

## **Job Vacancy Chains in Metropolitan Labor Markets**

**Joseph Persky**

Department of Economics, University of Illinois at Chicago  
email: [jpersky@uic.edu](mailto:jpersky@uic.edu)

**Daniel Felsenstein**

Department of Geography, Hebrew University of Jerusalem, Israel  
email: [msdfels@mscc.huji.ac.il](mailto:msdfels@mscc.huji.ac.il)

**Virginia Carlson**

Department of Urban and Regional Planning,  
University of Wisconsin, Milwaukee  
email: [vcarlson@csd.uwm.edu](mailto:vcarlson@csd.uwm.edu)

Paper to be presented at the 42<sup>nd</sup> European Congress of the  
Regional Science Association, Dortmund, Germany,  
August 27-31, 2002

## ABSTRACT

Metropolitan labor markets are characterized by gross flows, much larger than the traditional net measures of employment change might suggest. Standard impact analyses of employment change tend to either ignore these flows or treat them as a matter of 'job churning'. But in a metropolitan area experiencing involuntary unemployment and underemployment, these flows may offer real opportunities for individuals to improve their employment positions. Such improvement occurs along 'job chains' in which a new vacancy opens a sequence of job changes allowing workers to move closer to their full employment wage. Not all chains are of the same length, nor does every chain produce the same welfare gain. This paper presents a model of job chains that addresses chain length, welfare gains and distributional effects. The application of the model is illustrated using a hypothetical case of a new manufacturing firm in the Chicago metropolitan area. The job chains approach to estimating multiplier, efficiency and distributional effects associated with the firm, is compared with conventional impact analysis estimates. The conclusions discuss the implications of these estimates for the evaluation of local economic development projects

## 1. INTRODUCTION

The standard approach to dealing with the 'trickle down' of employment creation uses surface-level measurement of economic development impacts and traces the way they horizontally ripple-through the local economy. This kind of approach can be extended to include distributional outcomes in order to answer the question 'who gets what?' as a result of new job creation. However, it still falls a long way short in answering questions of economic welfare arising from new employment, i.e. 'who gains and who loses from new employment?' and 'how much better off are they?'. To do this, some measure of opportunity cost is needed that will allow us to assess the alternative opportunities forfeited when a worker moves into a new position. In addition, the standard mapping and tracking approach of input-output analysis, does not go beyond looking at those who actually get the jobs directly or those who feed-off them in secondary and tertiary rounds of employment creation.

To grapple with these issues, this paper goes one step further and introduces the notion of 'job vacancy chains'. Our approach here is that a 'surface-level' perspective on employment generation impacts is not sufficient. In order to answer questions of welfare and equity we need to understand what is happening 'sub-surface' when new employment is created. This involves adopting a vertical perspective on the local labor market, trying to trace-out all the subterranean movement set in motion once a new job is created. The job vacancy chain is an analytic device that lets us estimate the amount of movement triggered off by a new job and to record the traffic in and out of the newly created position until it ceases to exist. In the context of evaluating local economic development programs, the existence of job chains implies that some share of program gain is likely to be found amongst workers who were not the initial focus of the program.

A new job will set in motion a chain-like sequence of moves in the local labor market. For example, A moves to new job  $i$  and vacates job  $j$  for B who moves in, thereby vacating job  $k$  for C and so on. In this instance, we do not simply observe new job  $i$  and estimate (horizontally) how many surface-level jobs (indirect and induced) are stimulated by this new position. Rather, we take job  $i$  as a starting point and attempting to measure the vertical or sub-surface implications of this job. The job chain will continue until it is broken. This will occur when a worker moves into a new job without offering any replacement position, for example an in-migrant to the local area, and unemployed worker or someone entering from out of the labor force. It

should be noted that the focus of this approach is on the position (vacancy) or the job and not the worker.

In addition to measuring the number of sub-surface links in a chain, the job vacancy chain approach affords two further insights. First, it enables us to observe how individuals progress up a chain to higher levels of welfare and to measure the welfare that ensues. Existing approaches to measuring surface-level impacts of economic development programs seldom include measures of welfare improvement. At each completed step up the chain, workers move closer to their fully employed status. Workers can make employment and/or wage gains either in jobs newly generated by a subsidized program or as a result of vacancies opened by job chains. Welfare increments pertaining to the program are not just those directly generated by the new job. Rather they are represented by all the increases in welfare in all the chains opened up by the new job. Second, the job chains perspective allows us to measure the ‘trickle down’ effects of employment creation. While the ‘vacuum effect’ of vacating a job in order to move into a new position is often noted (Holt and David 1966), standard evaluations of economic development programs generally do not look beyond those who get the new (directly created) jobs. In this way they ignore the genuine ‘trickle-down’ effect preferring to concentrate instead on ‘trickle-across’ or ‘trickle-within’. Trickle-down implies positive spillover effects percolating beyond the confines of the original stimulus. Our approach suggests that job vacancy chains are the vehicle by which this percolation effect takes place. By observing the way in which new sub-surface opportunities are stimulated by direct job creation, we can posit for example, the effects on the poor, of jobs created for the more prosperous.

This paper proceeds in the following manner. The next section reviews the adoption of the chains metaphor in a variety of research contexts. We then present a model of job vacancy chains that addresses the issues of chain length, welfare gains and distributional effects. A hypothetical case of the employment effects of a new manufacturing firm in the Chicago metropolitan area is then addressed using the tools of conventional impact analysis. These results are contrasted with those derived from the application of the job vacancy chains model stressing the role of multiplier, efficiency and distributional effects. Finally, the paper concludes with some discussion of the implications of these estimates for the evaluation of local job generation programs.

## 2. APPLICATIONS OF THE JOB CHAINS METAPHOR

As the vacancy chain is the building block for understanding many social and economic phenomena that involve mobility and inter-dependence, it is not surprising that it has been applied in a diverse range of contexts. Some of these contexts, such as the housing market (Emmi and Magnusson, 1994, 1995, Hua 1989, Marullo 1985), are a 'natural' testing ground for this type of analysis. In this section we review three other areas of application with direct bearing on our interest in job chains: labor market studies, economic development studies and organizational studies.

At the heart of the chain model is the observation that a move by an individual will always simultaneously affect all other parts of the system. While Harrison White's seminal book is often credited with introducing the notion of chain-reactions in diverse social systems (White 1970), the roots of the idea can be traced to early descriptive studies in the housing market literature (Firestone 1951; Kristof 1965). These spawned the housing market 'filtering' literature that collected case study evidence from a variety of settings and tried to draw urban planning and policy conclusions as to efficient allocation of housing for the disadvantaged.

The vacancy model has been used in other diverse social science settings as an instrument for analysing how supply and demand conditions are matched and how a constant process of re-alignment between the two, takes effect. Aside from matching dwellings and house buyers, the vacancy model has been used for matching a pool of college football coaches with a pool of teams (Smith and Abbot 1983), a pool of clergy with a pool of parishes (White 1970a), a pool of musicians and a pool of orchestras (Abbot and Hrycak 1990) and even a pool of hermit crabs with a pool of shells (Chase, Weissburg and DeWitt 1988).

In all this literature much effort is expended in measuring and predicting chain lengths. The linear mathematics of Markov processes and Leontief multipliers provide ready-made tools for these analyses. Most of these studies however are rather devoid of any behavioural model to supplement the mechanics of chain formation. In the absence of a model of individual preferences for housing, the statistical regularities of chain lengths and housing moves remain rather sterile. Three areas of application are most pertinent to our model of job chains.

The first relates to *labor market studies*. Ostensibly, studies of labor market dynamics provide some of the work closest in spirit to the model of job chains presented below. Starting with the much-cited work of Holt and David (1966), labor economists have used vacancies, job searching and matching functions in order to understand the vacancy-unemployment relationship in imperfect markets. This early work also stressed the demand-side dynamics of the labor market rather than emphasizing supply side characteristics. In this work, vacancies and unemployment are the stock variables, regulated by the flow variables such as new hires, recalls into the labor market etc. and eventually the market reaches an equilibrium state.

Building on this approach, the ‘job flows’ literature further develops the vacancy-unemployment model showing how job quits are procyclical and how vacancy chains are created in tight labor markets. The existence of vacancy chains is also central to understanding the procyclical behavior of quits (Akerlof, Rose and Yellen 1988). Vacancy chains are shorter when unemployment is high as the probability of terminating the chain is high with so many job seekers available, who offer no job replacement. As opportunities expand, quits will increase and therefore quit behavior is procyclical.

‘Job flows’ studies of labor market dynamics stress that in imperfect labor markets, flows are often an important source of adjustment (Blanchard and Diamond 1992, Burgess 1994, Schettkat 1996a). Flows reflect high levels of mobility that are not captured in measures of net change. This labor turnover or ‘churning’ suggests that there are sub-surface movements that are not captured by indices of net employment change. An obvious source of this discrepancy is the existence of job chains. For the case of Germany, it has been estimated that 50 percent of employment mobility in periods of tight labor markets is due to this movement along job chains (the ‘churning’ effect) and that this figure drops to less than 10 percent in periods of slack labor markets (Schettkat 1996b). A variant application of job chains has been presented by Gorter and Schettkat (1999). They demonstrate how that unemployed job seekers crowd out employed job seekers. Again, the job chain is a central mechanism in this process. When the number of unemployed job-seekers filling vacancies rises, the implication is that job chains become shorter as these workers leave behind no replacement position and consequently opportunities for employed job-seekers are diminished.

