What are Jobs Worth?

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What Are Jobs Worth?

NOTE: This article highlights some of the research findings that appear in the authors’ new book, Does “Trickle Down” Work? which is available this summer from the Upjohn Institute (see p. 7).

How much are jobs subsidized by state and local governments really worth? Policymakers have achieved surprisingly little consensus on the character and size of gains from economic development projects. Measurement of such gains must inevitably derive from a vision of the labor market. For subsidies to generate real gains for local workers, those workers must be unemployed or underemployed. Recent research on job chains provides a natural approach to such measurement issues. It addresses not only the number of job vacancies created as a result of a subsidized business investment or expansion, but also the extent to which gains are achieved by the unemployed and the underemployed, whether skilled or unskilled.

The tide of strong economic growth at the state and local level lifts all boats. Workers in regions experiencing such growth are more likely to be employed, more likely to work full time, and more likely to take home a thicker paycheck than workers in sluggish regions. Studies by Bartik (1991, 1996) and others have forcefully made such points. But state and local governments seldom undertake economic development projects on a scale likely to affect the overall growth rate of the state or local economy. Most state and local efforts billed as economic development projects take the form of subsidies to a relatively small number of private firms. Project analysts are left in a quandary as to how to evaluate project benefits.

Any development project, whether a new auto firm or an airline terminal, announces new jobs, but the important question is, “How much are these new jobs really worth?” Wages generated by the project often are touted by sponsors as a dollar measure of benefits, but many, indeed most, of the workers hired into new jobs are already employed. Hence, the wage increases achieved by such job changers are likely to be relatively modest. Is this all a new job is worth? Common sense suggests there must be more. The natural question under the circumstances is to ask what happened to the jobs left vacant by the job changers. Of course, then we want to know what happened to any other vacancies left open further down the chain.

To value a new job, we need to value the gains made all along the job chain set in motion by the appearance of that job. For those eager to get to the bottom line, our estimate is that for every dollar of wages in a newly created job, the economic benefit is about 50 cents. That is a big discount on new payroll, but it still leaves a lot more than just the wage increases to new hires in the project itself. Below, we describe our logic for reaching this estimate using job chains.

Simulating Job Chains

The chain metaphor has been used to analyze a wide variety of markets involving durable goods, such as housing. Since every house has an address, housing chain research proceeds in a
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straightforward fashion. Just ask the incoming household of a new dwelling where he/she/they moved from and then go back to that unit and ask the new household moving in there the same question. Continue in this fashion through successive vacancies until the chain ends with an in-mover to the region, a newly formed household, or a demolition. Unfortunately, most jobs in the United States lack an identifying “address” or any other clear record independent of the workers holding those jobs. In general, job data are not collected as if jobs are entities in themselves, to be filled, vacated, or destroyed. Rather, job data are gathered essentially as by-products of collecting information on the individuals who occupy them. While a number of data sources allow researchers to track job histories of sample individuals, virtually none allow tracking of the successive individuals employed in a given position.

Under the circumstances, the possibilities for collecting data on actual job chains are slight.¹ The empirical problem is very similar to that facing an input–output (IO) researcher. After all, an IO multiplier for an apparel firm is not estimated by actually logging the sale of cloth to that firm, then the sale of cotton to the particular textile firm supplying the cloth, then the sale of petroleum to those specific farmers selling the cotton and so on. Instead, IO researchers estimate an average “input vector” for each industry, assume those vectors to remain constant whatever the use of the industry’s product, and then “simulate” the necessary character of production chains.

To use such a synthetic approach for job chains, we need to define and measure the equivalent of the IO input vector for each type of new job. If we break jobs down into discrete groups based on wages or some other general measure of quality, we simply ask what proportion of vacancies in a job at level 1 are filled by workers employed in level 2 jobs, workers employed in level 3 jobs, etc. To fill in the elements of such a vector, we need information only on a sample of those filling vacancies—their new jobs and their old jobs—or, if not coming from an existing job in the region, their previous labor force status.

Still following the IO model, we now assume that the probability of a given link in a job chain (e.g., the probability that the vacancy opened at level 3 is filled by a worker employed in level 5) depends only on the level of the vacancy being filled (e.g., level 3), and not on any other characteristics of the chain (e.g., the chain began with a new job at level 1). With this key assumption, we need no further information concerning job chains. In effect, once we are armed with these “input vectors,” we can synthesize the expected character of chains.

Table 1 Basic Wage Group Transition Matrix (entries are column percentages)

<table>
<thead>
<tr>
<th>Origin</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wage group 1</td>
<td>41.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wage group 2</td>
<td>25.0</td>
<td>52.9</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wage group 3</td>
<td>4.8</td>
<td>22.1</td>
<td>46.6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wage group 4</td>
<td>2.2</td>
<td>1.5</td>
<td>18.5</td>
<td>47.3</td>
<td></td>
</tr>
<tr>
<td>Wage group 5</td>
<td>0.0</td>
<td>0.3</td>
<td>2.4</td>
<td>13.3</td>
<td>34.5</td>
</tr>
<tr>
<td>Unemployed</td>
<td>2.9</td>
<td>3.8</td>
<td>9.7</td>
<td>15.8</td>
<td>24.7</td>
</tr>
<tr>
<td>Out of labor force</td>
<td>4.0</td>
<td>3.8</td>
<td>7.5</td>
<td>13.5</td>
<td>30.5</td>
</tr>
<tr>
<td>In-migrant</td>
<td>20.1</td>
<td>15.6</td>
<td>15.4</td>
<td>10.0</td>
<td>10.2</td>
</tr>
<tr>
<td>Column sum</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
</tr>
</tbody>
</table>

NOTE: The data are from 1987 to 1993 and relate to heads and spouses in the PSID. Level 5 has a lower bound at the national minimum wage. The upper bound for each wage group is about 50 percent greater than the lower bound. See Persky, Felsenstein, and Carlson (2004) for details including justification for triangularization.

