Models and Estimates

The analysis above provides a useful description of displaced workers. However, to better study the factors associated with worker displacement in nonmetro and metro areas, one must control for the influence of other variables. For example, more men than women are displaced workers in nonmetro areas. Because goods-producing industries are disproportionately male, and because goods-producing industries are more likely to have layoffs, and also because employment in nonmetro areas is disproportionately in goods-producing industries, nonmetro men were more likely to be displaced than nonmetro women during 1995-97. Sorting out the contribution of various factors, such as sex, industry, and area of residence, is done by use of regression models. In looking at displacement, a worker was displaced or was not displaced over the time period studied. For this type of binary outcome, a probit type of regression model is used, where the coefficient estimates on worker characteristics represent the contribution to the probability that the worker will be displaced.

Here, three questions will be addressed. First, what is the probability of displacement for different groups of workers in nonmetro and metro areas? Second, of those nonmetro and metro displaced, what is the probability of employment after displacement? Third, for those who find a new job after displacement, what are the factors that contribute to earnings loss in nonmetro areas?

Probability of Displacement

The analysis above on calculated displacement rates is a start at looking at probability of displacement. I also conducted a probit analysis to estimate the probability of job loss. I estimated the following models:

probability(y_i*=displacement) = f(age, education level, sex, race, industry, metro/nonmetro residence)*

probability(y_i*=displacement, nonmetro only) = f(age, education level, sex, race, industry)*

probability(y_i*=displacement, metro only) = f(age, education level, sex, race, industry)*

These models test the hypotheses that factors—age, education level, sex, race, industry, and residence—contribute to the probability of displacement. These models describe the data and estimate probabilities of displacement controlling for various factors; they are not designed as models of labor-leisure choice theory.[11]

Usually these models would contain a measure of regional labor markets such as a regional unemployment rate. Metro and nonmetro unemployment rates were similar during 1995-97, and having only one unemployment rate for the aggregate of nonmetro and the aggregate of metro in the model creates a variable equivalent to the metro/nonmetro dummy. Therefore, these variables were not successful in the models and so were excluded from analysis.[12] Also excluded as an explanatory variable is tenure. Job tenure is problematic because displaced workers by definition were displaced in the 3 years' prior to being surveyed, so their current job tenure would be short. Tenure then would serve as a proxy for displacement. If job tenure at displacement is used, then the difficulty is in how to treat tenure of workers who were not displaced. Expectations, drawn from the calculated displacement rates and the literature, were that higher probabilities of displacement would be experienced by younger and older workers, those with less education, men, nonwhites, workers in the goods-producing industries, and metro workers.

Table 9 contains both the probit estimates and the normalized estimates of the probit models.[13, 14, 15] Normalized estimates represent the probability of displacement given a one-unit increase in an independent variable. The normalized estimates are calculated at the mean of the independent variables. Note that when the independent variables are binary, the normalized estimates can be interpreted as rates. The probit analysis estimates of displacement rates in table 9 have the advantage that each rate is estimated controlling for the other factors, unlike the calculated rates presented above. The mean values of each variable are also presented in table 9. In this case, all the independent variables are 0-1 binary, so the mean represents the share of workers in each category. For example, a mean of 0.251 for the variable age 25-34 indicates that 25.1 percent of the workers analyzed are in that age group.

The data in this model include all workers who had reported being displaced during 1995-97 plus all workers who were employed when surveyed. Unlike other analysis in this report, displaced workers of all job tenures are included. Because the model estimates the probability of being displaced, it is more intuitive to think of the entire population of displaced and those