For our purposes, the upshot of the above is that job chains are often acknowledged as important mechanisms in understanding labor market dynamics. However, much of this interest does not progress beyond measuring chain length. The obvious next step would be to examine the welfare and distributional implications of chain effects, but in the current state of the literature, this issue is left unaddressed.

The second area is that of *organizational studies*. Sociologists and organizational scientists' have used the vacancy chain model to study intra-organizational mobility (see Stewman 1975a, 1986). The focus of these studies is on occupational advancement and the type of organizations that promote or hinder this. Thus Stewman (1986) uses extensive development of Markov chains in order to show that the probability of advancement within organizations is higher at intermediate levels than at lower levels. Harrison (1988) shows on the basis of U.S. data how the vacancy chain model can predict movement between different occupations nationally. Both these studies illustrate how the linear mobility model developed by White (1970) can be extended to organizational mobility applications.

One of the main uses of vacancy models in this literature has been to show remarkable similarities in the social organization of different mobility systems. Using vacancy chains to trace career paths, Stewman (1975b, 1986) has shown how similar career patterns develop in very different organizations. While much of this work is concerned with developing the mathematical and graphic frameworks for calculating the probability of advancement within the chain, the results show these mobility probabilities are relatively stable and do not decrease as much as expected as the individual moves up the career ladder. In fact mid level career positions often had greater mobility possibilities than did lower levels, suggesting segmentation in intra-organizational labor markets. Mobility considerations aside, this field of study, like the study of labor markets, has not conceptually or empirically expanded the chain model beyond the standard chain length and multiplier calculations.

Finally, the area of *local economic development studies* is the field of interest closest to the focus of emphasis in this study and ironically the area in which applications of the job chains model are least developed. The state of the art in applying the job chain notion to economic development issues, is particularly pedestrian. The sporadic studies that have appeared are mainly concerned with surveying and charting of chains. Two early papers looking at vacancy chains in the

context of local economic development efforts relate to ‘job shifting’ resulting from a program of employment creation in Alberta, Canada (Webster 1979) a similar process resulting from expansion of coal mines in the Hunter Valley New South Wales, Australia (Garner et.al. 1981). In both cases, extensive empirical charting leads no further than estimates of chain length.

More recently, the chain model has been utilized to evaluate the impacts of urban development corporations in three United Kingdom cities (Robson, Bradford and Deas 1999). Again, a non-probabilistic (mapping) method is employed in order to estimate chain length for commercial property vacancies and the role of the development corporations in encouraging economic regeneration in the cities. This study found particularly short local chains and uses this finding to buttress the case for local targeting.

The common feature of the above studies is that while they all make some attempt at measuring chain length, they all stop short of estimating welfare impacts and distributional (trickle down) effects. In order for public policy to make a difference, jobs have to be created for local workers who would not have employment opportunities in the alternative situation. The benefits of an employment program have to trickle down to those local residents most in need. To avoid a purely mechanistic perspective of employment on local labor markets we therefore need a model of job chains and the welfare gains arising from them. The remainder of this chapter presents a simple, linear model of local labor market dynamics under conditions of less than full employment. The welfare effects of job chains and their measurement is at the centre of this approach.

### 3. A GENERAL MODEL OF JOB VACANCY CHAINS

To move from intuitions to serious empirical work, we need to construct a formal model of job chains. We now consider the simplest possible job chain model, one in which all jobs can be ranked along a single dimension. Consider a local economy in which each job grouping can be represented by a rung along a single well-defined job ladder. A job vacancy is resolved in one of three ways:

- An employee occupying a job on the rung immediately below the vacancy moves up.



- An individual not currently employed along the ladder obtains the job in question. Such individuals might be drawn from the locally unemployed, those not currently in the labour force, or in-migrants to the community.
- The job disappears. The probabilities of these three outcomes ( $p_1, p_2, p_3$ ) sum to 1.0 and are fixed for the system.

In this setting, a newly created job opens a vacancy at the corresponding rung of the job ladder. Whatever its position in the ladder, it will be filled either by someone in the immediately lower rung (1, above) or by someone not currently employed in the local economy (2, above). The rigidity of the given probabilities necessitates a well defined hiring multiplier,  $m$ , the expected number of local job vacancies created *and filled* as the result of the appearance of a new job on any rung on the job ladder.

To see this, consider the probability that a new job will give rise to at least one more vacancy that is subsequently filled. This probability is just given by the probability that the new job was filled by someone on the ladder,  $[p_1/(1-p_3)]$ , times the probability that the job vacancy opened in this move was not destroyed,  $(1-p_3)$ . This product is simply  $p_1$ . Now clearly the probability that this filled vacancy will give rise to another must also be  $p_1$ , and so forth down the line. The expected number of filled vacancies generated by the new job will be:

$$m = 1 + p_1 + (p_1)^2 + (p_1)^3 + \dots = 1/(1-p_1)$$

Interestingly, the length of the chain depends only on  $p_1$ . This is true even though we count those moving onto the ladder in the same manner as those already on it. To appreciate this point, consider two sets of probabilities. Both have the same value for  $p_1$ , but in the first, vacancies can only be filled from the job ladder otherwise they disappear. This means  $p_2 = 0$  and  $p_3 = 1-p_1$ . In the second, jobs never disappear ( $p_3 = 0$ ), but they may be filled from off the ladder ( $p_2 = 1-p_1$ ). For either set of probabilities the new job is filled. Now, under the first case this must mean a vacancy is created. That vacancy in turn has a probability  $p_1$  of not disappearing and being filled; and so on down the chain. For the second case, we again start with a filled vacancy, but now there is a probability,  $p_2 = 1-p_1$ , that it is filled from off the chain

and produces no second vacancy. This means that the likelihood of a filled second vacancy is just  $p_1$  again; and so on down the chain.

To use this multiplier to estimate welfare effects, we must assign an expected welfare gain to each worker who fills a vacancy. A worker moving up the ladder forgoes his or her present wage  $w$ , in order to obtain a higher wage  $w$  at the next rung up. From the individual's perspective the lower wage is the opportunity cost of the higher wage. His or her welfare gain is just the difference between the two wages. For simplicity, assume the ratio  $d (= w/w < 1)$  remains independent of the rung in question and incorporates any non-monetary differences in working conditions. In this context, filling a single vacancy from the rung below increases welfare by  $(1-d)w$ , where  $w$  is the wage of the vacancy being filled.

But what of the welfare gains achieved by those who move into a vacancy from outside the labor force, from unemployment, or through migration? These are complex transitions; their welfare values have been long debated. For the present exercise, we keep matters simple and conservative by assuming that these transitions render the same welfare gain as a move up the ladder, i.e.  $(1-d)w$ . This assumption sets the opportunity cost of individuals moving onto the job ladder at an amount equal to the wage of the job just below the one they take. Such a proposition can be plausibly defended for both in-migrants and entrants to the labor force, but very likely underestimates the gains of those moving out of involuntary unemployment.

Now the calculation is straightforward:

$$V = (1-d)w[1 + dp_1 + (dp_1)^2 + (dp_1)^3 + \dots] = [(1-d)/(1-dp_1)]w$$

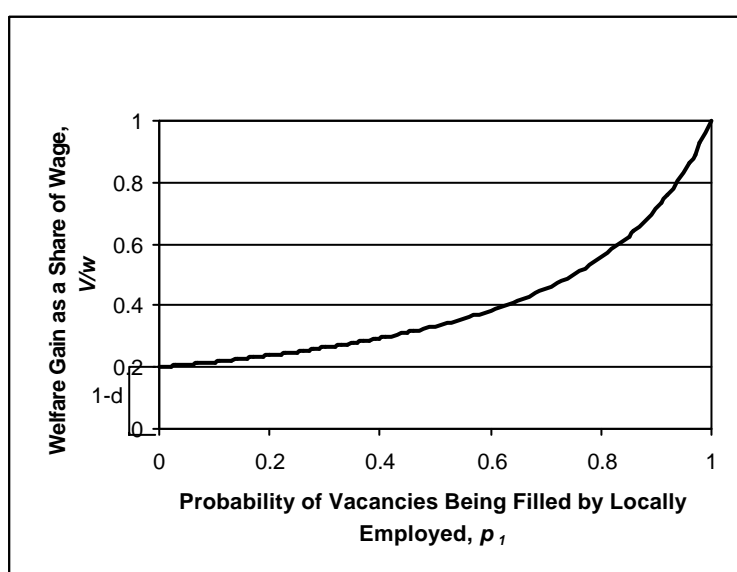
where  $V$  represents the total expected welfare gain set off by the creation of a job paying a wage of  $w$ . This result has two interesting and interrelated implications. Under the assumptions of the simplest job chain model, a new job in a community will yield an expected welfare gain less than its wage, since  $(1-d) < (1-dp_1)$ . But under those same assumptions, a new job will generate a gain larger than that enjoyed by the worker who actually fills it, since the probability of vacancies being filled from existing jobholders is taken greater than zero (i.e.  $p_1 > 0$ ).