This approach to job chains greatly simplifies empirical requirements. In recent work on trickle-down and economic development strategies, we use data from the Panel Study of Income Dynamics (PSID) to construct input vectors for an average state for five classes of jobs defined by wage level.² To build the input vectors for a given job level, we only need information on a sample of real job chains, we can now estimate all the relevant coefficients of the input vectors (Table 1). Not surprisingly, the largest entry in each column falls along the diagonal. Depending on the wage level, anywhere from 30 to 50 percent of hires in jobs come from workers already employed at the same level. But these hires add little to economic welfare. Gains must come from workers moving up from one job to a higher one, or from nonemployment.

Armed with these input vectors, it is a straightforward matter to generate the expected numbers of vacancies opened in each wage group as a result of a new initial job at any given level. These simulations are exactly analogous to the calculation of multipliers in IO analysis. They give job-chain multipliers. For example, a newly created job at level 3 is associated with an average chain of 2.7 vacancies, including 1.87 vacancies at level 3 itself, 0.66 vacancies at level 4, and 0.2 vacancies at level 5 (Table 2). The average chain is then terminated by the hiring of an unemployed worker, someone out of the labor force, or someone moving into the state. Perhaps not surprisingly, high-wage jobs like those at level 1 give rise to longer chains than low wage jobs like those at level 5. But the length of a chain is not in itself a measure of the chain’s value. To assess the worth of a new job, we also need to know the welfare gains made along the chain.

Valuing Average Chains

To the best of our knowledge, analysts of housing chains and the like have...
stopped short of calculating formal economic welfare benefits associated with particular chains. But chains in general and job chains in particular lend themselves neatly to such estimation. Again using the PSID data, we have calculated the average welfare gain of successful job applicants for each type of vacancy. The contributions to these averages of job changers are relatively easy to estimate from the empirical data. We simply count the actual increase in wages of similar job movers in the PSID. More difficult are the gains attributed to those moving from unemployment, out of the labor force, or outside the region. Such calculations are necessarily speculative. At root, any estimate of the welfare gains of these groups requires an evaluation of the alternative opportunities available to such workers. The gain, then, is the difference between the wages taken and what was given up. Again, see Persky, Felsenstein, and Carlson (2004) for details of our approach and sensitivity analyses.

Using these estimates of average welfare gains of hires at each vacancy level in conjunction with estimates of the number of each type of vacancy opened by a given chain, we construct estimates of the total welfare gain associated with each type of new job. In Table 3, these welfare gains are expressed as a share of the average wage of jobs at each level. Thus, we estimate new jobs at the highest levels (level 1 and level 2) generate welfare benefits equal to little more than 40 cents per dollar of wages. At the lowest levels (level 4 and level 5), these benefits amount to more than 60 cents per dollar of wages.

On average a job is worth about 50 cents per dollar of wages. Thus the normal practice of counting up new wages will considerably overstate the welfare gains generated by economic development projects. At the same time, just counting the gains to those workers actually taking the new jobs would set a much lower gain than estimated here. What accounts for this substantial discount? It is not job changers in the state or locality, because job changers leave behind vacancies for others to fill. If the entire chain consisted of such moves, the cumulative increase in wages would approach the wage of the new job. Rather, the discount originates in the opportunities facing those who at start hold no job in the region—the unemployed, out of the labor force, and in-movers. Of these, our analysis suggests that in-movers are the most important. Virtually all the difference between the two ends of Table 3 are accounted for by the greater proportion of in-movers filling level 1 vacancies as opposed to level 5 vacancies.

When it comes to economic development projects, questions of efficiency and distribution are very much intertwined. A dollar of wages created at the low end of the job distribution has an efficiency benefit more than 50 percent greater than a dollar at the high end. This is not based on any notion of diminishing marginal utility, although such a proposition would only strengthen the result. The simple logic here is that new high-end workers had substantially more attractive alternatives than new low-end workers. This result, too, seems much like common sense.

<table>
<thead>
<tr>
<th>Wage groups</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial new job</td>
<td>0.43</td>
<td>0.42</td>
<td>0.56</td>
<td>0.62</td>
<td>0.69</td>
</tr>
</tbody>
</table>

### Table 3 Welfare Gains, by Initial New Job

<table>
<thead>
<tr>
<th>Wage group of initial new job</th>
<th>Initial new job</th>
</tr>
</thead>
<tbody>
<tr>
<td>Welfare gains as a share of wages</td>
<td>0.43</td>
</tr>
</tbody>
</table>

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### Notes

1. The exceptions here are those jobs that are well defined in such organizational structures as religious denominations. Hence, White’s path-breaking efforts to trace job chains among the clergy (White 1970). Also see Webster (1979) for an early application of job chains.

2. The data are from 1987 to 1993 and relate to heads and spouses in the PSID. Level 5 has a lower bound at the national minimum wage. The upper bound for each wage group is about 50 percent greater than the lower bound. See Persky, Felsenstein, and Carlson (2004) for details including our justification for triangularizing the matrix in Table 1.

### References