Table 9—Probability of displacement, 1995-97

	U.S. total		Nonmetro		Metro	
	Mean	Estimate	Mean	Estimate	Mean	Estimate
All tenures-probit estimates:						
Intercept		-1.447**		-1.452**		-1.470**
		(.021)		(.050)		(.023)
Age 25-34	0.251	- .025	.224	-.006	.257	-.031
		(.021)		(.050)		(.023)
Age 35-44	.282	-.079**	.275	-.189**	.283	-.059**
		(.020)		(.050)		(.022)
Age 45-54	.217	-.124**	.233	-.189**	.214	-.112**
		(.022)		(.052)		(.024)
Age 55-64	.140	-.208**	.165	-.375**	.134	-.174**
		(.026)		(.064)		(.029)
Education—less than high school diploma	.133	.116**	.166	.069	.125	.130**
		(.020)		(.044)		(.022)
Education—some college	.288	.008	.269	-.042	.292	.022
		(.015)		(.035)		(.016)
Education—college degree	.174	-.090**	.108	-.194**	.189	-.073**
		(.017)		(.052)		(.019)
Education—advanced degree	.078	-.206**	.046	-.384**	.086	-.189**
		(.025)		(.087)		(.026)
Female	.510	-.060**	.511	-.141**	.509	-.046**
		(.012)		(.031)		(.013)
Nonwhite	.169	.009	.112	.083*	.183	-.0002
		(.016)		(.046)		(.017)
Goods-producing sector	.263	.063**	.361	.065*	.240	.056**
		(.014)		(.032)		(.015)
Nonmetro	.190	-.126**				
		(.016)				
Rescaled generalized R^2		.013		.026		.010
Log likelihood		-26,500.7		-4,248.1		-22,183.0
				Percent		
Association of predicted and observed:						
Concordant		54.2		59.1		52.9
Discordant		40.7		36.1		41.9
Tied		5.1		4.8		5.2

	U.S. total	Nonmetro	Metro
Normalized probit estimates:			
Intercept	-0.165	-0.139	-0.174
Age 25-34	-.003	-.001	-.004
Age 35-44	-.009	-.018	-.007
Age 45-54	-.014	-.018	-.013
Age 55-64	-.024	-.036	-.021
Education-less than high school diploma	.013	.007	.015
Education-some college	.001	-.004	.003
Education-college degree	-.010	-.018	-.009
Education-advanced degree	-.024	-.037	-.022
Female	-.007	-.014	-.006
Nonwhite	.001	.008	0
Goods-producing sector	.007	.006	.007
Nonmetro	-.014		

* Indicates significance at the 10-percent level using chi-squared statistic. Standard errors are in parentheses. ** Indicates significance at the 1-percent level using chi-squared statistic.

Note: The base (omitted) group for U.S. total: age 20-24, high school diploma, male, white, service sector, and metro. The base (omitted) group for nonmetro and metro: age 20-24, high school diploma, male, and white. The number of observations for U.S. total, 50,357; for nonmetro, 11,491; for metro, 38,746. Displaced are 5.7 percent, 4.9 percent, and 5.9 percent of the observations, respectively.

not displaced but working, than to consider only those with 3 or more years of tenure.[16]

The estimates show that older workers were less likely to be displaced. For the U.S. total, those age 55-64 have a displacement rate 2.4 percentage points lower (-0.024 in table 9) than the base (omitted) category of age 20-24, high school diploma, male, white, service sector, and metro. (Because of the nature of modeling with dummy variables, the estimates are relative to the omitted groups.) For nonmetro, those age 55-64 had an even lower displacement rate, 3.6 percentage points less than the base category. Those with college or advanced degrees had a lower displacement rate than the base categories. Those with less than a high school diploma had a higher rate of displacement with a probability 1.3 percentage points greater than the base group for the U.S. total. Women also had lower displacement rates than the base. Nonwhite workers had a probability of displacement the same as the base case for the U.S. total and metro, and a slightly higher probability, 0.8 percentage point for nonmetro. Those in the goods-producing sector—agriculture, mining, manufacturing, and construction—had a greater probability of displacement as expected. Being in a nonmetro area lowered the probability of displacement by 1.4 percentage points.

The normalized coefficient estimates of the nonmetro probit and the metro probit are generally about the same, consistent with the calculated displacement rates in table 2. The U.S. total model achieves a concordant level of 54 percent, meaning that it is slightly better than a coin toss, which is as expected given that only about 6 percent of the population analyzed were displaced.[17] The tepidness of the results imply that displacement is less about workers' characteristics, which are included in the model, but about other factors. This is not surprising in that displacement is a result of economic restructuring from import competition, technological advances, or firm downsizing. However, because some industries and companies are facing more economic restructuring than other industries and because there are demographic differences in the distribution of workers across industries and companies, worker characteristics indicate which groups may be more likely to be displaced.

Probability of Employment After Displacement

To answer the second question (for those displaced, what is the probability of employment after displacement?) I used the following models:

probability(y_i=employment after displacement) = f(age, sex, tenure on lost job, weekly earnings on lost job, skill level on lost job, metro/nonmetro residence)

probability(y_i=employment after displacement, nonmetro only) = f(age, sex, tenure on lost job, weekly earnings on lost job, skill level on lost job)

probability(y_i=employment after displacement, metro only) = f(age, sex, tenure on lost job, weekly earnings on lost job, skill level on lost job)

Expectations were that younger workers, men, those with less tenure on the lost job, and those with higher skill levels would have a higher probability of attaining a new job after displacement and that those in nonmetro areas would have a lower probability.

