Inter-Industry Labor Mobility and Knowledge Spillovers in Taiwan, China

Howard Pack*

and

Christina Paxson**

*University of Pennsylvania and the World Bank
**Princeton University

I. Introduction

Labor market flexibility has been a prominent factor often cited as one of the contributors to the spectacular growth of a group of Asian countries for the period since 1960. (Fields, 1982) Although questions have arisen about their macroeconomic policies since the mid-1990s, the benefits of their labor market flexibility has not been called into question. The discussion of flexibility has largely been a shorthand for the sensitivity of the real wage to changes in supply and demand rather than being set by government or union interventions. Such behavior has undoubtedly been an important contributor to successful growth by encouraging movement of labor among firms and sectors as demand shifted. In this paper, we consider whether it is possible to deepen our understanding of the role of labor market shifts by examining more precisely the impact of sectoral labor mobility. To do this we integrate surveys of Taiwanese households with the Taiwanese input-output tables to establish the basic facts of the labor reallocation process. We then consider the implications of the evidence for expanding our understanding of the contribution of flexible labor markets to the growth process.

The sectoral structure of Taiwan, China has changed considerably over the past several decades. There have been large increases in the fraction of workers engaged in services and commerce and large declines in agricultural employment. The mix of goods being manufactured in Taiwan, China has also shifted, with corresponding changes in manufacturing employment. A smaller share of Taiwanese workers are engaged in the production of textiles and rubber and plastic products, and a larger share are in metals, machinery, and electronics. This rapid change in industrial structure has been accompanied by a high degree of inter-industry labor mobility. As we show below, not only are new workers drawn into the quickly growing industries, but many experienced workers have switched industries. If labor market flexibility has indeed lubricated growth, this turnover should not be random but should exhibit a pattern that could be interpreted as likely to improve aggregate productivity. In particular, workers should move to sectors that make use of their skills rather than move to unrelated sectors in which any accumulated skills are not exploited.

There is a considerable literature that that argues explicitly that knowledge transmission is facilitated by worker mobility. This has been documented by Saxenian (1994) and others with case studies in Silicon Valley and other regions in industrialized economies that have a substantial high technology sector.[1] In some of the recent research on agglomeration externalities workers play a role in the diffusion of knowledge across industries. For example, Glaeser et. al. (1992) state that "the cramming of individuals, occupations and industries into close quarters provides an environment in which ideas flow quickly from person to person." In this view, workers are the conduits through which knowledge is transferred across firms, possibly within or across industries. Glaeser et.al. use city-level data from the United States and find that cities with a greater diversity of industries grow faster. They argue that the best interpretation of this evidence is that across-industry knowledge spillovers (within cities) are important. Although across-industry knowledge spillovers may occur without the movement of workers, for example, from informal exchanges in both professional and social contexts, most discussions have envisioned mobility as an important source of knowledge transmission. Rather than viewing productivity growth rates as dependent on the diversity of sectors alone, we procede a step further, exploring the mechanism by which growth is fostered by the rational movement of labor among sectors.

A number of recent theoretical papers have attempted to articulate the mechanism through which industrial development exhibits interdependencies. (Puge and Venables, 1998, Rodriques-Clare, 1996). These have argued that local development of supplying sectors may reduce their cost by increasing competition in monopolistically competitive markets, assuming that the benefits of lower cost are passed on to downstream firms. This reduction in cost may make the expansion of downstream sectors more profitable, encouraging their expansion, and thus generate greater sales and a feedback that encourages still more entry in upstream sectors. A complementary process may result if, as industries develop, they benefit from the knowledge brought by workers switching among industries

[1] See also Bartelsman, Cabllero, and Lyons, Ciccone and Hall, 1996.

who possess knowledge that improves the productivity of the recipient industry. This was one of the sources of real externalities discussed by Marshall.

Although the idea that workers transmit knowledge across sectors seems plausible, it has not been examined empirically. In this paper, we investigate the determinants of inter-industry labor mobility and the wages of those that change their industry. Our hypothesis is that workers acquire both general and industry-specific skills that can be transferred to other industries, but that the degree to which skills are transferable varies across pairs of industries. For example, the skills acquired in the textile industry may be of value in the garment sector, but are nearly useless in the production of transportation equipment. In this case, one would expect to see that textile workers who change industries would go disproportionately to the garment sector, and would possibly earn higher wages than migrants from other industries. More generally, we examine whether workers are more likely to move to industries that are "closer" to their industry of origin, where the proximity of any pair of industries is a function of the composition of intermediate inputs used by the industries. Specifically, we examine whether workers are more likely to move from industry i to industry j if: 1) industry i supplies a large share of industry j's intermediate inputs; 2) industry i receives a large share of its intermediate inputs from industry j; and 3) industries i and j use similar intermediate input bundles. We also examine whether workers who have come from "closer" industries receive higher wages than do other workers who are new to the industry.

Our basic finding is that the proximity of industries is strongly related to inter-industry labor mobility, and that there is some (weaker) evidence that workers who move to closer industries receive higher wages.

The rest of the paper is organized as follows. Section II describes the data, empirical methods, and results. In Section III we turn to the policy implications of our results.

