9	4	-3
Benton	16	41	16
Clackamas	55	62	82
Clatsop	12	14	-4
Columbia	13	12	27
Coos	15	10	23
Crook	10	7	4
Curry	9	2	0
Deschutes	26	17	22
Douglas	20	21	25
Gilliam	0	0	0
Grant	8	6	0
Harney	8	4	1
Hood River	0	0	0
Jackson	32	23	25
Jefferson	11	7	5
Josephine	16	17	31
Klamath	17	17	8
Lake	8	4	2
Lane	52	62	36
Lincoln	12	12	19
Linn	23	33	44
Malheur	12	13	6
Marion	60	44	0
Morrow	9	10	4
Multnomah	121	157	97
Polk	16	10	10
Sherman	8	5	0
Tillamook	10	9	6
Umatilla	20	34	0
Union	11	7	3
Wallowa	8	6	7
Wasco	0	0	0
Washington	95	59	84
Wheeler	0	0	0
Yamhill	20	24	22
Statewide Total	**763**	**751**	**602**

Given the comparison in Table 11, it is evident that our more complex explanatory model fails to do a better job of predicting future enrollment than our initial prediction model. In trying to get the net enrollment estimation to compare across all other models we came across many obstacles. First, there is a time lag in data reporting. By the time much of the demographic data reaches publication it is often from two years prior. This inhibits timely estimation. Second, due to the private nature of many of the vital statistics, many data cells are left blank to keep personal medical information secure. Therefore, while our explanatory model does a better job of explaining the variation within the DHS disability data, it proves to be impractical for use as a predictive model.

Additional Considerations

Specific Disability Classification Estimates

Although our model examines the net entrants from all disability categories it should recognized that specific disability classifications can also be estimated independently. A good example of this is the classification of mental retardation. The variation in demand for DHS services by individuals with mental retardation is explained more from our independent variables than any other classification. We explored this finding and ran regressions on the specific DHS disability classifications to see if we could accurately predict future enrollment of specific classifications.

Table 12: Mental Retardation Entrants

Variable	Model
Total Population	0.1733047*
	(0.0221412)
Total Population²	0.0002765*
	(0.0000387)
Trend	-0.3944909
	(0.4214376)
Constant	8.085022
	(2.728284)
Number of Obs.	308
R-Squared	**0.8622**
F-Statistic	F(3, 304) = 634.27

*: Statistically Significant at the 1 percent level

Table 13: Mental Retardation Exits

Variable	Model
Total Population	0.0601786*
	(0.0203807)
Total Population²	0.0002289*
	(0.0000354)
Trend	0.1070649
	(0.3827657)
Constant	4.322832
	(2.308133)
Number of Obs.	294
R-Squared	**0.7254**
F-Statistic	F(3, 290) = 255.31

*: Statistically Significant at the 1 percent level

The regressions on mental retardation proved to be very effective in explaining the variation in both new entrants and exits. The R-squared of 0.8622 in this model is very close to the R-squared found in our initial prediction model. The R-squared on the exits regression is higher than the R-squared on our initial prediction model. This tells us that we should indeed be able to estimate at least one of the specific disability categories with similar accuracy to our original net model. Given more time, we would be able to further pursue this finding and eventually obtain predictions on enrollments for future years. An extension of the project could yield valuable results on specific DHS enrollment categories.

Adding an Interaction Term

We further attempted to gain additional explanatory power from our prediction model by including an interaction term. The interaction term was used to tease out any additional explanatory power within the population and trend variables that we had not explicitly accounted for with other variables. Thus, the interaction term is defined as the total population multiplied by the trend term.

Table 14: Adding an Interaction Term

Variable	Model
Total Population	0.0917693*
	(0.0355091)
Total Population²	0.0001115
	(0.0000516)
Interaction	0.0027907
	(0.003813)
Trend	0.6471504
	(0.6176623)
Constant	-1.949834
	(4.483999)
Number of Obs.	308
R-Squared	**0.5122**
F-Statistic	F(4, 303) = 79.55

*: Statistically Significant at the 1 percent level

The results of the regression with the included interaction variable are listed above. The total population is the only term in the regression that remains statistically significant at the 1 percent level. Recall that our initial prediction model resulted in an R-squared value of 0.5114. Though the inclusion of the interaction term does increase the explanatory power of our model, it is a negligible amount of less than one tenth of one percent. For this reason, we decided not to include the interaction term in our prediction equation.

Omitting Outliers

We also explored the option of removing the outliers within our data to further improve our estimations. Multnomah County, with its large population, stood out from the rest of the data in our estimation procedures. Concerned that a single county with such high population could be skewing our results, we omitted it from the regression model to examine its effect.