Table 10 presents both probit estimates and normalized probit estimates.[18] The data include all workers in the 1998 DWS who reported being displaced during 1995-97 and who had 3 or more years of tenure on their lost job. Looking at the U.S. normalized probit estimates, those in all age categories—25-34, 35-44, 45-54, and 55-64—have higher probabilities of attaining a new job after displacement than the base category—age 20-24, male, not low-skill, and metro. However, the age group 25-34 years old had the highest probability of all groups, 21.8 percentage points higher than the base category for total United States, consistent with the expectation that younger workers are more likely to find a new job. The coefficients for the category age 55-64 were not significant for any of the three probit estimates, meaning that the probability of employment for this group is essentially the same as the base case. Women who were displaced had a lower probability of employment, as expected. Those with long tenures on their lost job had a lower probability of employment, as the probability declined 0.4 percentage point for each year of tenure. Those with higher weekly earnings had higher probabilities of employment. Those in low-skill occupations on their lost job were less likely to find employment, as expected. Workers in nonmetro areas had a lower probability of employment by 5.0 percentage points than those in metro areas.

I used other explanatory variables in determining the probability of employment after displacement. Education levels were used, and results were similar to using skill level on lost job. Advance notice of job loss was also used, but without success. Metro-nonmetro unemployment rates are typically used in explaining the probability of employment after displacement, but

Table 10—Probability of employment after displacement, 1995-97

	U.S. total		Nonmetro		Metro	
	Mean	Estimate	Mean	Estimate	Mean	Estimate
Probit estimates:						
Intercept		-0.246		0.061		-0.405
		(.298)		(.767)		(.330)
Age 25-34	.224	.770*	.259	1.124*	.219	.680*
		(.158)		(.427)		(.172)
Age 35-44	.347	.696*	.278	.741*	.358	.660*
		(.155)		(.418)		(.169)
Age 45-54	.270	.536*	.297	.758*	.265	.464*
		(.158)		(.420)		(.173)
Age 55-64	.132	.047	.142	-.083	.130	.033
		(.165)		(.451)		(.179)
Female	.473	-.229*	.410	-.234	.484	-.232*
		(.057)		(.152)		(.062)
Nonwhite	.134	-.084	.090	-.114	.141	-.082
		(.078)		(.247)		(.082)
Tenure on lost job	9.433	-.013*	9.283	-.0003	9.458	-.014*
		(.004)		(.010)		(.004)
Log(weekly earnings) on lost job	6.248	.136*	6.028	.014	6.285	.171*
		(.004)		(.103)		(.049)
Low-skill occupations on lost job	.489	-.151*	.554	-.156	.478	-.113*
		(.058)		(.148)		(.063)
Nonmetro	.143	-.117*				
		(.075)				
Rescaled generalized R^2		.146		.167		.142
Log likelihood		-1,411.4		-221.3		-1,185.9
				Percent		
Association of predicted and observed:						
Concordant		65.9		60.5		66.3
Discordant		33.6		38.0		33.1
Tied		.6		1.5		.6

	U.S. total	Nonmetro	Metro
Normalized probit estimates:			
Intercept	-0.070	0.020	-0.112
Age 25-34	.218	.361	.187
Age 35-44	.197	.238	.182
Age 45-54	.151	.243	.128
Age 55-64	.013	-.027	.009
Female	-.065	-.075	-.064
Nonwhite	-.024	-.036	-.023
Tenure on lost job	-.004	-.0001	-.004
Log (weekly earnings) on lost job	.038	.004	.047
Low-skill occupation on lost job	-.043	-.050	-.037
Nonmetro	-.050		

* Indicates significance at the 10-percent level using chi-squared statistic. Standard errors are in parentheses.

Note: The base (omitted) group for U.S. total: age 20-24, male, white, not low-skill occupation, and metro. The base (omitted) group for nonmetro and metro: age 20-24, male, white, and not low-skill occupation. The number of observations for U.S. total, 1,217; for nonmetro, 221; for metro, 996. Employed after displacement are 78.0 percent, 73.8 percent, and 78.9 percent of the observations, respectively.

they were not used as discussed above, because the metro/nonmetro unemployment rates were so close during 1995-97.