II. Data, Methods and Results

1. Measuring industry "proximity"

Our hypothesis is that workers who move to "closer" industries will be more productive. There are many possible ways to define industry proximity, and in this paper we use three measures. The first is based on the idea that workers who have been involved in the production of a good in sector i that is an important input in sector j will be more productive than others when they move to sector j. For example, workers who have production experience in the basic metals sector and have learned metallurgical properties of various metals possess knowledge that increases productivity in the metal products sector which uses a large amount of specialty metals. This productivity increase will be larger than that conferred by workers with previous experience in, say, textiles which sells few inputs to the metal products sector. To capture this idea, we measure the magnitude of sectoral interaction by a_{ij} which equals the ratio of inputs from sector i purchased by sector j to total sales of sector j. Suppose there are n sectors in the economy, and denote the input-output coefficient matrix as A, where A is an n by n matrix of individual sector coefficients a_{ij}. The measure a_{ij} is taken from ith row and the jth column of A.

An amplification of this approach would utilize the coefficients of the Leontief inverse matrix A^{-1} which measures the direct plus indirect interactions among sectors. In terms of indirect linkages, this would imply, for example, that metal product workers who had formerly been employed in basic metals will bring greater knowledge to their current industry if basic metals also sells considerable output to chemicals which in turn sells to the metal products sector. While the use of total input coefficients is typical in studies employing input-output tables, such effects seem less plausible to us.

A second measure of proximity is based on the idea that workers who have experience in sector i that buys a large share of its inputs from sector j will be more productive than others if they move to sector i. An example might be that experience in the garment industry makes one a better designer of textiles. Or using our example of basic metals and metal products, if metal products, j, itself sells large amounts of output to basic metals, i, (assembled steel containers), it may want to learn about the special needs of the basic metals sector and thus hire workers with experience in that sector. Our measure of this type of proximity, a_{ji} equals the ratio of inputs purchased by i from j to total sales of i.

The interactions described here about the potential flow of knowledge is not related to the standard discussion of backward and forward linkages in the development literature (Hirschman, 1957). In that discussion, forward linkages are generated by a sector which sells to many other sectors and which are presumably incapable of obtaining inputs from international sources. Thus, the building of a steel plant may encourage the development of domestic appliance and auto sectors. We are focusing on the mobility of workers from steel to autos or appliances, the critical issue being the transferability of knowledge rather than the physical delivery of inputs though the latter are the measure of the potential transferability. Backward linkages are viewed as the benefit conferred by the establishment of a domestic industry which acts as a purchaser of inputs from local sectors, usually viewed as subject to economies of scale. In contrast, our use of a_{ji} emphasizes the potential knowledge flows rather than the benefits of a larger domestic market.[2]

A third concept of proximity is that industries that make use of similar input bundles require workers with similar skills, so that workers find it easier to move among these sectors. For example, the transport equipment and metal products sectors use similar inputs (particularly primary metals), and many of the skills required to assemble transport equipment may carry over to the assembly of metal products. To measure similarity of input bundles for sectors i and j, we simply compute the correlation coefficient between the ith and jth column of the input-output coefficient matrix A. This measure is denoted Corr(i, j).

Our measures of the "proximity" of industries are constructed from detailed input-output tables for Taiwan, China, from 1976, 1984 and 1989. In each of these years, the input-output tables were disaggregated into a minimum of 29 sectors. We had to combine several industries (such as food, beverages, and tobacco) so that the industry categories matched those in the labor force surveys used to measure mobility and wages. After matching, we were left with 26 sectors, 16 of which were in manufacturing. Table 1 provides descriptive information on the highest values of a_{ij} and on high and low values of Corr(i,j). The values shown are as might be expected. For example, the petroleum product

---

2 For a recent discussion of linkages see Rodriquez-Clare (1996)

sector obtains a large fraction of its inputs from the mining sector, textiles supplies heavily to the garment sector, and the chemicals and plastics sectors use similar input bundles.

2. The Manpower Surveys

We measure wages and labor flows using data from the May rounds of the Taiwanese Manpower Surveys for 1979 through 1994. These surveys, which are similar to the Current Population Surveys conducted in the United States, collect monthly information on employment status and work hours for a large number of people (roughly 50,000 per month). Every May there is a supplement called the Manpower Utilization Survey that collects additional information on annual earnings, job tenure, and job search and mobility. Specifically, the survey asks workers who began their job in the last 18 months about their previous work experience. Workers who are in a new position are asked if they worked at a different job in the year before the current one started, and (if so) the industry and occupation of the previous job. This information is used to determine the effects of prior industry experience on mobility and wages. In all years before 1990, workers in new jobs were also asked whether they had any previous full-time work experience, information which allows us to distinguish between new workers and "re-entrants" who have spent more than a year out of the labor force between jobs. Unfortunately, the wording of the questions regarding previous work experience changed after 1989, so that it is not possible to define new workers and re-entrants in a consistent manner in all years.

