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Local Labor Market Conditions and the Jobless Poor: How Much Does Local Job Growth Help in Rural Areas?

Elizabeth E. Davis, Laura S. Connolly, and Bruce A. Weber

The employment outcomes of a group of jobless poor Oregonians are tracked in order to analyze the relative importance of local labor market conditions on their employment outcomes. Local job growth increases the probability that a jobless poor adult will get a job and shortens the length of time until she finds a job. After accounting for both the effects of personal demographic characteristics and local job growth, there is little evidence that the probability of employment or the duration of joblessness differs in rural compared with urban areas.

Key words: employment, local labor markets, rural labor markets, rural poverty, unemployment, welfare reform

Introduction

Jobless workers often face bleaker prospects in rural than in urban labor markets. Although the employment growth rate was lower and the unemployment rate higher in metropolitan than in nonmetropolitan areas in the early 1990s, unemployment and underemployment rates have historically been higher in nonmetro areas, and average earnings have been lower [U.S. Department of Agriculture/Economic Research Service (USDA/ERS); Gibbs; Findeis and Jensen; Mills 2001]. These differences may be due to both the different characteristics of the labor forces and the different types of jobs available in metro and nonmetro areas. Rural adults have lower average levels of formal education than urban adults, for example, and employment in rural areas is more concentrated in minimum wage and part-time jobs and more likely to involve routine work (Duncan, Whitener, and Weber).

Economic growth, particularly growth in jobs, has been found to improve the well-being of economically disadvantaged groups. Strong local labor demand has been shown to provide significant benefits to disadvantaged groups in metropolitan areas (Bartik

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Elizabeth E. Davis is assistant professor, Department of Applied Economics, University of Minnesota; Laura S. Connolly is associate professor, Department of Economics, University of Northern Colorado; and Bruce A. Weber is professor, Department of Agricultural and Resource Economics, Oregon State University.

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1991, 1996; Freeman and Rodgers; Cain and Finnie). Job growth may be less effective, however, in providing employment for the jobless rural poor. This could be because the jobless rural poor have individual attributes that make them less productive employees, such as lower levels of formal education. Job growth also may be less effective in providing employment in rural areas due to structural differences in employment opportunities or in work supports. Child care and transportation may be less available in rural locations, affecting the ability or willingness of the jobless poor to respond to employment opportunities.

The employment opportunities themselves may also differ, because the jobs created in rural areas may not match well with the skills of the rural jobless poor. Most importantly, the effectiveness of job growth in providing employment for the jobless rural poor could be limited by the low spatial densities in rural employment. Job search may take longer and the probability of getting a job may be lower in rural areas because lower density of employment lowers the likelihood of receiving a job offer within a given commuting radius (Mills 2001).

Recent changes in social policy have increased the importance of workforce attachment and earnings in providing income for the poor, and have given states and localities more flexibility in designing workforce and income support policies for low-income people. These changes increase the importance of understanding the role of local labor markets in providing jobs for the poor. Given the historical rural disadvantage in labor market outcomes, recent policy changes also raise the prospect that rural low-income people will be further "left behind" and benefit less from local job growth and development efforts.

In this study, the determinants of success in getting a job for the jobless poor in Oregon are investigated, focusing on the role of local labor market conditions in rural and urban areas. Two questions are posed. First, how important is local job growth in determining the employment success of the jobless poor? And second, is local job growth less effective in improving employment outcomes in rural than in urban labor markets?

Conceptual Framework

In the neoclassical static model of labor supply, the individual chooses her hours of work in order to maximize utility, which depends on income and leisure, subject to her budget constraint.[1] The budget constraint reflects both her own wages and any sources of non-earned income, such as potential welfare benefits or a spouse's earnings. Local labor market conditions may affect an individual's budget constraint by changing her earnings or the likelihood of finding a job. For example, in a job search model, areas with faster job growth are likely to provide more job offers or better wage offers to a job seeker, all else equal (Hoynes 2000). Alternatively, as Bartik (1996) notes, in a job-queuing model, job growth may increase wages and employment of disadvantaged workers by both reducing unemployment and increasing upward mobility into higher wage jobs. Thus, changes in local labor market conditions affecting the returns to working will influence the individual's labor supply decision and employment outcomes.

[1] The employment decision is frequently modeled as a joint household decision in the case of married adults. Unfortunately, this data set does not link spouses or identify families. As indicated below, separate estimations for men and women produce few qualitative differences in the main results. For an example of estimation of a joint labor supply model, see Tokle and Huffman.