This simple observation relates directly to the 'all or nothing' dilemma in evaluating wage and employment gains from local economic development programs (Felsenstein and Persky 1999). On the one hand, impact analyses meticulously count

all new wages arising from job creation as a local gain. In contrast, welfare economists, claim that converting job counts into incomes represents ‘a great deal of effort that could have been better spent asking different questions’ (Courant 1994, p. 863). Many workers in subsidised jobs could have invariably found alternative employment. Their welfare gain is not represented by their wage but by a much smaller amount, i.e. the difference between the new wage and the workers reservation wage. This is usually taken as reflecting the opportunity cost of the new job and empirical estimates of this cost fluctuate greatly (Jones 1989, Heywood and White 1990).

We can push our simple model a bit further to explore the sensitivity of expected welfare gains,  $V/w$ , to the key parameters,  $p_1$  and  $d$ . Figure 1 holds the latter constant, but allows the former to vary. Here we have set  $d$  at 0.8. The intercept on the vertical axis varies directly with  $1-d$ . If no hiring is done from existing local employees,  $p_1 = 0$ , the only expected welfare gain is 0.2 times  $w$ . The welfare fraction rises slowly as  $p_1$  increases away from zero, but then more quickly as  $p_1$  approaches 1.0. Keep in mind that  $p_1$  is just equal to  $1 - (p_2 + p_3)$ . Thus if we fix one of these probabilities, Figure 1 can tell us how the welfare ratio varies with the other. Of course, as the other probability rises we read the figure from right to left and not from left to right.

Figure 1: Welfare Sensitivity



Empirical estimates of  $V/w$  are presented below. These are contingent on establishing values for the  $p$  and  $d$  parameters. At this juncture however we make a few educated guesses to at least narrow the likely range. In this spirit, we set  $p_2$  at about .3, perhaps divided more or less equally between in-migrants and local residents not employed in the recent past. In average times,  $p_3$  is likely to be considerably smaller, say .05. This leaves us with an estimate of .65 for  $p_1$ . To allow a range for the crudeness of the estimate, we take  $p_1$  to lie between .6 and .7.

These parameters imply that on average a job chain will have a length of about three filled vacancies so  $m=3$ . On each link we assume that the worker (whether an in-migrant, unemployed, out of the labour force or previously employed) has a reservation wage ( $d$ ) equal to 80-90% of his or her new wage. Putting these estimates of  $d$  and  $p_1$  into our basic equation suggests that the welfare gain associated with an average new job will be between 20% and 40% of the new job's wage.

These figures reflect a considerable discount on wage gains calculated from simple impact models. Yet they also suggest that gains from economic development projects can be substantial. The simple model used here also provides a framework for handling differences across metropolitan areas in their unemployment rates and in-migration rates. However, the model cannot address the very real possibility that different new jobs generate different benefit ratios. Since our central question is the effectiveness of trickle down in the labour market, this deficiency must be corrected.

#### 4. THE MECHANICS OF JOB CHAINS: A LEONTIEF APPROACH

To operationalize the above and account for job chains of different lengths, welfare impacts and trickle-down effects, we present a Leontief-type model of chains. As noted earlier, the program-driven approach adopted here stresses the demand side impulses for economic development and 'trickle-down' is itself as demand-oriented concept. As a demand-driven construct, the Leontief model is particularly suitable for examining job chains. Our approach however, differs from the standard input-output approach used for estimating change in production chains, in a two respects. First, while the conventional Leontief input-output model implies the existence of production chains, these are never explicitly calculated. Rather, the standard input-

output approach is to infer inter-sectoral transactions from the origin-destination matrix and not to delve beneath the surface in search of production chains. Second, our chains model introduces a probabilistic element to estimating chain length that does not exist in Leontief models of production chains.

Chain Length: Our Leontief approach starts with the recognition that recruitment may look very different across the rungs of the job ladder. Some job vacancies will be filled only with workers already holding very narrowly defined skills/jobs, while others may draw on a wider range of candidates. If we can categorize all jobs into meaningful groupings on the basis of skill requirements, remuneration and conditions of work, then we can think of a new job vacancy as setting off a ‘multiplier’ effect as successive workers move from one job to another.

The inter-rung probabilities can be represented as a square (origin-destination) matrix ( $\mathbf{Q}$ ) with elements,  $q_{ij}$ , which show the chance that a job vacancy of a  $j$ -type position is taken by a worker currently in an  $i$ -type position. Notice that the sum of these elements over  $i$  for a given  $j$  will be less than one. The difference will be made up largely by workers drawn from unemployment, out of the labor force, and immigration. Finally, some vacancies will simply result in job destruction or disappearance. These terminating events play a role similar to primary inputs and imports in an input-output matrix. They act as leakages that dissipate the flow of demand in the local area.

We have strong theoretical reasons for modeling  $\mathbf{Q}$  as a triangular matrix. In general, workers will not voluntarily move from a better job to a worse one. Of course many such moves do take place, but presumably they are involuntary. In the context of a chain begun by an economic development project, such involuntary moves effectively guarantee that job vacancies always move ‘down’ the job ranking. For example, consider the consequences of a project-created semi-skilled (type 2) job being taken by a worker who was fired from a high skilled (type 1) job. The type 1 vacancy would occur whether or not the economic development project takes place. It is not part of the chain generated by the project. However, this high skilled worker would presumably have been able to take a job at the semi-skilled level even in the absence of the development project. The counter-factual is not that the high skilled vacancy would not have been created, but that a semi-skilled vacancy would have

been taken by this worker. In this sense vacancies can only move ‘down’ and never ‘up’ the job ranking.

The  $\mathbf{Q}$  matrix allows us to approximate the net consequences of job creation at each job level. A simple Leontief-type inversion of the locally based origin-destination matrix  $(\mathbf{I}-\mathbf{Q})^{-1}$ , will yield a multiplier-type matrix of  $m_{ij}$ ’s which show the gross number of local  $i$ -type vacancies generated by a  $j$  type vacancy. Summing down the columns of this matrix gives us the total number of links or vacancies per chain, triggered-off by jobs of different types. Thus  $M_j = \sum_i m_{ij}$  gives the total number of expected vacancies associated with a newly created  $j$ -type job including that initial vacancy. It seems natural to call  $M_j$  the length of a type  $j$  chain. A rough approach to estimating chain length has been presented above for the simple model. Here as there, the key to measuring the length of chains is estimating the probabilities of a chain being truncated by an in-migrant, unemployed worker or new entrant. But, since all of these can differ depending on the initial ‘new job’s’ level, expected chain length will also vary across levels.

Because  $\mathbf{Q}$  is taken to be triangular, the chain lengths,  $M_j$ , are relatively easy to calculate in a recursive manner. In particular, if we rank skill levels from 1 as the highest to  $n$  as the lowest, then:

$$M_n = 1/(1- q_{nn}),$$

$$M_{n-1} = [1/(1- q_{(n-1)(n-1)})] [ 1 + q_{n(n-1)} M_n ],$$

$$M_{n-2} = [1/(1- q_{(n-2)(n-2)})] ( 1 + q_{(n-1)(n-2)} M_{n-1} + q_{n(n-2)} M_n ),$$

....

*Welfare Impacts:* Having sketched the theory of chain lengths, we turn to an analysis of differences in the expected increments in local welfare arising from the creation of different new jobs. Again we emphasize the importance of opportunity costs in evaluating welfare gains. In particular for each type of vacancy,  $i$ , the welfare gain is equal to  $\sum_k q_{kj}(w_i - w_k)$ , where  $(w_i - w_k)$  represents the difference in wages between the new job  $i$  and the old job  $k$ . Notice we assume here that those changing jobs within the same occupational group,  $i$ , will experience no gain (or perhaps, only a

negligible one), i.e.  $w_i - w_{i+1} = 0$ . For in-migrants, unemployed or entrants who might take a vacancy at level  $i$  we assume that their opportunity cost is just equal to the wage of the group at the next lowest level,  $i+1$ . Again we take wages at each level to be a constant fraction,  $d$ , of the wages at the next highest level. Putting these elements together then suggests an overall expected gain of adding a  $j$ - type job ( $V_j$ ) is given by:

$$V_j = \sum_i m_{ij} [(\sum_k q_{ki} (w_i - w_k) + (1 - \sum_k q_{ki})(w_i - w_{i+1}))]$$

$$= w_j \sum_i m_{ij} d^{i-j} [(\sum_k q_{ki} (1 - d^{k-i}) + (1 - \sum_k q_{ki})(1-d))].$$

Finally we can use the chains matrix to make calculations concerning the distribution of gains across various groups of workers. In particular we might ask for any given chain, how much welfare gain goes to the lowest group of workers—those who would take the worst group- $n$  jobs if they were available. Given the assumptions used in the above equation this Rawlesian welfare measure,  $R_j$ , can be easily calculated for each  $j$ . The result is given in equation (4.5).

$$R_j = w_n m_{nj} (1 - q_{nn}) (1 - d)$$

The only term on the right hand side of this equation to vary with  $j$  is  $m_{nj}$ . Hence, this measure of the distributional consequences generated by a new type  $j$ -job depends only on the number of vacancies of the lowest level that ‘end’ the job chain.