Tables 2, 3, and 4 present basic information on the distribution of workers across sectors and on mobility between sectors. Table 2 shows the distribution of all workers (including "free" or unpaid family workers) across sectors in three of the survey years: 1979, 1986 and 1994. Several features of the table stand out. The first is the decline in agricultural employment over the fifteen year period, from 19.5% to 10.0% of the work force. The second is the fact that manufacturing employment has actually declined in Taiwan, China since the mid-1980's, after a long period of growth. The "new" jobs in Taiwan, China are concentrated in services, construction, and trade. Third, the decline in manufacturing employment is not evenly distributed across sectors within manufacturing. Although sectors such as textiles, plastic products and non-metal and rubber products still employ large numbers of people, they are substantially smaller than they were in the mid-1980's. Manufacturing employment has increased in metal products, machinery, electronics, and transport equipment. These features of the Taiwanese work force are also found in Table 3, which excludes “free” (i.e. unpaid) family labor. We excluded free family workers from all of the results that follow, since earnings are not reported for people in this group.

Table 4 provides information on labor mobility by industry in Taiwan, China. We show data for two time periods, 1979-1984 and 1985-1989. Numbers for the 1990s are not shown because, as noted above, we cannot consistently distinguish between re-entrants and new workers in these years. Taiwanese tenure patterns appear to be similar to those in the United States. Average job tenure (not shown in the table) is 7.7 years. The percentage of workers with tenure less than 1½ years is about 21% in both of the time periods. There is substantial variation in job tenure across industries. As might be expected, the sectors with declining employment generally have smaller shares of low-tenure workers. The fraction of workers who are new in their jobs is quite high in some of the faster growing sectors: for example, in both time periods over 30% of electronic machinery workers had been in their jobs for less than 18 months.

The high fraction of people with low tenure is not solely due to new workers entering the labor market, but also reflects high turnover within and across industries. In the 1979-1984 period, 41% of low-tenure workers were “new workers” (i.e. had no prior full-time work experience), and 12% were re-entrants (i.e. had prior full-time experience but no job in the year before taking the current job). Of the 47% of low-tenure workers remaining, 16% came from jobs in their current industry and 31% came from industries *other* than the current industry, indicating a high degree of inter-industry mobility. The patterns in the 1985-89 time period are similar, although the fraction of low-tenure workers who were new workers is lower (34% overall) and the fraction of re-entrants is higher (20%). The decline in the fraction of new workers is due to the aging of the Taiwanese population -- the percentage of people aged 15 and older who were aged 15-25 fell from 36% in 1976 to 27% in 1990. The increase in the fraction of re-entrants is largely due to an increase in the tendency of older women to return to work, presumably after having children. The "re-entrants" in 1989 were 44.4% female, as opposed to 29.9% in 1979. The female re-entrants in 1989 were on average 4 years older than the female re-entrants in 1979, whereas there was no change in the average age of male re-entrants between 1979 and 1989.

3. Inter-industry labor mobility and wages

The remainder of the paper focuses on inter-industry mobility. We examine how our measures of the proximity of industries affects the flow of workers between the two industries, and the wages received by workers who change industries. To start, we match the data from the Manpower Surveys with the information obtained from the input-output tables. We employ input-output tables from three years, 1976, 1984, and 1989. The information from the 1976 table is matched to the labor force data from 1979-1984. The 1984 input-output information is matched to the 1985-1989 surveys, and the 1989 table is matched to the 1990-1994 survey data.

The first set of equations which we estimate has the form:

$$\ln(N_{ijt}) = \delta_i + \theta_j + \mu_t + \beta z_{ijt} + \varepsilon_{ijt} \qquad (1)$$

N_{ijt} is the number of workers who moved from industry i to industry j in time period t. These numbers are computed from the Manpower Surveys, by adding up the number of survey respondents who report having moved from industry i to j during the time period t.[3] The equation includes a set of dummy variables for the industry of origin δ_i and a set for the industry of destination θ_j. These dummy variables account for the fact that expanding industries are likely to draw greater numbers of workers from all sectors, and that contracting industries are likely to provide workers to all other industries. There is also a set of dummies for the three time periods. The term z_{ijt} represents a vector of measures of industry

[3] Actually, we add up the survey weights of all respondents who moved from i to j, where the survey weight equals the number of people in the population that each survey respondent "represents."

proximity. In some specifications we include these measures one at a time, and in others we include all three at once.

Estimates of equation (1) are in Table 5. For this table, i and j are limited to manufacturing sectors. Columns 1 to 3 show estimates using the proximity measures one at a time, and column 4 includes them all together. The major result is that the coefficients on the proximity measures are all individually significant, and indicate that changes in the a_{ij} variables have fairly large effects on mobility patterns. For example, the results of column 1 indicate that an increase in a_{ij} of .06 (about 1 standard deviation) will raise $\ln(N_{ijt})$ by .45. When the three proximity measures are included together, in column 4, the size of the coefficients on each of the individual variables declines, but the coefficients are still individually and jointly significant.