Previous research suggests local labor demand will improve the economic outcomes of disadvantaged workers, yet the impact of labor demand growth may not be the same in rural and urban areas. The effectiveness of labor demand growth may be constrained in rural areas for a number of structural reasons. Workers (or potential workers) in rural areas may face greater barriers to labor force participation than their counterparts in urban areas. For example, lower levels of education, greater need for reliable transportation and lack of public transportation, and the absence of affordable childcare may create barriers that impede the ability of rural workers to take advantage of job growth opportunities. On the demand side, employers in rural areas may offer different types of jobs or need workers with different skills than those in urban areas. Job opportunities are more widely dispersed in rural than urban areas, which may increase the costs and lower the returns to job search (Mills 2001). Thus, for reasons related to both individual attributes and structural differences in rural labor markets, local economic conditions may have a differential impact on the jobless poor in rural versus urban areas. Understanding the impact of local labor market conditions on employment outcomes for low-income adults is crucial for understanding the impacts of social policy—including economic development policy and welfare reform—in rural versus urban areas.

Literature Review

A number of studies have taken advantage of variation in regional economic conditions to estimate the impact of local labor demand conditions on the employment and earnings of particular population subgroups such as the poor or particular racial and ethnic groups. Freeman and Rodgers, for example, found lower unemployment rates increase the employment rates and earnings of young African-American men in metropolitan areas. Based on results of his analysis using the Panel Study of Income Dynamics, Bartik (1996) concluded employment growth has significant positive effects on real earnings of males in metropolitan areas, and these effects are stronger for younger, less experienced workers.

In an examination of labor market outcomes during the 1980s, Bound and Holzer found that increases in predicted employment growth led to better labor market outcomes for metropolitan area residents. Cain and Finnie reported a positive relationship between the average number of hours worked by black youth and hours worked by white youth (where hours worked by white youth are assumed to capture the demand for young workers). Each of the studies cited above used data sets linking individual outcomes and local economic conditions to explore the effects of labor demand conditions on labor force outcomes for disadvantaged populations in urban areas.

Other studies approach the question of the impact of local economic conditions on employment and income by using aggregate data on population subgroups. Hines, Hoynes, and Krueger examined the impact of business cycles on the employment, wages, and hours of work of low-skill workers using aggregate data from metropolitan statistical areas (MSAs). Freeman relied on state-level data to investigate the impact of economic growth on the poverty rate. Both studies found, at the aggregate level, local economic conditions matter—i.e., employment and earnings improve for the less advantaged during periods of economic growth.

There has been little research on the impact of local labor market conditions on employment outcomes in rural areas, or on the possibility of rural-urban differences in the effects of local economic conditions. Recent studies by Mills (2000) and Davis and Weber are exceptions. Using 1989–93 data from the National Longitudinal Survey of Youth, Mills concludes nonmetropolitan areas are not "inherently" disadvantaged relative to metro areas. He found that rates of exit from unemployment for displaced workers were slightly higher for nonmetro workers, "mainly due to nonmetropolitan-metropolitan differences in individual characteristics and local economic conditions" (p. 697). Mills notes his findings may be attributable in part to relatively strong nonmetropolitan job growth during his study period. Findings reported by Davis and Weber reveal local job growth is associated with higher earnings and more frequent employment for the working poor, and some evidence suggesting the effect of job growth is weaker in rural areas.

The Data

Data on Jobless Poor Adults

Research on rural low-income labor markets has been severely hampered by the difficulty of obtaining data for rural areas that link employment outcomes with information on individual demographic characteristics and local labor markets. This study uses a unique administrative data set, the Shared Information System (SIS), which links demographic information on Oregon residents enrolled in the Oregon Health Plan (OHP) in both rural and urban areas with data on those residents' employment outcomes collected by the Oregon Employment Department.

The study population consists of adults aged 18 to 64 who qualified for the OHP in 1994.[2] To qualify, a family's income had to be below the relevant federal poverty threshold for at least one month. The focus of this study is the "jobless poor," those adults enrolled in the OHP who were not employed at the time of their OHP enrollment. Although the quarter of entry into the OHP differs across members of the sample, the linked data follow the employment status of each of these low-income adults for at least eight quarters after their enrollment in the OHP. Employment status is based on earnings reported to the Oregon Employment Department by employers. Self-employed persons and those employed out of state are counted as not employed. The employment data cannot distinguish between being out of the labor force (e.g., in school or caring for dependents) and being unemployed.

The database includes 88,453 adults aged 18 to 64 who enrolled in the Oregon Health Plan in 1994 and were not employed at that time. Of these adults, 40% are under age 30, and another 31% are between 30 and 39 years old (table 1). Over two-thirds are female (68%). Of those with complete data, more than half are high school graduates with no post-secondary education, and more than one-quarter do not have a high school degree. The remaining 19% have some post-secondary training or college education.[3]

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[2] The Oregon Health Plan includes an expansion of the federal Medicaid program to cover working poor families and was allowed under special waivers from federal regulations. The authors were given access to selected data from the SIS for the period 1994–1996 through a special arrangement with the Oregon Employment Department. It has not been possible to obtain data for a more recent time period.

[3] Information on education level is missing for more than 50% of the sample. We include a dummy variable for missing education information as a control variable in the analyses. The missing education dummy has a significant negative effect on employment outcomes, suggesting that missing this information may be a proxy for unobserved characteristics which affect employment.