Earnings Loss

Half the displaced workers who found a new job earned less in real terms when surveyed than they did on their lost job. Earnings loss is likely due to several factors. Workers may have firm-specific skills that would not be useful at another firm. The lost job earnings may include a wage premium due to unionization or due to efficiency wages—higher than market wages paid by the employer as an incentive for higher productivity and longer retention. Many employers reward longevity with a steep wage profile, meaning that long-tenured workers are paid more than their marginal product, and newer employees are paid less than their marginal product. Also, as a consequence of structural change, the workers' skills may no longer be valued if the skills are obsolete or the industry is in decline.

Here earnings loss is measured as the difference between current earnings (at the survey date) and real lost job earnings. Half of displaced workers who found new jobs experienced earnings loss, with about 30 percent suffering a real earnings loss of more than 20 percent. Not all displaced workers are as unfortunate, as one-third had real earnings on their current job 20 percent or higher than on their lost job (fig. 5).

This analysis is a direct measure of earnings loss and understates the total loss to displaced workers due to several factors. First, it does not account for the earnings growth that would have occurred were the worker still employed and had not been displaced. Second, this analysis only looks at displaced workers who found a new job; it does not incorporate nonemployment effects, that is, the earnings losses of those not employed at the time of the survey and the earnings losses of those who are now employed but experienced a period of joblessness. However, because the direct measure indicates substantial and widespread earnings loss, it is useful in analyzing the costs of displacement.

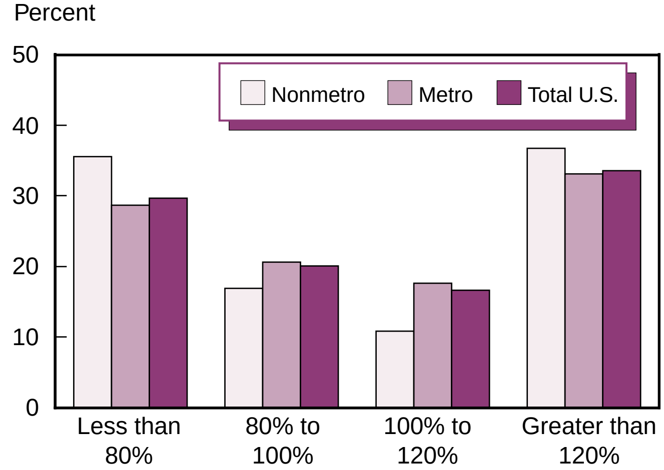
The model used here is based on the standard statistical earnings function derived from human capital theory.[19] For worker *i*:

$$\log(\text{earnings}_i) = f(\text{education}_i, \text{experience}_i, \text{demographic factors}_i, \text{job characteristics}_i) + u_i$$

Figure 5

Earnings on current job relative to real earnings on lost job

About 30 percent of all displaced workers who found a new job had substantial earnings losses



Source: Calculated by ERS using data from the Displaced Worker Survey supplement, February 1998 Current Population Survey, Bureau of Labor Statistics.

where u_i = random disturbance, normally distributed with mean zero, and constant variance

The model form is quadratic in experience; that is, both experience and experience squared appear. The model used here estimates the impact of the independent variables on the difference between the natural log of the earnings on the current job and the natural log of the real earnings on the lost job, or equivalently, the natural log of the ratio of current earnings to real lost job earnings. I estimated the following models:

log (current weekly earnings/real lost job weekly earnings) =

f (tenure on lost job,
tenure^2,
age as proxy for experience,
education level,
low-skill occupation on lost job,
sex,
race,
industry of lost job,
union status on lost job,
advance notice received on lost job,
change in industry,
change in occupation,
full-time status to part-time status,

weeks looking for work after displacement, metro/nonmetro residence)

log(current weekly earnings/real lost job weekly earnings, nonmetro only) = f(tenure, ..., weeks looking for work after displacement)

log(current weekly earnings/real lost job weekly earnings, metro only) = f(tenure, ..., weeks looking for work after displacement)

Expectations were that the displaced workers who experienced greater earnings loss would be those who were longer tenured, older, less educated, in low-skilled occupations, male, nonwhite, in the goods sector industries, in a union, not given advance notice, and had changed industry or occupation for a new job, were now working part time but were full time on their lost job, and had experienced a long period of joblessness before finding a new job. Again, residential unemployment rates were not included because the metro and nonmetro rates were so similar over this period.