Workers who change jobs but stay in the same industry have high values of z_{ijt}, i.e., the interindustry flows measured by the diagonal elements a_{ii} are typiclly the largest elements in either rows or columns. Thus, many industries (such as metals, and food and beverages) are heavy suppliers of inputs to themselves. By definition, Corr(*i*, *i*) is equal to one, the maximum value possible. The results in columns 1 to 4 may reflect the fact that workers who move tend to stay in the same sector. In columns 5 through 8, we include a dummy variable that equals one if i equals j, and is zero otherwise. As expected, the coefficient on the dummy variable is positive, indicating that there are larger flows of workers within rather than across sectors. This in itself is very strong evidence that workers acquire industry-specific human capital that is better suited to work in "closer" industries insofar as each two digit sector employed here often contains more than fifteen more finely defined industrial branches.[4] Workers with experience in spinning synthetic yarns are more likely to find employment in the weaving, knitting, and cloth finishing sectors than in machinery. Some of the knowledge gained in spinning is in fact useful in these related sectors. The proximity variables still have positive and generally significant

---

[4] While more disaggregated input output tables are available, we are constrained to work at the two digit level of disaggregation by the definitions employed in the manpower surveys.

effects on mobility. In column 9 the sample is limited to industry pairs for which i is not equal to j. Even in this specification the proximity variables are jointly, although not always individually, significant.

Finally, the evidence on sectoral mobility suggests one of the benefits of labor market flexibility. The growth rate of output in many industrial sectors has been more than 10 percent per annum for three decades but the growth rate of both output and employment has been uneven (Table 3). In this environment, workers who perceived themselves to have accumulated knowledge that could usefully be deployed in another branch have been more likely to switch to growing sectors, especially if they are growing or their current sector is declining, a possibility confirmed by the coefficients of δ_i and θ_j. In contrast to slowly growing economies or those characterized by significant government regulation that increases the cost of hiring workers who have mastered knowledge that would be of use in another sector, Taiwan's labor markets encouraged productive shifts among sectors.

The second set of equations which we consider also has the form:

$$\ln(w_{ijt}) = \theta_j + \delta_i + \mu_t + \beta z_{ijt} + \varepsilon_{ijt} \qquad (2)$$

but the dependent variable is now a measure of the wage rate for those who have moved from sector i to sector j. Instead of simply averaging the wage rate of all movers for each pair of industries (in each of the three time periods), we first estimate a set of wage equations to control for the effects of individual-level characteristics (such as age, sex, and education) on the wage. Specifically, for each industry i in each time period t, we estimate the following wage equation:

$$\ln(w_{nit}) = X_{nit}\beta_{it} + \Sigma_j\, \omega_{ijt} I(\text{ n moved from i to j in t}) I(\text{tenure}<1\ 1/2 \text{ years}) \qquad (3)$$

where w_{nit} is the wage of worker n in industry i in time period t, and where X includes a set of controls for age and age squared, dummy variables for whether the worker is a teen or is elderly, years of education, a marital status dummy, a gender dummy and interactions of the gender dummy with all age, education and marital status variables, and a set of dummy variables for the size of the current firm, the survey year, and whether job tenure is less than 1½ years. The coefficients ω_{nit} measure the effect on the wage of having moved from i to j, after controlling for differences in other worker attributes. The omitted category is those who moved to j who had no prior industry, i.e. were either new workers or "re-entrants." These coefficients are used as the dependent variables in equation (2).

Estimates of equation (2), for manufacturing only, are in Table 6. Overall, these estimates yield mixed support for the idea that workers who move to "closer" industries earn higher wages than other movers. Columns 1 through 3 of the table show that there is a positive and significant relationship between each of the proximity measures (entered one at a time) and the wage measure. However, when all three are entered at the same time, only a_{ij} and Corr(i,j) are positive, and only Corr(i,j) is statistically significant. As in the mobility equations, the effects of proximity are reduced when a dummy for i equal to j is included (although one could argue that this dummy is itself another measure of proximity.) The proximity measure that consistently has a positive and fairly precisely estimated coefficient is Corr(i,j): all else equal, workers who move to industries that use input bundles that are similar to their industry of origin earn higher wages. This is true even of the results in column 9, for which movers who did not change industry are excluded.

Equations (1) and (2) were re-estimated on a sample of all, not just manufacturing, industries. These results are in the first two columns of Table 7. The basic conclusion of the earlier results, that the proximity of industries affects labor flows and only weakly affects wages, is true of this larger sample. We also experimented with splitting the sample of workers into production and non-production workers -- this distinction can be made using the occupation categories provided by the survey. In theory, both white collar and production workers could accumulate relevant general training and/or tacit knowledge that is transportable across industries. The large literature on learning-by-doing emphasizes the cumulative production experience of operatives. Yet many of the white collar skills, such as those dealing with organization on the factory floor, material flow, and accounting, may also be of value in related industries. The results, shown in the second two sets of columns in Table 7, indicate that only the effects of Corr(i,j) are precisely estimated. The effects of industry proximity on mobility and wages appears to be slightly larger for production workers.

III. Interpretations and Policy Implications

Our basic result is that workers are more likely to move to industries that are more "similar" to their industry of origin (including intrasector moves that, in fact, are often intersectoral if we were employing a greater degree of sectoral disaggregation), and that moves to more similar industries result in larger wage gains. The degree of "similarity" between two industries is measured in several ways, all of which are based on the input-output flows across industries. Workers are more likely to move from industry i to industry j if i supplies a large share of j's inputs, receives a large share of its inputs from j, or uses many of the same inputs as j. The evidence that wage gains are large for those moving to more similar industries is strongest when the third of these measures of similarity is used. Our results indicate that gains are likely to have accrued to industries as a result of labor mobility. Shifts of workers among sectors were not random – they are explained well by the linkages in the goods market which we believe also measures the probability that workers in i have knowledge valuable in j. Some confirmation of this is provided by our last wage equation that shows a positive wage effect for workers going to sectors with input structures similar to the one in which they were initially employed.