Table 1. Sample Statistics and Comparison of Demographic Characteristics of Jobless Poor Adults (18–64 years of age)

Description	Jobless Oregon Health Plan Participants [a] (*N* = 88,453)	Jobless Poor Oregonians [b] (*N* = 292)
Age:	<------------ (%) ------------>	
Under 30	40.4	37.9
30–39	31.5	28.3
40 and older	28.2	33.8
Gender:		
Female	68.1	66.4
Male	31.9	33.6
Ethnicity:		
African-American	3.1	1.4
Asian	2.8	2.1
Hispanic	5.1	11.1
Native American	1.9	2.1
Caucasian	85.3	81.0
Other/Missing	1.8	2.4
Education Level: [c]		
Less than High School Degree	27.3	23.2
High School Degree	53.4	40.8
More than High School Degree	19.3	35.9
Reside in Nonmetropolitan Commuting Zone	22.8	NA
Average Job Growth, 1994–96:		
Metropolitan Commuting Zones	7.3	NA
Nonmetropolitan Commuting Zones	5.2	NA

[a] Data on jobless Oregon Health Plan participants are taken from the Oregon Shared Information System (SIS).
[b] Data on jobless poor Oregonians are authors' calculations using the respondent file of the 1994 Oregon Population Survey (Oregon Progress Board).
[c] Education level excludes those for whom information is missing on educational status.

One drawback of this database is that the participants in the OHP are, to some extent, self-selected. Eligible poor adults who choose not to participate may differ systematically from the poor adults who do participate. Table 1 compares the demographic characteristics of the study sample to those of a comparison group from the 1994 Oregon Population Survey (Oregon Progress Board). The characteristics of the study sample are quite similar to those of all jobless poor working-age adults in Oregon. The fraction under the age of 40 is slightly larger in the study group than in the population of jobless working-age adults, as is the fraction of females. On the other hand, the study sample under-represents Hispanics. Despite the selective nature of the data set, the similarity of the study group to the overall population suggests the conclusions should be generally applicable to the broader population of jobless poor working-age adults.

Data on Local Labor Market Conditions

Empirical studies have used a variety of geographic classifications to define the spatial extent of "local labor markets" (LLMs). In their study of wage labor participation of farm and rural nonfarm couples, Tokle and Huffman use states as proxies for local labor markets, due to constraints imposed by their data set. Other studies use substate regions. Several use Metropolitan Statistical Areas (MSAs) to define LLMs (Bound and Holzer; Hoynes 1999; Bartik 1991, 1996; Freeman and Rodgers; Cain and Finnie). In analyses of local labor market conditions and welfare spells, Hoynes (2000) uses counties, and Fitzgerald uses both counties and Labor Market Areas as defined by the USDA's Economic Research Service to characterize local labor markets.

Each of these definitions has both advantages and drawbacks. States are generally too large and counties too small to capture the local labor market. MSAs exclude rural areas. To measure the set of labor market opportunities available to the individual in urban and rural areas more accurately, this study uses commuting zones as defined by Tolbert and Sizer. These zones are based on actual cross-county commuting patterns from census data and so reflect more realistic labor markets by including multiple counties and allowing for cross-state commuting. There are 18 commuting zones in Oregon, several of which cross state boundaries, and vary in size from one major metropolitan area to 12 nonmetropolitan zones with either a small town or small urban center.

Many different variables have been used to measure local labor market conditions: unemployment rates (Freeman and Rodgers; Fitzgerald); predicted employment growth, which is calculated by weighting national sector growth rates by local industry sector shares (Bound and Holzer); changes in the "wage premium" implied by regional industry mix (Bartik 1996); and employment growth (Bartik 1991, 1996). This study uses local employment growth (percentage change in local employment) to measure local labor market conditions rather than unemployment rates because it is less likely to confound the effects of changes in labor demand with those of labor supply (Blanchflower and Oswald). Bartik (1996) notes, "local employment growth is probably less endogenous than local unemployment rates" (p. 161). In addition, it is a straightforward measure available at the local level.[4]

Economic conditions varied widely across the commuting zones of Oregon over the 1994–1996 period. Average employment growth was higher in metro than nonmetro labor markets, and higher in the largest metro area (8.5% change in employment) than in the smaller metro areas (averaging 2.6%). Average changes in employment were also higher in nonmetro labor markets with large urban centers (6.6%) than in those with small town centers (3.5%). However, conditions varied considerably across commuting zones of the same type, particularly those with small urban and small town centers. Not all rural areas performed worse than the urban parts of the state. For example, job growth between 1994 and 1996 in several of the small-town commuting zones was greater than job growth in the small metropolitan labor markets. Generally, however, economic conditions are less favorable in nonmetro as compared to metro labor markets.