Table 15: Excluding Multnomah County

Variable	**Model**
Total Population	0.1219744*
	(0.0439526)
Total Population²	0.00008
	(0.000109)
Trend	0.8344609
	(0.4803766)
Constant	-3.601606
	(3.960959)
Number of Obs.	300
R-Squared	**0.3438**
F-Statistic	F(3, 296) = 51.69

Table 15 shows the results of our regression with Multnomah County omitted. The low R-squared, only 0.3438, and loss of statistical significance on the population-squared term provides evidence of this model's inferiority to our initial prediction model. We believe that, although an outlier, Multnomah County still adds valuable explanatory power to our initial model.

Conclusion

Our research on the DHS Developmental Disabilities Program explains variation within the entrant and exit data. Utilizing this information, we produced a powerful prediction model with the capacity to estimate demand for DHS disability services years into the future. We found that total demand for these services will be growing at an annual rate of 4.82 percent until the year 2010. We also made predictions out to 2020 on changes in enrollment; however, a reexamination of population data in the year 2010 will yield more pertinent results. The ability to accurately anticipate new program entrants allows DHS to reduce the burden of wait listing. Eliminating the wait listing problem will enable timely access to services for all eligible individuals.

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Appendix

AP 1.1 Entrants: Predicted Values vs. Actual Data

Year	County	Predicted	Actual	Omitted Projections*
2004	Baker	13	13	
2004	Benton	31	21	
2004	Clackamas	126	118	
2004	Clatsop	18	6	
2004	Columbia	20	36	
2004	Coos	25	34	
2004	Crook	14	9	
2004	Curry	14	7	
2004	Deschutes	44	40	
2004	Douglas	36	40	
2004	Gilliam	0	0	9
2004	Grant	11	2	
2004	Harney	11	2	
2004	Hood River	0	0	13
2004	Jackson	63	60	
2004	Jefferson	13	8	
2004	Josephine	29	42	
2004	Klamath	24	45	
2004	Lake	11	3	
2004	Lane	117	112	
2004	Lincoln	20	41	
2004	Linn	35	66	
2004	Malheur	16	10	
2004	Marion	93	74	
2004	Morrow	11	6	
2004	Multnomah	285	305	
2004	Polk	25	24	
2004	Sherman	9	0	
2004	Tillamook	15	10	
2004	Umatilla	25	16	
2004	Union	14	9	
2004	Wallowa	11	8	
2004	Wasco	0	0	15
2004	Washington	167	133	
2004	Wheeler	0	0	9
2004	Yamhill	30	43	
Statewide Total:		**1377**	**1343**	

Year	County	Predicted	Actual	Omitted Projections*
2005	Baker	14	11	
2005	Benton	31	24	
2005	Clackamas	130	101	
2005	Clatsop	19	10	
2005	Columbia	20	26	
2005	Coos	26	35	
2005	Crook	15	11	
2005	Curry	15	14	
2005	Deschutes	48	44	
2005	Douglas	36	33	
2005	Gilliam	0	0	10
2005	Grant	11	0	
2005	Harney	11	7	
2005	Hood River	0	0	14
2005	Jackson	65	70	
2005	Jefferson	13	7	
2005	Josephine	30	25	
2005	Klamath	25	40	
2005	Lake	11	4	
2005	Lane	119	105	
2005	Lincoln	21	31	
2005	Linn	36	46	
2005	Malheur	16	29	
2005	Marion	95	108	
2005	Morrow	12	4	
2005	Multnomah	293	422	
2005	Polk	25	25	
2005	Sherman	10	0	
2005	Tillamook	16	17	
2005	Umatilla	25	24	
2005	Union	15	10	
2005	Wallowa	11	5	
2005	Wasco	0	0	15
2005	Washington	176	127	
2005	Wheeler	0	0	10
2005	Yamhill	32	51	
Statewide Total:		**1420**	**1466**	

**Some projections were omitted because entrant and exit data was not available at the county level*
Note: Gilliam, Hood River, Wasco, Wheeler County did not have individual county level data

AP 1.2 Exits: Predicted Values vs. Actual Data

Year	County	Predicted	Actual	Omitted Projections*
2004	Baker	4	16	
2004	Benton	15	5	
2004	Clackamas	72	36	
2004	Clatsop	6	10	
2004	Columbia	6	9	
2004	Coos	10	11	
2004	Crook	4	5	
2004	Curry	5	7	
2004	Deschutes	18	18	
2004	Douglas	16	15	
2004	Gilliam	0	0	2
2004	Grant	3	2	
2004	Harney	3	1	
2004	Hood River	0	0	3
2004	Jackson	31	35	
2004	Jefferson	2	3	
2004	Josephine	13	11	
2004	Klamath	7	37	
2004	Lake	3	1	
2004	Lane	65	76	
2004	Lincoln	8	22	
2004	Linn	13	22	
2004	Malheur	3	4	
2004	Marion	33	133	
2004	Morrow	2	2	
2004	Multnomah	165	208	
2004	Polk	9	14	
2004	Sherman	2	0	
2004	Tillamook	5	4	
2004	Umatilla	5	16	
2004	Union	3	6	
2004	Wallowa	2	1	
2004	Wasco	0	0	4
2004	Washington	72	49	
2004	Wheeler	0	0	2
2004	Yamhill	10	21	
Statewide Total:		**614**	**800**	