An alternative interpretation for the result that the industry of origin affects mobility is that industries that use common inputs and who supply inputs to each other tend to locate in the same region, and the proximity of industries facilitates the mobility of workers. In this view, workers are more likely to go to "similar" industries not because their experience makes them more productive in those industries, but because mobility costs are lower. The results from the wage equations, however, makes this interpretation seem unlikely, since one would expect the closer workers (with lower mobility costs) to earn wages that are lower, not higher, than other new workers.

What policy implications follow from our findings? The "thickness" of industrial structure is not a policy variable. Countries can increase the degree of interaction by policies encouraging upstream industries that supply downstream industries but often these potential sectors are inefficient and they should not be protected simply to obtain more specialized inputs, including trained labor. More narrowly, conditional on the existence of efficient suppliers and purchasers, should governments encourage training?

Suppose it is the case that the first of these two interpretations is correct, and workers obtain skills that are transferable to similar industries. Does this imply that the amount of training in these skills that workers receive is suboptimal, or that the level of mobility is too low? If there are productivity gains that arise from workers carrying skills and knowledge across sectors, then it is likely that there is too little training in skills that are of use to other industries, and too little mobility of workers between sectors. This would be the case whether it is workers who "pay" for training, through reduced wages, or firms who finance skill acquisition. When general knowledge is generated, neither workers nor their employers would have adequate incentives to invest in skills that would be useful to other industries, and workers would have inadequate incentives to move to sectors where their skills generate an increase in productivity. Implementation of optimal subsidies is likely to be very difficult. Each sector is likely to be both the recipient and provider of training. Determining the net effect in a general equilibrium framework is exceptionally difficult. Thus, even though our results indicate that the necessary condition for gains from training may be satisfied, we are still far from the precise numerical estimates that would be required to implement a first best set of training subsidies.

Quite apart from the general equilibrium issues, even if there are benefits to other sectors, training subsidies may not be warranted. Becker's theory of human capital acquisition (Becker, 1975) indicates that, insofar as training yields benefits that are not firm-specific, but increases productivity in other firms (and, in our case, other industries), workers rather than firms will pay for training through reduced wages. This will be true whether these transportable skills and knowledge are obtained through explicit training programs, or fall in the category of "tacit knowledge." (Nelson and Winter, 1982). In the latter case, one would expect wages in sectors that provide tacit knowledge that is of use in other sectors to be bid down by workers who realize that, by working in those sectors, they will increase their future productivity. In the absence of market imperfections (and externalities), workers will choose the efficient level of training within each industry, and will also choose the optimal pattern of mobility across jobs and industries during their careers.

There are a number of reasons why Becker's theory of human capital acquisition may not apply. First, there may be market imperfections, such as credit constraints or asymmetric information, that result in firms rather than workers paying for general training--see, for example, Katz and Ziderman (1989) and Acemoglu and Pischke (1997). In these cases general training and (by extension of the same arguments) training that increases productivity in "close" industries, will be underprovided to workers. Second, it is possible that in an economic environment that has changed as rapidly as has Taiwan's, it is possible that firms and workers have found it difficult to distinguish which skills are "firm-specific" and which skills are "general." Such considerations may have led Taiwan's government to provide general training subsidies (San, 1988) despite the difficulty of determining the optimal level for each sector.

Employment growth in manufacturing and especially in expanding sectors has been rapid (Table 3) while the unemployment rate has been very low, typically below 3 percent. In this environment, workers who perceived themselves to have accumulated knowledge that could usefully be deployed in another branch are more likely to switch to such sectors, especially if they are growing or their current sector is declining, a possibility confirmed by the coefficients of δ_i and θ_j . In contrast, in slowly growing economies or those characterized by high and variable unemployment rates, even if workers have mastered knowledge that would be of use in another sector, they may be more reluctant to switch. The low unemployment-high growth scenario acts to facilitate optimal reallocation of labor much as an efficient financial sector allocates capital to its optimal uses. The high growth rate of output and employment may itself generate an endogenous growth mechanism which benefits the entire industrial sector.

IV. References

Acemoglu, D. and S. Pischke (1996) "Why Do Firms Train? Theory and Evidence," NBER Working Paper #5605, Cambridge.

Becker, G. (1964) *Human Capital*, Chicago: The University of Chicago Press.

Ciccone, A. and R.E. Hall (1996) "Productivity and the Density of Economic Activity," *American Economic Review* 86(1):
54-70.

Glaeser, E.L., J. Scheinkman, and A. Shleifer, 1992, "Growth in Cities," *Journal of Political Economy* 100(6), pages 1126-52.

Griliches, Zvi, 1991, "The Search for R & D Spillovers, " NBER paper No. 3768

Hirschman, Albert, 1957, The Strategy of Development, New Haven, Yale University Press.

Katz,E. and A. Ziderman (1990) "Investment in General Training: The Role of Information and Labour Mobility," *Economic Journal* 100(403), pages 1147-58.