Empirical Model

An approach similar to that used by Bartik (1996), Bound and Holzer, and Freeman and Rodgers is followed to determine the relative importance of human capital and

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[4] An alternative approach would be to use employment growth in specific sectors of the economy, particularly retail or services, rather than total job growth. If the jobless poor are more likely to be employed in certain sectors than others, their outcomes may be more closely linked to the growth rates in those sectors. To test this hypothesis, the models were reestimated using manufacturing, services, and retail sector employment growth rates in place of total employment growth. Only retail employment seemed to matter, with results similar to those for total employment. Because of concerns about multicollinearity across the sectors, only the results using total employment growth are reported.

demographic characteristics versus local labor market conditions in determining employment outcomes for the low-income workforce in Oregon. The model takes the following form:

$$Y_i = f(\mathbf{x}_i, LM_i), \tag{1}$$

where Y_i is the employment outcome for individual i; $\mathbf{x}_i$ is a vector of human capital and sociodemographic variables, and LM_i measures local labor market conditions in the commuting zone.

Two measures of employment "success" may be affected by local labor market conditions: (*a*) the probability of becoming employed at any time after intake, and (*b*) the length of time needed to become employed. For the first measure, the probability of ever becoming employed, a logit model is estimated. The signs of the parameter estimates indicate whether each variable has a positive or negative influence on the probability that a jobless person will become employed at any time during the follow-up period. While the data track these adults for up to 11 quarters after intake into the OHP, only the first eight quarters of information are used for each individual in order to equalize the length of time available for finding a job. The estimates also are used to calculate the marginal effect of each variable on the probability of employment.

The second measure, duration of joblessness, is also of interest because it provides information on the rate at which jobless individuals become employed. The model can be estimated in two ways. The duration of joblessness can be used directly as the dependent variable (an accelerated failure time model), or a hazard model can be used instead. Under certain distributional assumptions (discussed below), the two models are mathematically equivalent, so the choice between the two is based on ease of interpretation. Hazard models are more familiar to economists, but the duration model has a straightforward interpretation, so both sets of estimates are presented. The hazard model defines the dependent variable as the probability of becoming employed at time t, conditional on not having been employed up to that point. Thus, the formulation of the hazard model differs from the unconditional probability estimated in a logit model. Models of this type generally have data that are right-censored and the current model is no exception. Of the people in the sample, 45% never become employed over the follow-up period, so the standard correction for right-censoring is made.

One problem arises in the hazard model because the entire sample is jobless at the beginning of the observation period and the actual starting date of each spell of joblessness is unknown. Thus, all observations in the sample are left-censored. This problem is quite common in survival analysis. For example, in medical studies of patient survival, it would usually be preferable to use the onset of disease as the point of origin, but in most cases, this value is unknown. Time of diagnosis is generally used instead. This introduces measurement error with the consequence that estimated coefficients tend to be biased toward zero (Allison). This limitation must be considered when interpreting the parameter estimates.

Both the logit and the hazard models are estimated using maximum-likelihood methods. If the error terms of individuals living within the same commuting zone are correlated, even after controlling for the labor market characteristics of the commuting zone, the true likelihood function will not be the product of the individual density functions (e.g., Skinner, Holt, and Smith). In linear models estimated with panel data, fixed or random effects can be used to correct this problem, but this solution is not available for nonlinear logit or duration models. The estimators used here do not make specific assumptions about the form of within-cluster correlation, but they do allow for consistent estimation of the variance-covariance matrix in the presence of clustering within commuting zones.

The covariance matrix, a modification of the robust ("sandwich") estimator of Huber or White, is denoted by:

$$\text{(2)} \qquad \mathbf{V}_{CLUSTER}(\hat{\beta}) = \left(\frac{J}{J-1}\right)\left(\frac{-\partial^2 \ln L(\hat{\beta})}{\partial\beta\partial\beta'}\right)^{-1}\left[\sum_{j=1}^{J}\left(\mathbf{u}_j^G \mathbf{u}_j^{G'}\right)\right]\left(\frac{-\partial^2 \ln L(\hat{\beta})}{\partial\beta\partial\beta'}\right)^{-1},$$

where $\hat{\beta}$ is the $\{K \times 1\}$ vector of parameter estimates; J is the number of groups; and $\mathbf{u}_j^G$, a $\{K \times 1\}$ vector, equals $\partial \ln L_j(\hat{\beta})/\partial\beta$, the contribution of the jth group to $\partial \ln L(\hat{\beta})/\partial\beta$ (Stata Press; Williams). Wooldridge (2002) proves this estimator is consistent for nonlinear models.[5]

Standard explanatory variables are included in each of the employment equations: the individual's race, gender, education level, age and age squared, and a disability indicator. Unfortunately, the database does not include information on marital status or the number of children, two factors that may strongly influence labor force participation decisions. The omission of these variables may bias the estimates of the included variables.