## 5. THE LIMITS TO EXISTING APPROACHES : AN EXAMPLE

In order to appreciate the limits of impact analysis, we present a hypothetical example that illustrates the current state of the art. In this example, we envisage a new production plant in the industrial instruments sector moving into the Chicago metropolitan area. Assuming that the city government is interested in an evaluation outlining the local economic impact of the plant, what is the maximum that could be expected given the current state of practice in this field?

A prerequisite for any impact analysis is an accurate account of the employment impact of the plant. The 100 direct jobs that the plant creates need to be adjusted to account for demand displacement, deadweight employment that would have been created in the absence of the plant and local jobs taken by outsiders

(commuters or other ‘in-migrants’). Only after this downward adjustment, can direct jobs be expanded by a suitable multiplier, to account for the indirect and induced jobs.

In our example, the 100 direct jobs reduce to 62 (Table 1). The magnitude of this adjustment is estimated using parameters generated by the REMI econometric model calibrated for Cook County, IL and from actual Census-derived proportions for the geographic area under consideration. Export-base theory posits that new non-basic employment will compete with existing local employment serving local demand. These displaced local jobs are estimated using REMI-generated export shares for the instruments industry. Local endogenous employment growth (i.e. deadweight employment) also has to be subtracted. This is calculated using a modified shift-share approach in which the local share of regional employment growth that would have occurred even in the absence of the plant, is considered as employment that cannot be credited to the new program. Finally, suburban commuters who take some of the new jobs also have to be discounted. Their shares are based on actual census-derived data on commuting patterns. To complete the jobs account, the 62 direct new resident jobs are expanded to 97 using the relevant industry-based REMI employment multiplier.

**Table 1: Hypothetical Example: Benefits and Costs of Chicago Instrument Plant**

<b>EMPLOYMENT</b>	<b>DIRECT</b>	<b>TOTAL</b>
Projected Jobs:	100	–
Minus: Displaced Local Jobs Endogenous Growth Suburban Commuters		
New Resident Jobs	62	97
<b>OVERALL ECONOMIC IMPACT</b>	<b>DIRECT</b>	<b>TOTAL</b>
Earnings (\$Th, 1992)	7,362	11,453
Costs (\$Th, 1992)	2,500	2,500
<b><u>BENEFIT MEASURES</u></b>		
Cost/Job (\$Th, 1992)	40	26
Cost/Earnings	0.34	0.22

The next stage is to convert direct and total employment into earnings using REMI-generated data. This is based on the average earnings in the instruments sectors and those secondary and tertiary rounds of activity stimulated by the direct



employment. We arbitrarily assume that project costs are \$2.5 million. Two summary ‘benefit’ measures can then be calculated: cost per job and a cost:earnings ratio. Both are measures of project efficiency. The former measures program output and the latter program yield. As noted earlier, these ‘benefits’ are really measuring gross impacts of the project rather than its social worth or value.

In most instances, this type of account would represent the maximum extent of impact analysis. At best, some effort will be expended in trying to create an accurate employment picture. This means considering demand displacement, ‘deadweight’ employment and indirect and induced jobs. In many instances, an attempt will further be made to translate program-attributable jobs into an earnings estimate. It should be noted however, that very rarely are these earnings ever discounted to account for the different opportunities foregone by workers who take project generated jobs, rather than alternatives (i.e. opportunity costs). Nor are distributional issues ever considered. While great pains are taken to accurately account for all new jobs and income, very rarely is the question posed as to how much better off different lower income groups really are given all this new employment and income.

A cursory, first-cut attempt at observing distribution effects within an impact analysis framework can be easily accomplished using census-derived proportions. In this way, all direct and indirect employment are distributed across five income classes in accordance with real-world proportions derived from the census. Table 2 goes beyond standard impact analysis practice and presents direct and total employment distributed across five income classes according to census-derived proportions for the instruments sector in the Chicago area. On the employment side, we can see that once total employment is considered (and not just direct employment) the share of employment going to the poorest group (income class 5) rises slightly. However the share of employment going to the most wealthy (income class 1) also increases slightly so overall the distribution has hardly become more progressive.

**Table 2: Hypothetical Example:  
Distribution of Employment and Earnings by Income Groups**

		<u>INCOME GROUP</u>					
		1	2	3	4	5	SUM
<u>Distribution of EMPLOYMENT</u>							
Absolute							
	Direct	2	5	21	29	5	62
	Total	5	8	31	40	13	97
Share (%)							
	Direct	3.4	8.1	33.3	47.3	7.9	100
	Total	4.7	8.6	31.7	41.7	13.2	100
<u>Distribution of EARNINGS</u>							
(\$Th, 1992)							
Absolute							
	Direct	699	1,129	2,891	2,466	177	7362
	Total	1,519	1,842	4,266	3,367	460	11453
Share (%)							
	Direct	9.5	15.3	39.3	33.5	2.4	100
	Total	13.3	16.1	37.3	29.4	4.0	100

The distribution of earning shows a similar, and even more accentuated, pattern. Earning are distributed across the five income classes using to census-derived proportions for the instruments sector in the Chicago area. While there does seem to be a slight distributional shift in favor of the lowest earners when total earnings are considered (from 2.4% to 4.0%), this is more than offset by a rise in the share of earnings going to the highest earners (from 9.5% to 13.3%).

While the impact analysis above represents state of the art, its limitations are all too obvious. First, it has only treated the question of the counter-factual situation in a very partial manner. We have simply (and mechanically) distributed estimated employment and earnings across different income classes without asking whether some of this income would have been attained even in the absence of the instrument plant. Presumably, many of the higher income workers could have attained a similar level of earnings in alternative employment. Consequently, they have a high opportunity cost which should be discounted from the earnings calculation. As illustrated here, standard impact analysis routinely credits all workers with all new earnings, irrespective of their alternative employment possibilities. This is a major source of over-estimation and probably accounts for the distributional patterns of employment and earnings as described above. As a rule, impact analyses do not discount the opportunity costs of different income classes from any calculation of new earnings or income. Second, these impact analysis results do not allow us to say anything substantial about changes in welfare and distribution. The results in Table 2

do not give us any idea as to the welfare gains to Chicago workers as a result of the new instruments plant, i.e. how much improvement over their current situation can be credited to the new plant. Finally, despite the attempt to distribute earnings across income classes, these impact analysis results provide very little insight as to distributional effects. Are income or employment gains to the poorest greater than to all other income classes ? Is there a process of leveling-up going on whereby the poorer groups do proportionately better from the new project than the wealthier groups? These are issues that economic development evaluation would like to be able to answer. Current practice however, falls short of fulfilling these aspirations.

## 6: THE JOB VACANCY CHAINS APPROACH

### *6.1 The Empirical Strategy*

Great difficulty exists in tracing actual job chains. In housing market studies, a moving household's residence of origin is well defined and the new occupants of that housing unit can be ascertained in a relatively straight forward manner. But in the case of job chains, the definition of a job changer's origin position is more difficult and to determine the new worker now holding that position often impossible.

Under the circumstances the possibility of using actual chains as the underlying data source for empirical work on U.S. job chains seems slight. But this does not imply that we can make no progress in estimating the coefficients of an origin-destination matrix. Even where direct chain data are lacking, we can adopt a synthetic approach, not unlike that used in input-output analysis. After all, input-output researchers do not trace back through actual market transactions at every stage of production for a given good. They do not actually log the sale of the cloth to the apparel firm, then the sale of the cotton to the textile firm, the sale of petroleum to the farmer and so on. Instead, they estimate an average "input vector" for each industry, assume that vector to remain constant whatever the use of the industry's product, and then infer 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. If we break jobs down into discreet 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 job changers—their new jobs and their old jobs. 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 distribution of job chains.

This approach to job chains greatly simplifies the empirical requirements of the theory. To construct “input vectors” for a given job level, we only need information on job changers. We do not need observations on entire chains, but only a representative sample of unrelated chain links. Such data are available from workers’ longitudinal job histories. Without ever creating a sample of real job chains, we can now estimate all the relevant coefficients of the “input vectors” including those that make up the origin-destination matrix ( $\mathbf{Q}$ ).