Lucas, R. Jr. (1988) "On the Mechanics of Economic Development," *Journal of Monetary Economics* 22(1), pages 3-42.

Nelson, Richard R. and Sidney Winter, 1982, An Evolutionary Theory of Economic Change, Cambridge, Harvard University Press.

Puga, Diego and Anthony J. Venables, 1998, "Agglomeration and economic development: Import Substitution vs. trade liberalization," London, Centre for Economic Performance, processed.

Rodriquez-Clare, Andres, 1996, "Multinationals, Linkages, and Economic Development," American Economic Review , 86:852-873.

Rudd, J. ,1997,"Empirical Evidence on Human Capital Spillovers," manuscript.

Saxenian, AnnaLee, 1994, Regional Advantage: culture and competition in Silicon Valley and Route 128, Cambridge, Harvard University Press.

San, Gee, 1988, In-Service training in Taiwan, R.O.C., Chung-ha Institution for Economic Research, Taipei, China.

Stewart, F. and E. Ghani (1992) "Externalities, Development, and Trade," in G.K. Helleiner, ed. *Trade policy, industrialization, and development: New perspectives*. World Institute for Development Economics Research Studies in Development Economics, Oxford and New York: Oxford University Press, Clarendon Press.

Table 1

Descriptive Information on input/output tables

All industries			Manufacturing industries		
i	j	value	i	j	value
Highest values of a_{ij} if $i \neq j$, 1984					
primary metals	machinery	0.279	metal products	primary metals	0.222
petroleum prods	chemicals	0.280	elec. machinery	metal products	0.223
petroleum prds	gas and water	0.329	textiles	plastics	0.234
textiles	garments	0.341	machinery	primary metals	0.279
agriculture	food & bev.	0.419	chemicals	petroleum prds	0.280
mining	Petroleum prod	0.629	garments	textiles	0.341
Highest and lowest values of Corr(i,j) if $i \neq j$, 1984					
services	petroleum prds	-0.187	misc. industry	petroleum prds	-0.130
fishing	construction	-0.167	misc. industry	food &bev	-0.127
plastics	construction	-0.153	misc. industry	non-metal/rubber	-0.107
chemicals	gas and water	0.977	transport equip.	metal products	0.961
machinery	metal products	0.981	metal products	machinery	0.982
plastics	chemicals	0.986	chemicals	plastics	0.986

Notes: a_{ij} is the ratio of purchases of i's intermediate goods output to total sales of j. Corr(i, j) is the correlation between industry i and industry j's intermediate input purchases, a_{ij}, from all industries other than i and j.

Sources: Unpublished DGBAS input-output table tapes and unpublished manpower survey tapes.

Table 2: Employment and employment shares by industry, selected years. All workers.

	1979		1986		1994	
	N (‘000s)	share	N (‘000s)	share	N(‘000s)	share
Agriculture	1233.172	19.5	1170.789	15.3	888.197	10.0
Forestry	25.411	0.4	23.241	0.3	7.528	0.1
Fishing	73.237	1.2	113.434	1.5	81.505	0.9
Mining	57.349	0.9	34.554	0.5	16.728	0.2
Food, bev and tobac.	122.866	1.9	147.321	1.9	147.512	1.7
Textiles	281.457	4.5	273.321	3.6	153.256	1.7
Garments	203.508	3.2	311.905	4.1	261.827	2.9
Wood Products	178.622	2.8	156.938	2.1	131.668	1.5
Paper	85.888	1.4	125.022	1.6	118.67	1.3
Chemical materials	31.649	0.5	27.327	0.4	42.494	0.5
Plastics	164.742	2.6	208.408	2.7	167.672	1.9
Consumer chemicals	48.141	0.8	55.362	0.7	53.404	0.6
Petroleum products	15.821	0.3	11.957	0.2	12.89	0.1
Non-metal & rubber	127.456	2.0	166.858	2.2	137.05	1.5
Primary metals	47.547	0.8	51.861	0.7	67.587	0.8
Metal products	180.675	2.9	267.543	3.5	342.571	3.9
Machinery	110.858	1.8	136.256	1.8	143.132	1.6
Electronic machinery	233.588	3.7	355.173	4.6	454.651	5.1
Transport equipment	73.794	1.2	96.108	1.3	119.291	1.3
Misc. ind	156.041	2.5	240.01	3.1	139.877	1.6
Construction	501.629	7.9	533.315	7.0	981.138	11.0
Electricity	26.667	0.4	25.55	0.3	24.639	0.3
Gas and water	8.493	0.1	8.816	0.1	11.612	0.1
Trans & comm	360.462	5.7	413.701	5.4	458.549	5.2
Trade	944.434	15.0	1356.346	17.7	1842.388	20.7
Services	1019.194	16.1	1336.694	17.5	2086.488	23.5
All manufacturing	2062.653	32.7	2631.37	34.4	2493.552	28.0

Notes: “All workers” is defined as all those who worked in the week before the survey, and includes those who are self-employed and who work as “free” family workers.

Source:Unpublished DGBAS tapes.

Table 3: Employment and employment shares by industry, selected years, excluding unpaid workers.