A bias in the estimated effect of local job growth would arise if marital status or the number of children were correlated with job growth. For example, low job growth may result in marital stress, causing more divorce or fewer marriages. If this is the case, the effect of being married would be positively correlated with that of job growth, and omission of marital status would result in an overestimate of the impact of job growth. However, low job growth also makes marrying an employed partner more attractive, reversing the sign of the bias. In addition, any correlation between job growth and marital status is unlikely to differ across urban and rural areas, so this will not affect our estimates on the interaction terms. There is also little reason to believe the number of children in a household would be substantially correlated with job growth.[6]

As noted above, local labor market conditions are measured by the percentage change in total employment from 1994 to 1996. A dummy variable for rural areas (which equals one if the person resides in a nonmetropolitan commuting zone) is used to test whether outcomes differ in rural and urban areas after controlling for differences in demographic characteristics. To ensure all important differences between urban and rural areas are measured, the interaction of the rural dummy with each of the independent variables

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[5] These variance-covariance matrices are estimated using the "cluster" option provided with the logit and streg procedures in the Stata® statistical software package. An additional complication arises from the fact that consistency of the variance-covariance matrix estimator relies on a large number of clusters, or groups. In the present case, the clusters are the 18 commuting zones. Wooldridge (2003) provides a two-step estimation procedure to be used when the number of clusters is small but the number of observations within each cluster is large. Because Wooldridge's article is so recent, the method so far has been described only in the context of a linear model. The models in the current study are nonlinear, but the technique yields parameter estimates and significance levels similar to those obtained using Stata's prepackaged commands. This similarity provides further confidence in the robustness of the results.

[6] The effects of excluding marital status and number of children can be assessed partially by estimating separate equations for men and women, as omitting these variables will likely affect women's labor force status more than that of men. The main results of interest (the effects of job growth) were qualitatively similar for men and women. The results are available from the authors upon request.

Table 2. Proportion of Oregon Health Plan Participants Employed and Duration of Joblessness (N = 88,453)

No. of Quarters Until Employed	No. of Participants Becoming Employed	No. of Participants Censored	Proportion of Participants Becoming Employed	Cumulative Joblessness (Survival) Rate	Quarterly Hazard Rate
1	13,215	0	0.1494	1	0.1615
2	8,583	0	0.1141	0.8506	0.1210
3	5,981	0	0.0897	0.7536	0.0939
4	4,514	0	0.0744	0.6859	0.0773
5	3,862	0	0.0688	0.6349	0.0712
6	3,357	0	0.0642	0.5913	0.0663
7	2,853	0	0.0583	0.5533	0.0600
8	2,332	0	0.0506	0.5210	0.0519
9	1,785	9,399	0.0457	0.4947	0.0468
10	1,431	8,185	0.0502	0.4721	0.0515
11	606	13,285	0.0371	0.4484	0.0378
Total	48,519	30,869	0.5485	NA	NA

Notes: Cases are "right-censored" if the adult is not observed to be employed in any quarter between enrollment and the end of 1996. Enrollment in the Oregon Health Plan occurred in 1994. Those who enrolled in the first quarter of 1994 are tracked for 11 quarters, those who enrolled in the second quarter of 1994 are tracked for 10 quarters, and so on. The hazard rate is calculated at the midpoint of each interval.

is included in the models. The interaction term between the rural dummy and the local job growth variable is of particular interest as it indicates whether job growth has a differential impact in rural versus urban areas.

Estimation Results

Findings: Labor Market Outcomes

Table 2 summarizes the employment outcomes in the raw data for the adults on the Oregon Health Plan (OHP). Of the 88,453 adults on the OHP not employed at intake, 48,519 (55%) became employed at some point in the following 11 quarters. Those who became employed generally did so quickly, with 44% of those eventually employed reporting earnings within the first six months. In addition, the likelihood of becoming employed declined over time. The hazard rate, or proportion who become employed in a particular quarter given they are not employed up to that time, declines steadily from 0.16 to 0.04 (see figure 1). Note, however, the hazard rate shown here does not control for local labor market or demographic characteristics. The OHP adults who were jobless at intake worked only an average of 48% of the quarters in the 1994–96 follow-up period. Even though more than half became employed, most of those who worked were employed for less than half of the quarters.