Ordinary least squares (OLS) estimates are presented in table 11 for total United States, nonmetro, and metro.[20] Equations (1), (3), and (5) in the table are estimated for the full model as presented above, and equations (2), (4), and (6) are estimates for a parsimonious model, that is, a model with a minimal number of regressors. The R^2's are low, as expected for an earnings model and for a difference model.

The reduction in hours worked—full-time to part-time status—is the largest contributor to earnings loss, and the estimated coefficient is significant at the 10-percent level. The coefficient estimate of -1.207, combined with the intercept, indicates that the reduction of hours by itself, all other things equal, would yield current earnings that would be 48 percent of lost-job earnings. [Log(current earnings/lost job earnings) = 0.463 - 1.207. Ratio = $e^{-0.744}$ = 0.475.] The change in status from full time to part time was large and significant in all six models. Indeed, the mean weekly earnings loss for displaced workers who were employed full time on their lost job and then were working part time when surveyed was $380, compared with a mean earnings loss of $36 for the rest of the displaced workers who had found a new job. About 11 percent of all the displaced workers who found a new job were working reduced hours (table 3).

The estimated coefficient on tenure is negative and significant in all but one of the models. Longer job tenures lead to a smaller ratio of current weekly earnings to real lost job earnings, that is, greater earnings loss. Tenure squared is also significant in the full model for equations (1) and (5); however, whether one would expect the ratio of the two earnings to be quadratic in form even if each of the two earnings functions were quadratic in form is unclear. The tenure squared coefficient is small enough that its effect combined with the tenure coefficient is a steady decline in the ratio of earnings over a 45-year tenure.

All age groups experienced greater earnings loss than the base group of age 20-24. Interestingly, the coefficients do not show a steady decline over age. The age 45-54 group had the smallest decline of the four groups.

Education was not generally successful as a variable; however, low-skill occupation on lost job was. The expectation was that the coefficient on low-skill would be negative; that is, displaced workers in low-skill occupations would have greater earnings loss, but the coefficient is positive in all models, indicating less earnings loss. This is partly due to the two minimum wage increases, one October 1, 1996 ($4.25 to $4.75 an hour) and one September 1, 1997 ($4.75 to $5.15 an hour), which would affect earnings of low-skill workers at or just above the minimum wage. Perhaps also this is because low-skill jobs are likely to be paid low wages; thus, a worker displaced from a low-skill job is likely to find a similar job at similar pay. Also, the number of low-skill jobs has been growing steadily during this economic expansion of the 1990s, and with the tight labor markets starting in 1996, wages for low-skill jobs have seen wage increases above the increases in the minimum wage.

Of the displaced workers who found a new job, women tended to fare better in terms of replacing their lost job earnings—the coefficients on female were significant in all models. Race and a new job in a different industry (as measured by 1-digit SIC code) did not affect earnings loss. In contrast, changing occupation (as measured by major occupational group) did lead to greater earnings loss. Perhaps one can maintain earnings by getting a job in the same occupation as the lost job, but in a different industry.

The number of weeks jobless after displacement was not significant. Economic theory would say that those with more weeks jobless had a higher reservation wage, the lowest wage that that person would accept, and were engaged in search unemployment.[21] The

Table 11—Regression analysis of earnings loss

Dependent variable: Log of the ratio of current weekly earnings to real lost-job earnings