	1979		1986		1994	
	N (‘000s)	share	N (‘000s)	share	N(‘000s)	share
Agriculture	848.068	15.2	746.138	11.1	590.164	7.3
Forestry	23.679	0.4	20.321	0.3	7.528	0.1
Fishing	62.698	1.1	89.678	1.3	64.828	0.8
Mining	54.996	1.0	31.233	0.5	16.524	0.2
Food, bev and tobac.	112.808	2.0	132.967	2.0	131.027	1.6
Textiles	271.436	4.9	263.529	3.9	145.395	1.8
Garments	197.088	3.5	303.331	4.5	251.747	3.1
Wood Products	169.105	3.0	143.073	2.1	122.587	1.5
Paper	79.542	1.4	112.663	1.7	109.927	1.4
Chemical materials	30.642	0.5	27.071	0.4	42.057	0.5
Plastics	158.45	2.8	195.783	2.9	158.798	2.0
Consumer chemicals	45.305	0.8	53.408	0.8	52.257	0.7
Petroleum products	15.821	0.3	11.734	0.2	12.693	0.2
Non-metal & rubber	123.809	2.2	161.555	2.4	128.678	1.6
Primary metals	45.93	0.8	49.295	0.7	64.887	0.8
Metal products	168.31	3.0	253.936	3.8	314.246	3.9
Machinery	103.01	1.8	125.699	1.9	130.719	1.6
Electronic machinery	228.979	4.1	350.075	5.2	443.024	5.5
Transport equipment	72.781	1.3	92.807	1.4	116.112	1.4
Misc. ind	145.837	2.6	228.585	3.4	131.148	1.6
Construction	488.815	8.8	510.469	7.6	951.004	11.8
Electricity	26.667	0.5	25.55	0.4	24.639	0.3
Gas and water	8.493	0.2	8.654	0.1	11.408	0.1
Trans & comm	348.817	6.3	404.099	6.0	449.762	5.6
Trade	761.984	13.7	1096.263	16.3	1552.638	19.3
Services	985.246	17.7	1280.394	19.1	2014.492	25.1
All manufacturing	1968.853	35.3	2505.511	37.3	2355.302	29.3

Notes: This sample is the same as for Table 1 only unpaid family workers are excluded.

Source: See Table 2

Table 4: Descriptive information on labor mobilit

% with tenure <1.5 years		of those with tenure<1.5 years			
		new workers	re-entrants	same industry	different industry
1979-1984					
Agriculture	6.7	22.7	12.7	20.7	43.9
Mining	12.0	26.6	14.2	31.8	27.4
Food, bev and tobac.	22.7	38.8	12.2	7.7	41.3
Textiles	28.2	51.0	11.5	14.4	23.2
Garments	35.9	45.9	11.1	15.2	27.7
Wood Products	27.3	40.7	12.3	14.7	32.3
Paper	25.9	40.4	14.3	15.9	29.4
Chemical materials	14.7	43.2	8.9	4.5	43.4
Plastics	34.9	42.7	10.2	14.5	32.7
Consumer chemicals	22.3	35.9	16.7	7.1	40.4
Petroleum products	7.6	56.8	0.0	0.0	43.2
Non-metal & rubber	27.6	37.8	10.9	13.0	38.3
Primary metals	17.4	33.6	13.5	7.5	45.3
Metal products	29.5	40.5	12.2	14.9	32.4
Machinery	29.1	45.2	11.7	15.1	28.0
Electronic machinery	31.6	52.2	11.2	11.7	25.0
Transport equipment	22.9	45.1	12.7	8.6	33.6
Misc. ind	34.1	47.7	13.0	7.2	32.0
Construction	18.5	36.8	11.9	11.2	40.1
Electricity	11.7	43.0	9.0	12.8	35.2
Gas and water	9.0	47.5	9.3	7.4	35.9
Trans & comm	17.4	28.8	13.5	20.4	37.3
Trade	20.1	36.5	13.0	20.1	30.5
Services	18.7	47.2	11.6	20.5	20.7
1985-1989					
Agriculture	5.5	21.9	22.1	13.2	42.8
Mining	9.4	17.0	26.9	27.4	28.6
Food, bev and tobac.	22.6	37.4	17.4	7.5	37.7
Textiles	25.0	41.0	17.4	15.5	26.1
Garments	30.0	35.3	19.7	18.6	26.3
Wood Products	23.0	28.7	20.4	17.2	33.8
Paper	24.5	32.7	21.3	16.4	29.6
Chemical materials	12.8	32.9	19.9	9.9	37.2
Plastics	29.5	37.7	18.6	15.3	28.4
Consumer chemicals	23.5	34.5	22.3	8.3	34.8
Petroleum products	12.0	24.0	34.3	5.4	36.4
Non-metal & rubber	27.9	29.4	20.5	15.6	34.5
Primary metals	19.7	26.9	17.3	15.4	40.4
Metal products	25.9	34.0	17.5	15.1	33.4
Machinery	23.8	33.3	19.9	18.1	28.7
Electronic machinery	32.1	39.4	21.8	15.1	23.7
Transport equipment	21.8	35.6	18.0	5.9	40.4
Misc. ind	34.0	39.8	20.5	6.0	33.7
Construction	13.7	27.7	23.7	13.7	34.9
Electricity	6.9	18.8	17.8	23.4	40.0
Gas and water	8.7	22.8	20.6	7.1	49.5
Trans & comm	15.8	19.3	23.0	20.5	37.1
Trade	23.0	31.5	22.1	20.1	26.3
Services	20.0	39.6	19.3	20.9	20.1

Note: The sample is of all workers with earnings. “New workers” are those who have been in their jobs less than 1 ½ years and have no prior full-time work experience. Re-entrants are those in new jobs who did not have a job immediately before the new job, but who indicate that they have previous full-time work experience. In the 1990's the survey stopped collecting the information needed to ascertain whether a worker was a “new worker” or a “re-entrant.”