Employment outcomes varied across the 18 commuting zones. Across commuting zones, between 45% and 59% became employed. The percentage of quarters worked ranged from 40% to 50%, with those in the larger metro areas working 48% or more of the quarters. Employment outcomes on average tended to be worse in the rural areas,

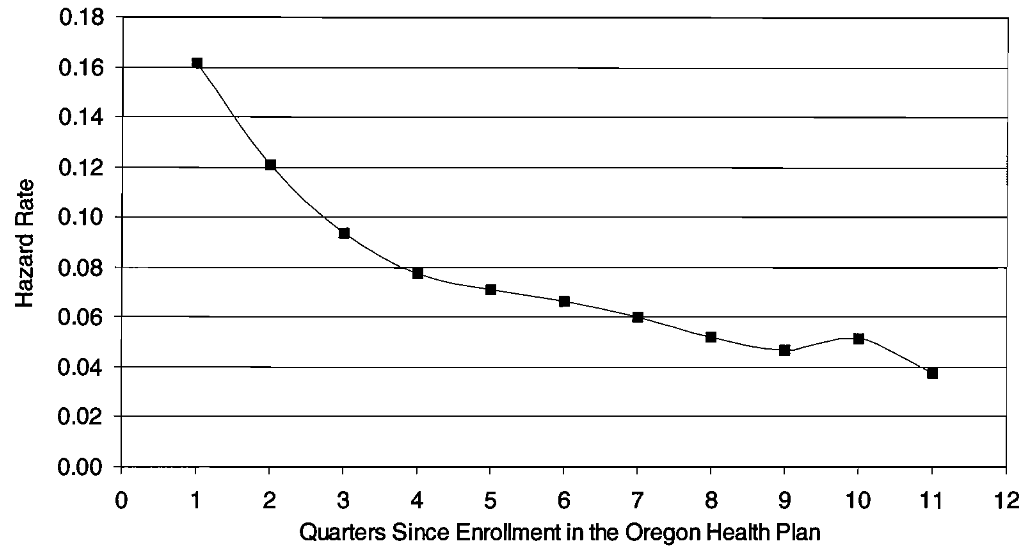

Figure 1. Employment hazard rate for Oregon Health Plan adults

although the smallest commuting zones experienced a wide range of outcomes. The difference in outcomes between rural and urban areas is reflected in the estimation of models (not reported) in which the probability of employment and the duration of joblessness are regressed only on the rural dummy variable. In these simple models, the probability of employment is significantly lower in rural than urban labor markets (at the 5% level), and the duration of joblessness is longer (but the difference is significant only at the 10% level).

Findings: The Impact of Local Job Growth on Employment Outcomes

Table 3 reports the results for the maximum-likelihood estimation of the logit model for employment status. The findings suggest job growth in urban areas is associated with a greater likelihood of employment for low-income adults on the Oregon Health Plan. The estimate, 0.062, is significant, with a p-value of 0.005. The marginal effect of 0.015 is estimated at the sample mean of the job growth variable, 4.6%. This estimate indicates a one percentage point increase in job growth would increase the probability of employment by 1.5%. To make the interpretation of this estimate clear, consider two commuting zones where the difference in the rate of job growth is one percentage point. According to the estimate, if each of the two commuting zones had 1,000 jobless poor adults with identical demographic characteristics, about 15 more people would find jobs at some point during the follow-up period in the commuting zone with higher job growth.

The estimated coefficient on the interaction term between the rural dummy and job growth equals -0.044, but is statistically insignificant. This estimate does not provide evidence supporting the hypothesis that job growth has a differential effect across the two types of regions, but neither can it be used to refute this hypothesis. To investigate further, we also test the hypothesis that the impact of job growth in rural areas itself is zero. If there is no difference in the effect of job growth between rural and urban areas,

Table 3. Logit Model: Impact of Local Job Growth on Probability of Employment

Variable	Parameter Estimate	p-Value	Marginal Effect	Std. Error of Marginal Effect
Constant	2.053	0.000	—	—
Job Growth	0.062	0.005	0.015	0.005
RURAL * *Job Growth*	-0.044	0.141	-0.011	0.007
Demographic Characteristics:				
Less than High School Degree	-0.441	0.000	-0.110	0.020
High School Degree	-0.201	0.000	-0.050	0.010
Missing Education Information	-1.592	0.000	-0.368	0.009
African-American	-0.056	0.349	-0.014	0.014
Hispanic	0.266	0.002	0.064	0.017
Asian	-0.155	0.054	-0.038	0.019
Native American	-0.104	0.191	-0.026	0.019
Other Race/Ethnicity	0.542	0.003	0.127	0.033
Male	0.068	0.006	0.017	0.005
Disabled	-0.373	0.008	-0.093	0.031
Age	-0.025	0.000	-0.006	0.001
Age Squared	-0.0003	0.000	-0.0001	0.00001
***RURAL* Dummy Variable**	-0.335	0.368	-0.083	0.090
Interactions between *RURAL* Dummy and Demographic Characteristics:				
Less than High School Degree	0.073	0.494	0.018	0.025
High School Degree	0.093	0.133	0.023	0.014
Missing Education Information	-0.001	0.992	-0.0002	0.015
African-American	-0.135	0.467	-0.033	0.045
Hispanic	-0.070	0.543	-0.017	0.028
Asian	0.228	0.086	0.055	0.030
Native American	0.124	0.229	0.030	0.024
Other Race/Ethnicity	-0.317	0.194	-0.079	0.059
Male	-0.140	0.027	-0.035	0.014
Disabled	-0.163	0.301	-0.041	0.038
Age	0.026	0.119	0.006	0.004
Age Squared	-0.0003	0.131	-0.0001	0.00005
Sample Size = 88,453; Log Likelihood = -53,236				