Our primary data source is the Panel Study of Income Dynamics (PSID) from the Survey Research Center in the Institute for Social Research at the University of Michigan, which contains detailed information on a broad sample of households, including many job changers. It should be noted that first, detailed job data from the PSID are only available for household heads and their spouses. While basic employment status and earnings are reported for other household members, these data are not sufficient to determine job changes. As a result our sample consists only of changes by heads of households and spouses of heads. Second, the PSID data set does not provide a continuous job history even for heads and spouses. Rather it reports detailed data concerning length of tenure for the primary job position, if any, held at the time of the annual interview. Thus we know when a head or spouse took his/her present job, but not what other jobs they may have been hired into and separated from since the last interview. These data miss those multiple job changes that occur within a year. Hence estimates of the overall frequency of job changes from PSID data have a second source of underestimation.

Third, a positive feature of the PSID data set is that it allows us to define both job changes and position changes, where the first denotes a change of employers and the second a change of activities within the same business. In principle, this means we can consider intra-firm mobility as well as inter-firm mobility as workers move

along job chains. For the national PSID sample, about 600 individuals (heads and spouses) a year take new positions, with sufficient documentation to be included in this study. Of these half are starting with a new employer. To increase the sample size in our basic analysis, we include all job takers in the most recent six years for which full data are available, 1987-1993. The resulting data can be interpreted as relating to a representative region of the country.

## 6.2 Estimating the Augmented $Q$ Matrix

In practice then, we assign every reported job, whether it's just being taken or just being left behind, to one of five a real-wage groups. The highest of these runs from \$25.50 to \$40 per hour in 1992 prices, group two is then \$16.40 to 25.50, group three \$10.50 to \$16.40, group four, \$6.70 to \$10.50 and group five \$4.25 to \$6.70. While somewhat arbitrary, each group's lower bound is approximately two-thirds of its upper bound.

Using these definitions we can estimate the probability that a group  $j$  vacancy is filled by a worker currently employed in a group  $i$  job, i.e. the  $q_{ij}$ 's above. Taking the sample period, 1987-1993, we simply calculate the ratio of workers who made the  $i \rightarrow j$  move to the total number of workers who took  $j$  group jobs. As in a Leontief input matrix, every column in the resulting  $Q$  matrix adds up to less than one. The residual in each column indicates the probability that jobs of that group are filled outside of a vacancy chain.

The residual probability for a wage group can be disaggregated into the probabilities of filling vacancies from each of our three residual categories: unemployed, out of the labor force, and in-migrants. While differentiating among these categories is not crucial to determining chain lengths or the multiplier effect, such differentiation becomes crucial in estimating welfare and distribution effects. We look to the PSID data source for this information, i.e. what proportion of jobs taken at any given job level draw on each of the residual categories. The PSID includes data on the month an individual took his or her present job as well as monthly data on whether that individual was employed, unemployed or out of the labor force. In addition it records both the state of residence of a household in each year and whether it lives in a metropolitan area. We define in-migrants as those who change their state of residence between two years and/or change from a non-metropolitan county to a metropolitan one.

Before turning to our results one further point should be made. In the real world, not all job moves increase an individual's wage level. For wage groups 2-5, a fraction of all vacancies is filled by workers stepping down the wage hierarchy. In our data this fraction rises from about 4% for group 2 to 10.6% for group 5. These downward movers create a problem in interpretation. It is difficult to conclude that such job changers are actually worse off for the presence of a vacancy at the level they ultimately find work. Presumably, in the absence of the vacancy they actually take, such downwardly mobile workers would have found a job at about the same low level, or perhaps lower. But such a downward move is essentially exogenous to a job chain initiated by a new (net) job.

Under the circumstances it seems fitting to reallocate these downward movers among all other movers in some manner. This stratagem can be interpreted in either of two ways. One possibility, is to think of the downward mover as "sinking" to some other job (or one of the residual categories) and then "moving up" to the vacancy they actually take. Alternatively, the downward mover might be considered as taking the new vacancy at the level he/she actually settles, but in so doing opening another equivalent vacancy at that level that otherwise they would have filled. Thus in the empirical work that follows downward movers are allocated proportionally to all other categories. In effect, this adjustment triangularizes the  $\mathbf{Q}$  matrix which simply amounts to the mathematical expression of the proposition that new vacancies do not cause downward job movements.

Table 3 presents our basic estimates for the  $\mathbf{Q}$  matrix relating to the entire period 1987-1993. Each column in the table shows the "input vector" for the corresponding job group after adjustments for triangularization. An element in a column gives the proportion of the column vacancies filled from that origin row. Every column must sum to 100%.

**Table 3: Basic Origin Destination Matrix**

Origin	New Wage Group				
	1	2	3	4	5
Wage Group 1	41.1%	0.0%	0.0%	0.0%	0.0%
Wage Group 2	25.0%	52.9%	0.0%	0.0%	0.0%
Wage Group 3	4.8%	22.1%	46.6%	0.0%	0.0%
Wage Group 4	2.2%	1.5%	18.5%	47.3%	0.0%
Wage Group 5	0.0%	0.3%	2.4%	13.3%	34.5%
Unemployed	2.9%	3.8%	9.7%	15.8%	24.7%
Out of Labor Force	4.0%	3.8%	7.5%	13.5%	30.5%
In-Migrant	20.1%	15.6%	15.4%	10.0%	10.2%
Column Sum	100.0%	100.0%	100.0%	100.0%	100.0%

Starting with job vacancies in the highest wage group, as reported in column 1, the element in the top row tells us that 41% of vacancies at this level are taken by individuals who already have a job in the same group. About 25% of the vacancies go to workers employed in the second wage group and switching up to higher paid jobs in the first group. As we might well expect, workers holding jobs in groups 3, 4 take few vacancies in the top group and workers in group 5 take virtually none. The unemployed and those out of the labor force are also relatively unimportant recruiting fields for these high end jobs. However, a large share of group 1 vacancies, about 20%, go to in-migrants.

The data in the matrix suggest several generalizations. First, job changes within a wage group, the diagonal elements of the matrix, are somewhat more common for groups 2,3 and 4 than for the highest group. But group 5 vacancies are less likely to go to those already employed in the group. Second, upward job movement remains largely limited to workers leaving their current job to fill a vacancy in the immediately higher group. Third, the importance of recruiting from the unemployed and the out of the labor force groups falls steadily as wage level rises. Finally, the share of vacancies filled by in-migrants rises steadily with rising wage levels.

### 6.3 Chain Lengths

These observations are of considerable interest. A first, but incomplete, summary of the matrix can be gleaned from calculating the basic Leontief multipliers

as defined above. Recall that these multipliers provide direct estimates of the chain lengths associated with a new job. Given the substantial dependence of low wage job recruitment on non-employed workers, it is not surprising that the multiplier for the lowest category comes out at only 1.5. Still, this implies that, on average, a net expansion of a hundred jobs at this level gives rise to another fifty opening at the same level. 150 individuals, not 100, will fill vacancies. The chains generated, in this case, are particularly simple. We expect about two-thirds, say 65, of the new jobs to be immediately filled by the non-employed and hence to create no chain effects. The other third of the new jobs, about 35, go to workers already employed in group 5 jobs, thus opening 35 additional vacancies at this level. Again about two-thirds of these vacancies draw on the non-employed. One third on the employed. The probability of a chain consisting of just two vacancies is then  $1/3 * 2/3 = 2/9$ , i.e. about 23 of the initial chains will have exactly two vacancies. In the same manner, we can calculate that  $2/27$  of the chains (or about 7 out the initial hundred) will have three vacancies,  $2/81$  will have four, and so on. Taking the full range of possibilities then, we know that the average chain length will just be our multiplier of 1.5. Ideally this predicted distribution of chain lengths and its mean would be empirically tested against an actual distribution taken from a sample of chains. But as noted above, generating data on full chains remains highly problematic.

Expected chain length for the lowest wage jobs are short. Calculating Leontief multipliers for each of the other wage groups shows a rise in expected length with skill/wage level. The longest chains, with an average of 3.5 links, are found in the top two wage groups. These results answer one of our key questions. Yes, immigrants are more likely to fill high-wage vacancies and the unemployed are more likely to fill low wage vacancies. But on net, the chains for high wage jobs are considerably longer than those for low wage jobs. With about 80% of all vacancies filled by employed workers, these high end jobs generate more second round vacancies. And since these induced vacancies are mostly at high wage levels, they in turn generate quite a few third round vacancies.

To explore the nature of these chains further, we can disaggregate the chain multipliers to show for each type of chain the expected number of vacancies generated at each level. As discussed earlier, this disaggregation is just the equivalent for our chain system of the  $(\mathbf{I}-\mathbf{Q})^{-1}$  matrix from standard input-output theory. The results for our basic matrix are presented in Table 4. The ‘All Groups’ row at the



bottom of the matrix gives the set of chain-length multipliers we have just been discussing. The column above each of these entries shows a disaggregation of the generated vacancies by wage group. For example, reading down column 1 we find that on average a new job in wage group 1 generates 1.7 vacancies in its own wage group, 0.9 vacancies in group 2, 0.5 in group 3 and so on. The column adds to the vacancy multiplier of 3.5.