	Total U.S.			Nonmetro			Metro		
	Mean	(1)	(2)	Mean	(3)	(4)	Mean	(5)	(6)
Intercept		0.463*	0.437*		-0.358	-0.363		0.590*	0.524*
		(.183)	(.171)		(.600)	(.554)		(.192)	(.178)
Tenure	9.149	-.031*	-.012*	8.690	.006	-.026*	9.221	-.044*	-.010*
		(.012)	(.004)		(.037)	(.010)		(.013)	(.004)
Tenure	132.7	.001*		142.2	-.001		131.2	.001*	
		(.0004)			(.001)			(.0004)	
Age 25-34	.244	-.420*	-.387*	.300	.235	.499	.235	-.544*	-.511*
		(.174)	(.170)		(.593)	(.553)		(.181)	(.178)
Age 35-44	.366	-.448*	-.433*	.288	-.007	.260	.378	-.522*	-.526*
		(.173)	(.169)		(.600)	(.558)		(.180)	(.176)
Age 45-54	.269	-.416*	-.383*	.307	-.007	.314	.263	-.495*	-.475*
		(.176)	(.172)		(.606)	(.558)		(.183)	(.180)
Age 55-64	.102	-.489*	.428*	.090	-.037	.251	.103	-.546*	-.505*
		(.186)	(.183)		(.691)	(.621)		(.193)	(.190)
Education:									
Less than high school diploma	.100	.097		.164	.120		.090	.164	
		(.085)			(.217)			(.094)	
Some college	.311	.071		.304	.128		.312	.064	
		(.061)			(.182)			(.065)	
College degree	.208	.146*		.094	.175		.226	.148*	
		(.071)			(.280)			(.073)	
Advanced degree	.071	.199*		.014	.789		.080	.175*	
		(.103)			(.685)			(.103)	
Low-skill occupation	.469	.152*	.127*	.535	.123	.076	.459	.164*	.138*
on lost job		(.051)	(.047)		(.168)	(.149)		(.054)	(.050)
Female	.450	.150*	.135*	.400	.278*	.282*	.458	.140*	.116*
		(.050)	(.048)		(.171)	(.159)		(.052)	(.051)
Nonwhite	.130	.034	.032	.093	.083	.054	.136	.022	.031
		(.070)	(.069)		(.258)	(.244)		(.072)	(.072)
Goods-producing sector	.334	-.065	-.101*	.446	.036	.011	.316	-.085	-.117*
		(.053)	(.052)		(.169)	(.157)		(.056)	(.055)
Union	.136	-.050		.126	-.199		.137	-.015	
		(.072)			(.256)			(.075)	
Advance notice	.444	-.015		.358	-.021		.457	.008	
		(.048)			(.165)			(.051)	
Change in industry,	.518	.047		.537	-.036		.515	.080	
lost job to current job		(.049)			(.155)			(.052)	
Change in occupation,	.461	-.110*	-.106*	.533	.011	-.050	.450	-.134*	-.120*
lost job to current job		(.049)	(.047)		(.165)	(.143)		(.052)	(.050)
Change in status,	.109	-1.207*	-1.233*	.113	-1.011*	-.982*	.108	-1.204*	-1.25*
full time to part time		(.079)	(.076)		(.248)	(.227)		(.083)	(.081)
Weeks jobless after	13.6	-.001		12.4	-.225		13.8	-.132*	
lost job		(.001)			(.212)			(.072)	
Moved to a different city	.147	-.137*		.177	.004		.142	-.002	
or county since lost job		(.067)			(.005)			(.001)	
Nonmetro	.134	-.036	-.031						
		(.071)	(.069)						
Number of observations		925	937		159	161		765	775
R^2 *(adjusted)*		.257	.262		.138	.175		.280	.281

* Indicates significance at the 10-percent level. Standard errors are in parentheses.

Note: The dependent variable is the difference between log weekly earnings current job and log real weekly earnings lost job. This is equivalent to the log of the ratio of current earnings to lost job earnings. The base group for U.S.: age 20-24, high school diploma, not low-skill on lost job, male, white, service sector, not in union in lost job, no advance notice, did not change industry, did not change occupation, was full time to full time or part time to full time, did not move, and metro. The base groups for nonmetro and metro are the same but without metro/nonmetro residence.

reservation wage concept implies that a higher reservation wage would result in a longer spell of joblessness, but ultimately a higher wage on a new job than had the first available job been accepted. However, longer periods of joblessness are in fact associated with greater earnings loss among displaced workers.[22] In addition, more weeks jobless would indicate softer local labor market conditions, so then, weeks jobless might serve as a proxy for local labor market conditions. Those who moved after displacement, however, experienced an earnings loss. The coefficient for moved to a different city or county is significant and negative in model (1). Perhaps this measure may be serving as a proxy for local labor market conditions; for example, those who see no opportunities for employment where they are, so they move and find a new job, albeit at lower earnings.

Nonmetro residence was not significant in either the full model (1) or the parsimonious model (2), and the two nonmetro models (3) and (4) were not particularly successful. Perhaps this is so because there is not much difference in the distribution of the ratio of current earnings to lost job earnings, in metro versus nonmetro areas (fig. 5). Modeling the level of earnings on the current job or the lost job results in the nonmetro residence coefficient being significant and negative (not shown here), because nonmetro earnings are on average lower than metro earnings.

Because this model is a direct measure of earnings loss which does not include the earnings losses of those not employed at the time of the survey, estimated earnings loss is underestimated with an upward bias. If displaced workers not employed were included, the nonmetro coefficients in models (1) and (2) would be smaller since nonmetro areas had a larger share of displaced workers who were not employed at the survey. Because these coefficients are small and are not significant at the 10-percent level, the bias does not appear to affect the conclusions.[23]