Notes: The marginal effects for all continuous variables are calculated at the sample means, holding all other variables constant at their sample means. The marginal effects for binary variables are calculated as the difference in probability with the binary variable equal to one and zero, with other variables at their sample means. Estimated standard errors of the marginal effects, shown in the last column, are calculated using the delta method described by Greene. The rural-demographic interaction terms are jointly insignificant at the 5% level, with a Wald test statistic, adjusted for the small number of clusters (Korn and Graubard), of 3.39 (p-value = 0.07).

then rural job growth should have a significantly positive effect, just as urban job growth does. However, we cannot reject the null hypothesis that job growth has no effect in rural areas.[7] Thus, because of the lack of precision of the estimates, the confidence intervals

[7] This hypothesis could be tested by calculating the standard error of the sum of the coefficients of urban job growth and the rural-job growth interaction term for use in the t-statistic, but an easier way is to reestimate the model, replacing the rural-job growth interaction term with an interaction term between an urban dummy variable and the job growth variable instead. The estimated coefficient on job growth (which now measures the effect in rural areas only) is 0.018, with a p-value of 0.41, suggesting the effect of job growth is not significantly different from zero in rural areas. Note that 0.018 is the sum of the two logit coefficients from table 3 (0.062 + –0.044), as it must be.

overlap. We cannot reject the hypothesis that the effect of job growth in rural areas is significantly different from zero, nor can we reject the hypothesis that it is significantly different from the job growth effect in urban areas. Yet the job growth effect in urban areas is significantly different from zero. In a model with no rural variables or interaction terms (not shown), the estimates of the effect of job growth on both outcome variables are highly significant and very similar to the estimate for urban areas. This is further evidence that job growth does affect outcomes for the jobless poor, and that the data just do not allow us to distinguish between urban and rural effects very precisely. The lack of precision is not surprising because the effect of local labor markets is identified by the variation in job growth across only 18 commuting zones.

The rural dummy variable by itself is not significant at the 5% level, which implies that after accounting for local job growth and personal characteristics, no significant difference in the probability of employment between rural and urban areas remains. This result is consistent with the findings of Mills (2000), who concluded those in non-metropolitan areas were not "inherently" disadvantaged relative to metro areas, once differences in characteristics and job growth are taken into account.

The second outcome measure focuses on the probability of becoming employed at a specific point in time, given the individual has not been employed up to that point. The shape of the hazard function after controlling for the set of covariates is indeterminate a priori. If the jobless tend to hold out for a better job for a while after they first become unemployed, then the hazard function could increase initially. On the other hand, it could fall if those who remain jobless the longest are less and less likely to find jobs. The lognormal distribution allows for this shape, but statistical tests indicate the exponential function fits the data best, so the estimates reported here are based on this distribution.[8] Using the exponential distribution implies that, after controlling for covariates, the hazard rate is constant. In other words, once relevant factors are taken into account, the probability of a jobless individual finding a job in a given period of time is not dependent on the duration of her spell of joblessness. A constant hazard rate means the duration of unemployment for those remaining unemployed falls at a constant rate.

The first numeric column in table 4 shows the effects of the set of covariates on the hazard rate for employment. A hazard ratio greater than one means that an increase in the covariate increases the conditional probability of becoming employed, while an estimate less than one implies a negative effect. The second column provides the coefficient estimates from the duration formulation of the model. In this case, a negative coefficient is interpreted as shortening the duration of joblessness and thus improving the employment outcome. This alternative measure of labor market success does not change the conclusions qualitatively—total job growth has a positive effect on the conditional probability of employment and shortens the duration until employed. The estimates indicate that each one percentage point increase in local job growth raises the hazard of employment by 4%. Equivalently, it lowers the duration of joblessness, as shown by the estimated coefficient on job growth, by about 4%.

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[8] The exponential distribution was chosen based on the Akaike information criterion and the scale parameter in the Weibull model, estimated to be 0.99. Because the exponential distribution is a special case of the Weibull in which the scale equals 1, these two models provide virtually identical results. In fact, estimates of coefficients and standard errors are very robust to differing distributional assumptions, including the lognormal. Estimates from other distributions are available from the authors upon request.