**Table 4: Disaggregated Multiplier Matrix**

Wage Groups	Initial New Job				
	1	2	3	4	5
Wage Group 1	1.70	0.00	0.00	0.00	0.00
Wage Group 2	0.90	2.12	0.00	0.00	0.00
Wage Group 3	0.52	0.88	1.87	0.00	0.00
Wage Group 4	0.28	0.37	0.66	1.90	0.00
Wage Group 5	0.08	0.12	0.20	0.39	1.53
All Groups	3.48	3.48	2.73	2.28	1.53

Perhaps, the most interesting observation to be made from this disaggregation, concerns the extent to which high level chains reach down to open vacancies in low level wage groups. A new job in the highest wage group generates .36 vacancies in the two lowest wage groups. This connection is not so much a direct one. As noted above, only 2% of group 1 vacancies are filled by workers currently holding group 4 or group 5 jobs. Rather, the vacancies generated at these lower jobs come toward the end of typical job chains. If in the first round a vacancy is opened up in group 2, then in the next round a vacancy might open in group 3. A group 3 vacancy, unlike a group 1 vacancy, has a real possibility of being filled by a worker in group 4 or group 5. Indeed, from Table 4 we can read this probability as about 20%. While not all chains initiated in group 1 will reach these later rounds, those, which do, will contribute to building vacancies at the lower end of the job hierarchy.

A new job in groups 1 opens .36 vacancies in group 4 and 5 together. Similarly, from the second column of Table 5-2, we find that a new group 2 job is expected to generate almost .5 vacancies in groups 4 and 5 together. These levels of impact on low wage job vacancies create at least the possibility of significant benefit

trickle down. However, we cannot really evaluate such trickle down benefits, until we have used our job chains as a basis for measuring welfare gains.

#### 6.4 Individual Welfare Gains

*Job Changers:* Given the definition of our wage groups, it is not difficult to determine the average gains of upwardly mobile job changers. From the PSID we can estimate wage levels for both the original job and the new job. The average gains for each origin-destination pair are given in Table 5. Since we are primarily interested in what portion of a new wage represents a welfare improvement, these figures are calculated as a percentage of the wage at the new destination job, not the original job. In general these gains are quite impressive. As might be expected, workers moving up one step in the job hierarchy gain less than the average difference between those two steps, i.e. they are either earning above average in their old job, or below average in their new job or both. This one step gain comes in at about 23% of their new wage, where the average difference between levels is about 37%. For two or three step movers the difference between actual change and average difference becomes a good deal narrower, 54% as compared to 58%. Throughout, we use the percentage changes from our sample.

**Table 5: Average Wage Gains by Job Changers**

Origin Wage Groups	Destination Wage Group			
	1	2	3	4
Wage Group 1				
Wage Group 2	24.1%			
Wage Group 3	54.0%	21.2%		
Wage Group 4	73.6%	55.7%	23.3%	
Wage Group 5	-	66.8%	53.3%	24.1%

Note: All changes as a percentage of the destination wage, not the original wage.

Clearly upward job changes generate significant improvements in welfare. These are relatively easy for us to estimate. Much more difficult to determine are the welfare gains for job takers who were previously unemployed, out of the labor force, or lived elsewhere. At root, any estimate of the welfare gains of these groups requires an evaluation of the alternative opportunities available to such workers. The gain is

the difference between the wages taken and what was given up. As suggested above, these alternatives, or opportunity costs, are notoriously difficult to estimate.

*The Unemployed:* We start by considering workers obtaining jobs from unemployment. The key question here hinges on the degree to which such unemployment is voluntary. In a world with imperfect knowledge, unemployed workers and job vacancies may exist side by side. As search theory tells us, both workers and employers may make gains from improving their information. These gains from search represent a real opportunity cost when an unemployed worker takes a job. Put somewhat differently, a voluntarily unemployed worker “knows” that he/she can obtain a reasonable position either in this labor market or somewhere else. For such a worker, the opportunity cost can be reasonably associated with the reservation wage that worker seeks from a new job. That reservation wage is likely to be a substantial fraction of the actual wage this worker finally commands.

But of course, not all unemployment is voluntary. Where does voluntary unemployment stop and involuntary unemployment begin? We adopt a simple approach to this problem. We take as the cutoff point between voluntary and involuntary unemployment, a rate of 2.5%. This rate presumably covers the type of job searching in a labor market characterized by less than perfect information. Such a figure of this has often been mentioned in connection with frictional unemployment. Moreover, it comes very close to the actual unemployment rates we measure for college graduates in our sample in a tight labor market year, 1989. In good times these workers can obtain solid jobs relatively easily. Hence, if they report themselves to be unemployed at such times, we can expect that they are voluntarily unemployed.

In principle, then, an unemployment rate in excess of 2.5% indicates the presence of involuntary unemployment. But how can we determine unemployment rates for each of our wage groups? By definition, once a worker has a job in a specific wage group, he or she is employed. Our approach to this dilemma rests on estimating an unemployment rate based not on actual wages received, but rather on expected wages. We first estimate a wage equation of the type common in the human capital literature. This equation regresses the logarithm of the hourly wage on sex, age, age squared, and a set of educational dummy variables. The regression is for all PSID heads and spouses employed in 1992. This equation allows us to then calculate a predicted wage for both the unemployed and employed workers in the PSID data set. On the basis of these predicted wages, it is straightforward to assign all labor force

participants to a wage group and calculate an unemployment rate for each of these groups. Since 1992 was the bottom of the recession, we go on to repeat the calculation of unemployment rates (using the same wage equation) for the boom year of 1989.

For individuals with predicted wages in our two highest wage groups our average estimated unemployment rate comes out at about 2.25%. By assumption, then, a worker moving from unemployment to a job in wage group 1 or group 2, is voluntarily unemployed. The resulting effective rates are 5%, 8.5%, and 19.5% for groups 3, 4 and 5, respectively. Presumably, then, all the unemployed in a group over 2.5% are involuntarily unemployed, i.e. 2.5% of group 3, 6% of group 4, and 17% of group 5.

These somewhat speculative calculations give us a way to divide the unemployed into voluntary and involuntary. But what is the opportunity cost to place on each of these. The most extreme assumption would be to claim the involuntarily unemployed face no opportunity cost to taking a job, while the voluntarily unemployed face an opportunity cost equal to just about 100% of their ultimate wage. A more reasonable approach recognizes that even the involuntarily unemployed gain some welfare from their time, and the voluntarily unemployed generally set their reservation wage below the wage they actually obtain. Rather than setting the opportunity cost of the involuntary unemployed at 0%, we place it at 25%. For the voluntary unemployed we place the opportunity cost at 75%. The main point here is not the specific numbers chosen, but maintaining a significant difference between them.

The final piece in this rather involved train of logic, is to assume that the unemployed hired into a job of a given wage class are drawn randomly from the unemployed population with a predicted wage at that group's level. In effective this makes the opportunity cost for such a new worker a weighted average of the opportunity costs of the voluntarily and involuntarily unemployed, the weights being the shares of that group's unemployment pool in each unemployment category, i.e.

$$OC_i = (u_i - .035) * OC_{involuntary} + .035 * OC_{voluntary} ,$$

where  $OC$  refers to opportunity cost,  $i$  is the wage group, and  $u_i$  is the unemployment rate of that wage group.

The resulting opportunity costs given by this approach seem plausible. The highest two groups have values of 75%, group 3 is 50%, group 4 is 40%, and

group 5 is 31%. These opportunity costs play the same role for those drawn from unemployment that original wages play for job changers. Hence, an individual coming from unemployment to a group 1 or group 2 wage should be credited with a welfare gain of 25% of that group 1 wage. Coming into a group 3 job, a worker gains about 50% of the new wage, in a group 4 job 60%, and in a group 5 job 69%. Thus for those originating in unemployment, this last set of figures provides the equivalent to a row in Table 5 for those originating in a particular wage group.

*Out of the Labor Force:* Perhaps the trickiest opportunity costs to determine are those for workers drawn from outside the labor force. Rather than compare those who enter employment from the out of the labor force category to that category as whole, it seems more reasonable to compare them to unemployed workers with the same general skills. In tight labor markets, where most unemployment remains voluntary, those entering the labor force will have similar opportunities to the voluntarily unemployed. On the other hand, in markets where involuntary unemployment is high, new entrants are likely to face fewer opportunities and more immediate pressures. From this perspective, the appropriate opportunity cost for labor force entrants will be quite similar to that for the unemployed. This is the approach we take in all our empirical work. Hence, using our estimates for the unemployed, we set a high opportunity cost, 75%, for the top skill/wage groups and a relatively low opportunity cost, 31%, for the lowest wage group.

*In-migrants:* In-migrants, both from elsewhere in the country and from abroad, are generally in a position to scan across geographic areas searching for their best opportunities. Very likely in-migrants face roughly similar opportunities in a number of alternative places. This logic applies most strongly to high wage/high skilled workers, but it is likely to extend to low-wage workers as well. For simplicity we use the same opportunity cost for them as for the unemployed in the same wage group. The simplifying assumptions used to construct the opportunity cost estimates for the unemployed, out of the labor force, and in-migrants involve considerable speculation. Under the circumstances it seems useful to perform a sensitivity analysis, supplementing these “best estimates” with a range of alternatives.