Table 5: Labor mobility equations

$\ln(N_{ij})$
N_{ij} is the number of workers who have moved from industry i to industry j
t-statistics in parentheses under coefficents
i and j are all manufacturing industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SAME (equal to 1 if i=j, else 0)					2.109 (17.28)	2.153 (19.22)	1.982 (18.46)	1.640 (12.56)	
a_{ij}	7.538 (22.88)			3.136 (5.61)	1.964 (4.05)			1.104 (2.09)	.826 (1.21)
a_{ji}		7.397 (15.17)		2.657 (5.19)		1.781 (4.05)		0.821 (1.54)	.524 (.77)
Corr(i,j)			1.672 (25.83)	.9211 (9.93)			.6325 (7.16)	.5625 (6.72)	.594 (7.17)
F: Industry of destination dummies jointly insignificant	80.72	94.89	111.43	99.42	109.54	114.18	122.85	120.57	134.14
F: Industry of origin dummies jointly insignificant	78.48	47.80	39.99	61.44	75.84	66.92	75.52	64.31	62.20
F: a_{ij}//Corr variables are jointly insignificant (p-value)				313.66 (.0000)				23.55 (.0000)	22.38 (.0000)
Sample size	659	659	659	659	659	659	659	659	612

Notes: The t-statistics are based on "Huberized" standard errors. The samples consist of 1 observation per i/j/time-period cell, where j is the industry of destination, i is the industry to origin, and there are three time periods corresponding to 1979-1984, 1985-1989, and 1990-1994. The a_{ij} and Corr variables are defined in the text. The a_{ij} and Corr variables are measured in three time periods: 1976 (matched to the 1979-84 labor data); 1984 (matched to the 1985-89 labor data); and 1989 (matched to the 1990-1994 data.) All equations contain dummy variables for 2 of the 3 time periods, and dummies for industry of destination and origin. Columns 1-8 include observations for all possible combinations of i and j. Column 9 excludes observations with i=j.

Table 6: Wage equations

$\ln(\omega_{ij})$ t-statistics in parentheses under coefficents i and j are all manufacturing industries									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SAME (i=j)					.057	.083	.038	.040	
					(2.39)	(3.15)	(2.26)	(1.55)	
a_{ij}	.246			.148	.094			.098	.0838
	(4.08)			(1.31)	(.92)			(.82)	(0.58)
a_{ji}		.188		-.066		-.029		-.111	-.131
		(2.50)		(.47)		(.22)		(.73)	(0.77)
Corr(i,j)			.066	.0547			.0454	.046	.0502
			(4.71)	(2.64)			(2.42)	(2.24)	(2.14)
F: Industry of destination dummies jointly insignificant	22.75	22.85	22.35	21.74	24.92	25.23	23.08	22.54	16.16
F: Industry of origin dummies jointly insignificant	1.64	1.43	1.35	1.38	1.50	1.52	1.37	1.39	1.30
F: a_i/Corr variables are jointly insignificant (p-value)				8.66 (.0000)				2.14 (.0935)	2.38 (.0690)
Sample size	659	659	659	659	659	659	659	659	612

Notes: See notes to Table 5. Columns 1-8 include observations for all possible combinations of i and j. Column 9 excludes observations with i=j.

Table 7: Labor mobility and wage equations

	Sample of manufacturing and non-manufacturing sectors. i j		Manufacturing sectors only; production workers only. i j		Manufacturing sectors only, nonproduction workers only. i j	
	$\ln(N_{ij})$	$\ln(\omega_{ij})$	$\ln(N_{ij})$	$\ln(\omega_{ij})$	$\ln(N_{ij})$	$\ln(\omega_{ij})$
a_{ij}	1.054 (2.00)	-.139 (1.14)	.634 (.75)	.089 (.73)	.344 (.45)	-.176 (.55)
a_{ji}	.791 (1.75)	.032 (.26)	.472 (.57)	-.174 (.99)	-.148 (.20)	-.229 (1.25)
Corr(i,j)	.539 (6.87)	.058 (1.93)	.673 (5.72)	.0605 (2.50)	.319 (2.55)	.040 (.81)
F: Industry of destination dummies jointly insignificant	173.25	21.04	387.08	2.79	27.27	9.39
F: Industry of origin dummies jointly insignificant	112.19	2.71	34.51	0.90	27.85	1.53
F: a_{ij} /Corr variables are jointly insignificant (p-value)	29.37 (.0000)	1.35 (.2560)	19.47 (.0000)	3.04 (.0288)	4.50 (.0040)	.67 (.5724)
Sample size	1457	1457	566	566	516	516

Notes: See notes to Tables 4 and 5.