Year	County	Predicted	Actual	Omitted Projections*
2005	Baker	3	3	
2005	Benton	14	14	
2005	Clackamas	73	58	
2005	Clatsop	6	5	
2005	Columbia	5	7	
2005	Coos	10	8	
2005	Crook	3	1	
2005	Curry	4	5	
2005	Deschutes	21	20	
2005	Douglas	15	11	
2005	Gilliam	0	0	1
2005	Grant	2	4	
2005	Harney	2	1	
2005	Hood River	0	0	2
2005	Jackson	31	36	
2005	Jefferson	1	4	
2005	Josephine	11	17	
2005	Klamath	7	14	
2005	Lake	2	1	
2005	Lane	66	52	
2005	Lincoln	7	12	
2005	Linn	12	17	
2005	Malheur	2	6	
2005	Marion	34	116	
2005	Morrow	1	1	
2005	Multnomah	173	189	
2005	Polk	8	16	
2005	Sherman	1	0	
2005	Tillamook	4	3	
2005	Umatilla	3	10	
2005	Union	3	2	
2005	Wallowa	1	4	
2005	Wasco	0	0	3
2005	Washington	82	40	
2005	Wheeler	0	0	1
2005	Yamhill	10	16	
Statewide Total:		**614**	**693**	

**Some projections were omitted because entrant and exit data was not available at the county level*
Note: Gilliam, Hood River, Wasco, Wheeler County did not have individual county level data

AP 1.3 Net Change: Predicted Values vs. Actual Data

Year	County	Prediction	Actual	Omitted Projections*
2004	Baker	9	-3	
2004	Benton	16	16	
2004	Clackamas	55	82	
2004	Clatsop	12	-4	
2004	Columbia	13	27	
2004	Coos	15	23	
2004	Crook	10	4	
2004	Curry	9	0	
2004	Deschutes	26	22	
2004	Douglas	20	25	
2004	Gilliam	0	0	8
2004	Grant	8	0	
2004	Harney	8	1	
2004	Hood River	0	0	11
2004	Jackson	32	25	
2004	Jefferson	11	5	
2004	Josephine	16	31	
2004	Klamath	17	8	
2004	Lake	8	2	
2004	Lane	52	36	
2004	Lincoln	12	19	
2004	Linn	23	44	
2004	Malheur	12	6	
2004	Marion	60	0	
2004	Morrow	9	4	
2004	Multnomah	121	97	
2004	Polk	16	10	
2004	Sherman	8	0	
2004	Tillamook	10	6	
2004	Umatilla	20	0	
2004	Union	11	3	
2004	Wallowa	8	7	
2004	Wasco	0	0	10
2004	Washington	95	84	
2004	Wheeler	0	0	7
2004	Yamhill	20	22	
Statewide Total:		**763**	**602**	

Year	County	Prediction	Actual	Omitted Projections*
2005	Baker	10	8	
2005	Benton	18	10	
2005	Clackamas	57	43	
2005	Clatsop	13	5	
2005	Columbia	15	19	
2005	Coos	16	27	
2005	Crook	12	10	
2005	Curry	11	9	
2005	Deschutes	27	24	
2005	Douglas	21	22	
2005	Gilliam	0	0	9
2005	Grant	9	-4	
2005	Harney	10	6	
2005	Hood River	0	0	12
2005	Jackson	34	34	
2005	Jefferson	12	3	
2005	Josephine	18	8	
2005	Klamath	18	26	
2005	Lake	10	3	
2005	Lane	53	53	
2005	Lincoln	14	19	
2005	Linn	24	29	
2005	Malheur	14	23	
2005	Marion	61	-8	
2005	Morrow	11	3	
2005	Multnomah	120	233	
2005	Polk	18	9	
2005	Sherman	9	0	
2005	Tillamook	12	14	
2005	Umatilla	21	14	
2005	Union	12	8	
2005	Wallowa	10	1	
2005	Wasco	0	0	12
2005	Washington	94	87	
2005	Wheeler	0	0	9
2005	Yamhill	22	35	
Statewide Total:		**806**	**773**	

**Some projections were omitted because entrant and exit data was not available at the county level*
Note: Gilliam, Hood River, Wasco, Wheeler County did not have individual county level data