### 6.5 Welfare Gains Along Average Chains

We are now in a position to put together the various pieces and estimate the welfare gains associated with job chains. The key to this exercise is simply to weigh each of the expected moves in a chain with the welfare gain associated with that move. This involves using an equation, that allows for different opportunity costs applied to each of the residual categories. More specifically we calculate the following equation for each wage group,  $j = 1, 5$ .

$$V_j / w_j = \mathbf{S} m_{ij} (w_i / w_j) [(\mathbf{S} q_{ki} g_{ki} + q_{ui} (1 - oc_{ui}) + q_{ni} (1 - oc_{ni}) + q_{mi} (1 - oc_{mi})]$$

where  $V_j$  stands for the expected welfare gain from a chain launched by new job in the  $j$ th group,  $w_j$  is the average wage in the  $j$ th group,  $m_{ij}$  is the disaggregated vacancy multiplier that tells how many openings at the  $i$ th level are generated from a new opening at the  $j$ th level,  $q_{ki}$  is an entry in our basic origin-destination matrix ( $\mathbf{Q}$ ),  $g_{ki}$  refers to the percentage wage gain in moving from job type  $k$  to job type  $i$  (from Table 4), and  $oc$  stands for opportunity cost, with  $u$ ,  $n$ , and  $m$  subscripts representing unemployed, out of the labor force and in-migrant.

Notice that the above equation represents the welfare gain of initiating a  $j$ -chain as a percentage of the average  $j$ -wage. This seems a good summary measure since so many impact studies simply add up expected wages. In this context,  $(V_j / w_j)$  can be viewed as a discount or mark-up factor to be applied to wages from new  $j$ -group jobs.

Carrying out the calculations (Table 6, Row 1), we find that all the  $V/w$  figures are substantially less than 100%, implying that the multiplier effects of the job chains are more than offset by the opportunity costs associated with employed workers and others filling vacancies. Given the relative magnitudes of the multipliers and the opportunity costs reported above, this result is not surprising.

The real story lies in the range of values of  $V/w$  across the five wage groups. For chains starting with a new job in any one of the top two wage groups the total welfare gain to all affected workers runs about 40% of the direct wage of the initial job. But this ratio is not constant across all wage groups. Rather it rises sharply as we move to the lower wage groups facing the burden of higher unemployment rates. The ratio is 56% for group 3, a bit over 60% for group 4 and almost 70% for group 5

(Table 6, Row 1). Hence, what we labeled the efficiency effect in Chapter 4, favors low wage job creation over high wage job creation. If subsidy costs for generating a dollar of wages remain roughly constant across wage groups, it will be more efficient to choose projects in which the wage bill is more heavily concentrated at the lower end of the job hierarchy.

**Table 6: Efficiency and Distributional Effects**

	Wage Group of Initial New Job				
	1	2	3	4	5
<i>V/w</i>	0.43	0.42	0.56	0.62	0.69
Share to Job Changers Per initial new job:	0.52	0.37	0.21	0.10	0.00
Dollars per year to Lowest ( R )	\$397	\$550	\$960	\$1,888	\$7,202
Dollars per year to Low	\$4,654	\$4,303	\$6,600	\$10,582	\$7,202

In addition to the basic results for  $V/w$ , Table 6 includes answers to several of the empirical questions we raised earlier in this chapter. Dropping the terms in the above equation which involve movement from unemployment, out of the labor force, or outside the region allows us to calculate the share of welfare gains achieved by job changers participating in job chains. These shares reported in Row 2 fall steadily from 52% in the highest wage group to zero in the lowest. Welfare gains at the high end are much more likely to go to the already employed. Welfare gains at the low end go to those without work.

Row 3 in the table presents the Rawlesian measure of distributional impact. Here we calculate the share of all gains going to those taking vacancies in group 5. The pattern is quite striking. Creating jobs at the top of the job hierarchy does relatively little for those at the very bottom. The chains may be long at the top, but they are still cut off before creating vacancies at the bottom. Even if we take a wider measure of those in need, including all those workers either coming from the two lowest groups or taking jobs in the two lowest groups, we still find that adding jobs in the two lowest groups has the strongest distributional impact. Trickle down just is not very strong.

## 6.6 Sensitivity Analysis

The results presented so far underscore the potential usefulness of a job chains approach. If robust, these estimates could add significantly to our ability to evaluate economic development activities. But are these figures highly sensitive to the assumptions that have peppered our empirical methodology? We can address this question most directly by altering key assumptions and observing the results.

**Table 7: Sensitivity Analysis of Efficiency Results ( $V_i/w_i$ )**

Alternative Opportunity Cost Assumptions	Wage Group of Initial New Job				
	1	2	3	4	
Basic Assumptions	.43	0.42	0.56	0.62	0.69
0.75 for All In-Migrants	.41	0.39	0.47	0.54	0.62
0.25 for All Unemp & Out of Labor Force/ 0.75 for all In-Migrants	.51	0.51	0.57	0.63	0.67
0.25 for All Non-Job-Changers	.74	0.72	0.74	0.74	0.75

Table 7 reports the estimated values of ( $V_j/w_j$ ) under four alternative sets of assumptions. These are: 1) set the opportunity costs as defined in the basic assumptions of the study; 2) use a high opportunity cost (75%) for all in-migrants; 3) set the opportunity costs for all the unemployed and those out of the labor force at 0.25, leaving the opportunity cost for in-migrants at 0.75; and 4) set the opportunity cost for all non-employed job takers at 0.25. These exercises suggest that the findings under the basic assumptions stand up well to alternative specifications of opportunity costs. Only in the fourth alternative, does the pattern of the ( $V_i/w_i$ )'s change substantially. The key change here is the reduced opportunity cost for in-migrants. With this lower cost, new jobs in the higher wage groups yield considerably more welfare per wage dollar, rising from about 40 cents/dollar in the basic run to over 70 cents/dollar in the alternative. If all in-migrants have low opportunity costs, then new high wage jobs that draw heavily on high skilled in-migrants generate real gains. But the assumptions necessary to generate this conclusion seem unrealistic. Recognizing the considerable uncertainty that surrounds



our estimates of opportunity costs, the sensitivity evidence support the robustness of our basic findings. Welfare generated per dollar of wages remains lower for high skilled jobs, despite their larger multipliers. Distributional concerns also favor lower skilled jobs over high wage jobs.

### 6.7 Job Vacancy Chains: Expanding on Impact Analysis

Returning to the impact assessment presented above (section 5), we can re-estimate the gains attributable to that economic development project in light of our enriched understanding of how vacancy job chains. Again these calculations are for a hypothetical instruments manufacturing plant in Chicago. The plant employs 100 workers. The left side of Table 8 reproduces our previous results on job multipliers as presented in Table 2. The right side shows the revisions if we use a chain approach to calculate job vacancies.

**Table 8: Distribution of New Jobs and All Vacancies by Earnings Groups**

	<b>New Jobs</b>						<b>All Vacancies</b>					
Number	1	2	3	4	5	Sum	1	2	3	4	5	Sum
Direct	2	5	21	29	5	62	3	12	44	71	24	154
Total	5	8	31	40	13	97	8	21	67	100	43	240
Share	1	2	3	4	5		1	2	3	4	5	
Direct	3.4%	8.1%	33.3%	47.3%	7.9%	100%	2.2%	8.0%	28.5%	45.8%	15.4%	100%
Total	4.7%	8.6%	31.7%	41.7%	13.2%	100%	3.5%	8.9%	28.0%	41.7%	17.9%	100%

Using job chains we recognize that many more individuals are influenced by the new plant than we first expected. The jobs in the instrument plant ultimately result in 240 vacancies filled by Chicago workers. This vacancy multiplier includes not only the horizontal creation of new jobs through the traditional input-output multipliers, but also the vertical opening of job chains as each new job, whether direct or indirect sets off a string of job moves. In terms of vacancies we do see a

trickle down effect as the lowest earnings group enjoys the greatest overall ratio of total vacancies to direct new jobs, 43/5.

The lowest group which accounted for only 8% of direct new jobs, ultimately offers 18% of total vacancies. The next to the lowest job group shows a more muted pace of expansion, from 29 direct jobs to 100 total vacancies, roughly in line with the results for more skilled jobs.

While these vacancy effects are of interest, what we really want to know are the welfare implications of the job chains created by the project. Taking both the horizontal and the vertical multiplier processes into account we estimate that overall welfare benefits generated by the new instrument plant are about equal to \$5.3 million, down from the initial estimate of total earnings gain of \$11.6 million. While chains imply that more workers are affected by a project, this abundance of vacancies cannot offset the explicit accounting of opportunity costs.