Table 4. Hazard Model: Impact of Local Job Growth on Duration of Joblessness

Variable	Hazard Ratio	Estimated Coefficient	*p*-Value
Job Growth	1.040	-0.039	0.039
RURAL * *Job Growth*	0.971	0.029	0.243
Demographic Characteristics:			
Less than High School Degree	0.740	0.300	0.000
High School Degree	0.855	0.157	0.000
Missing Education Information	0.356	1.031	0.000
African-American	0.969	0.032	0.198
Hispanic	1.232	-0.209	0.000
Asian	0.926	0.077	0.261
Native American	0.960	0.041	0.401
Other Race/Ethnicity	1.280	-0.247	0.000
Male	1.191	-0.175	0.000
Disabled	0.800	0.223	0.006
Age	0.993	0.007	0.015
Age Squared	1.000	0.0003	0.000
***RURAL* Dummy Variable**	0.842	0.172	0.523
Interactions between *RURAL* Dummy and Demographic Characteristics:			
Less than High School Degree	1.047	-0.046	0.308
High School Degree	1.078	-0.075	0.011
Missing Education Information	0.931	0.071	0.022
African-American	0.884	0.124	0.275
Hispanic	0.917	0.086	0.226
Asian	1.112	-0.106	0.336
Native American	1.011	-0.011	0.850
Other Race/Ethnicity	0.795	0.229	0.017
Male	0.892	0.114	0.009
Disabled	0.881	0.127	0.210
Age	1.020	-0.019	0.068
Age Squared	1.000	0.0002	0.071
Sample Size = 88,453; Log Likelihood = -112,365			

Notes: The hazard ratios and coefficients are estimated using the proportional hazard model and the accelerated failure time (AFT) parameterizations, respectively, of the exponential model. The *p*-values are calculated from the estimated coefficients and robust standard errors from the AFT model. The rural-demographic interaction terms are jointly significant at the 5% level, with a Wald test statistic, adjusted for the small number of clusters (Korn and Graubard), of 6.58 (*p*-value = 0.015).

As before, the effect of local job growth is smaller in rural areas but the coefficient on the rural-job growth interaction term is not statistically significant. If there is a difference in the effect across urban and rural areas, these estimates are not precise enough to detect it. Recall that the existence of left-censoring implies estimates in the duration model may be biased toward zero. Thus, the lack of significance of the rural interaction term may be due to this bias. This argument also suggests the effect of job growth in urban areas may be stronger than indicated by these estimates. Again, the rural dummy variable by itself is insignificant, implying that differences in personal characteristics and job growth explain differences in urban and rural labor market outcomes.

Findings: The Impact of Personal Characteristics on Employment Outcomes

While the primary focus of this study is on the effect of local labor market conditions on employment outcomes, the coefficients on the demographic characteristics and their interactions with the rural dummy variable also provide some interesting insights. The effects of age and disability status are as expected: in both models, being older or disabled is a statistically significant detriment to the employment outcome. Neither of these effects is significantly different between urban and rural areas at the 5% level.

The effect of education is somewhat more complicated because the education data are missing for a large portion of the sample. An indicator variable is included in each model for individuals for whom education data are missing. Employment outcomes are much worse for this group than for the baseline category, which consists of those who completed some post-secondary schooling. This finding suggests that missing this information may be a proxy for unobserved characteristics which affect employment.

Among the portion of the sample for whom education status is known, the effects are as expected: having less education harms each employment outcome. Rural adults having exactly a high school education experience a much shorter duration of joblessness compared with otherwise similar urban adults (table 4). One way to interpret this finding is that a lack of education is not as detrimental to rural adults as it is for urban adults. However, it also implies the marginal benefit of additional education is smaller, though still positive, for rural adults.

Conclusions

Local labor market conditions affect the employment outcomes of urban jobless poor Oregonians. Local job growth increases the probability that a jobless poor adult will get a job and shortens the length of time until she finds a job in urban areas. The estimated rural-job growth interaction term is consistently of the opposite sign, which indicates job growth would have a smaller impact in rural areas, but it is not statistically significant at the 5% level in any of the specifications. On the other hand, the estimated impact of job growth in rural areas is not significantly different from zero either. If job growth has the same impact in rural as in urban areas, it should be significantly positive also. Consequently, these results suggest the impact of rural job growth is estimated imprecisely. The imprecision stems, in part, from the small number of commuting zones in Oregon. Additional data from a larger number of rural areas might yield more precise estimates.

The results also imply that the labor market disadvantages often observed in rural areas can be attributed to slower job growth and less beneficial demographic characteristics, and are not structurally related to the low densities of population in rural areas. Rural workers may be disadvantaged because of demographic characteristics which affect worker productivity, and job seekers may face higher barriers and have fewer opportunities in rural economies generally. However, the characteristics affected by public investments that make workers more productive (education or accommodations for disability, for example) appear to have generally similar impacts in rural as in urban places.

In addition, based on the estimates from this study, job growth, which can be stimulated through public policy, may have similar impacts on employment outcomes in rural and urban labor markets. However, further research is needed to estimate more precisely the impact of job growth on employment outcomes for disadvantaged workers in rural areas. If the impact of job growth is confirmed to be the same in rural and urban areas, then policies to stimulate job growth in rural areas are likely to have similar anti-poverty effects for those with similar education and other individual attributes. Even so, it may take more resources to stimulate jobs in rural than in urban areas, and to bring the rural workforce to the education levels of the urban workforce.

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