Using job chains we can explore distributional issues identifying individuals on the basis of what jobs they ultimately hold. Thus we ask what proportion of welfare gains accrue to workers who ex-post occupy jobs in the various earnings classes. Table 9 gives our results using the job vacancy estimates. In section 5 (above) we found that 6% of total earnings (including horizontal multiplier effects) went to workers holding new jobs in the lowest earnings group. Here we see that the welfare gain achieved by all workers filling vacancies (as opposed to those taking only newly created jobs) in this earnings class amounts to about 7.5% of estimated overall welfare gains. Group 4's share rises even more, from 30% to 34%. Group 3 is the only other group to have a higher share of welfare gains than of earnings, and not by much at that. All groups show absolute welfare gains are less than our simple estimate of earnings gains

**Table 9: Distribution of New Earnings and Welfare Gains  
Across Ex-Post Earnings Groups**

Number	Earnings						Welfare Gains					
	1	2	3	4	5	Sum	1	2	3	4	5	Sum
Direct	\$674	\$1,021	\$2,741	\$2,516	\$268	\$7,218	\$287	\$430	\$1,532	\$1,566	\$184	\$3,999
Total	\$1,684	\$1,633	\$4,075	\$3,470	\$697	\$11,558	\$718	\$688	\$2,279	\$2,160	\$478	\$6,322
Share	1	2	3	4	5		1	2	3	4	5	
Direct	9.3%	14.1%	38.0%	34.8%	3.7%	100%	7.2%	10.8%	38.3%	39.2%	4.6%	100%
Total	14.6%	14.1%	35.3%	30.0%	6.0%	100%	11.4%	10.9%	36.0%	34.2%	7.6%	100%

## 7. CONCLUSIONS

Summarizing the above results for the hypothetical instruments manufacturing plant considered here and expanding an impact evaluation model to include job vacancy chain effects suggests the following:

- more people than first estimated are positively affected by the economic development project.
- overall benefits are substantially lower than “new earnings.”
- trickle down increases the proportion of benefits going to those starting in the two lowest earnings groups.

While local employment generation an issue high on the public policy agenda, considerable uncertainty still surrounds the evaluation of welfare benefits from local job creation and retention. Cities and states have engaged in expensive programs of subsidizing business with only a very imperfect understanding of the social value of those programs. When evaluation has been done at all, it has most often taken the form of simple impact analysis-an adding up of new payrolls and taxes. But even assuming the new jobs can be traced to the public subsidies involved, standard impact assessments can hardly answer the most telling criticisms of local economic

development efforts, that they bring jobs to those who don't need them: to high skilled workers who already hold jobs and to those who have little claim on the local community: in-migrants from elsewhere in the country.

The job vacancy chains model presented above has attempted to deal with these issues and at the same time avoid the pitfalls of too mechanistic a perspective on labor market dynamics. In much of the social science literature using the chains metaphor, a pool of workers and a pool of jobs exist and the issue is simply one of matching. No attention is given to markets, prices do not change and the vacancy model simply gives an account of the rippling-through effect that occurs sub-surface with the creation of new jobs. On the other hand, market models of this process where a price structure emerges and the market clears, can give a sterile perspective on what is essentially the dynamic process in which all of us make our career paths.

The job chains model presented here looks at welfare gains from chains at different skill levels and incorporates insights from opportunity cost theory. We have attempted to show that prices alone do not control the supply and demand for jobs and have credited workers with more autonomy. Their decisions to in-migrate, re-enter the labour market or retire, affect the labour supply. Similarly, by assuming under-employment and a fairly rigid wage structure, we note that demand impacts on chains and on the welfare that accrues from chains set-off by different skill levels. Echoing Bartik's 'hysteresis' theory of local job growth (Bartik 1991), we note that both supply and demand shocks affect chain length and welfare impacts. In this view of labour market processes, short run dynamics such as movement through a job chain, have long-term effects. Once a chain is triggered-off and workers start to move up to a new platform. They accumulate new levels of human capital, skills and work habits that serve them in any further progressions along the job chain. Even if the external agent of change (the job chain), was removed, they would not return to their initial state. Local employment creation, via the chain process, can therefore lead to long-run changes beyond the initial (short-term) effect of the job creation itself.

A important implication of the above is the inter-relatedness inherent in employment creation. Chains limit our ability to use targeting as an economic development strategy. The job chains model shows us that targeting one group in the population will always affect other sub-groups, as they are all inter-connected via job chains. At the very least targeting economic development efforts must be undertaken

in a more sophisticated context; one that accounts for the ramifications generated through labor vacancy chains.

## REFERENCES

Abbott A. and Hrycak A. (1990) Measuring Resemblance in Sequence Data: An Optimal Matching Analysis of Musicians Careers, *American Journal of Sociology*, 96, 144-185.

Akerlof G.A., A.K. Rose and J.L. Yellen (1988), Job Switching and Job Satisfaction in the US Labor Market, *Brookings Papers on Economic Activity*, 2, pp. 495-594.

Blanchard O. and Diamond P. (1992) The Flow Approach to Labor Markets, *American Economic Review*, 82 (2), 354-359.

Burgess S. (1994) Matching Models and Labor Market Flows, *European Economic Review*, 38, 809-816.

Chase I.D., M. Weissburg and T.H. DeWitt (1988), The Vacancy Chain Process: A New Mechanism of Resource Allocation in Animals with Application to Hermit Crabs, *Animal Behavior*, 36, pp. 1265-1274.

Courant P.N. (1994), How would you know a good economic development policy if you tripped over one? Hint: don't just count jobs, *National Tax Journal*, 47 (4), pp. 863-881.

Emmi P.C. and Magnusson L. (1994) The Predictive Accuracy of Residential Vacancy Chains Models, *Urban Studies*, 31 (7), 1117-1131.

Emmi P.C. and Magnusson L. (1995) Opportunity and Mobility in Urban Housing Markets, *Progress in Planning*, 43, 1-88.

Felsenstein D. and J. Persky (1999), When is a cost really a benefit? Local welfare effects and employment creation in the evaluation of economic development programmes, *Economic Development Quarterly*, 13 (1), pp. 46-54.

Firestone O.J. (1951), *Residential Real Estate in Canada*, Toronto: University of Toronto Press.

Garner B.J., Holsman A, Phibbs, and van Kempen T (1981) Assessing the Socio-Economic Effects of Coal Mine Developments with Special reference to the Upper Hunter, NSW in Hannan J.C. (ed.) *Environmental Controls for Coal Mining*, Australian Coal Association, Sydney.

Gorter C. and R. Schettkat (1999), *On Musical Chairs and Matching Models: Do Employed Job Seekers Crowd-Out the Unemployed?*, Amsterdam: Department of Regional Economics, Free University (unpublished).

Harrison R.I. (1988), Opportunity models: adopting vacancy models to national occupational structures' *Research in Social Stratification and Mobility*, 7, pp. 3-33.

Holt C. and David D. (1966) The Concept of Job Vacancies in a Dynamic Theory of the Labor Market, in *The Measurement and Interpretation of Job Vacancies*, National Bureau of Economic Research, Cambridge, MA.

- Hua C. (1989) Linking a Housing Vacancy Model and Behavioral Choice Model for Improved Housing Evaluation, *Annals of Regional Science*, 23, 203-212.
- Kristof F.S. (1965), Housing policy goals and the turnover of housing, *Journal of the American Institute of Planners*, 31, pp. 232-245.
- Marullo S. (1985), Housing opportunities and vacancy chains, *Urban Affairs Quarterly*, 20, pp. 364-388.
- Robson B.T., Bradford M.G., and Deas I.A. (1999) Beyond the Boundaries; Vacancy Chains and the Evaluation of Urban Development Corporations, *Environment and Planning A*, 31, 647-664.
- Schettkat R.(1996a) Flows in Labor Markets; Concepts and International Comparative Results, pp. 14-35 in Schettkat R. (ed.) *The Flow Analysis of Labor Markets*, Routledge, London.
- Schettkat R.(1996b) Labor Market Dynamics in Germany, pp. 256-270 in Schettkat R. (ed.) *The Flow Analysis of Labor Markets*, Routledge, London.
- Smith D.R. and A. Abbott (1983), 'A labor market perspective on the mobility of college football coaches', *Social Forces*, 61, pp. 1147-1167.
- Stewman S. (1975a) An Application of a Job Vacancy Chain Model to a Civil Service Internal Labor Market , *Journal of Mathematical Sociology*, 4, 37-59.
- Stewman S. (1975b) Two Markov Models of Open System Occupational Mobility: Underlying Conceptualizations and Empirical tests, *American Sociological Review*, 40,298-321.
- Stewman S. (1986), Demographic models of internal labor markets, *Administrative Science Quarterly*, 31, pp. 212-347.
- Webster D. (1979), A Regional Development Application of Employment Shifting Concepts: DREE's Alberta Special Area Program, *Plan Canada*, 19 (3), 226-236.
- White H.C. (1970), *Chains of Opportunity: System Models of Mobility in Organizations*, MA: Harvard University Press, Cambridge.