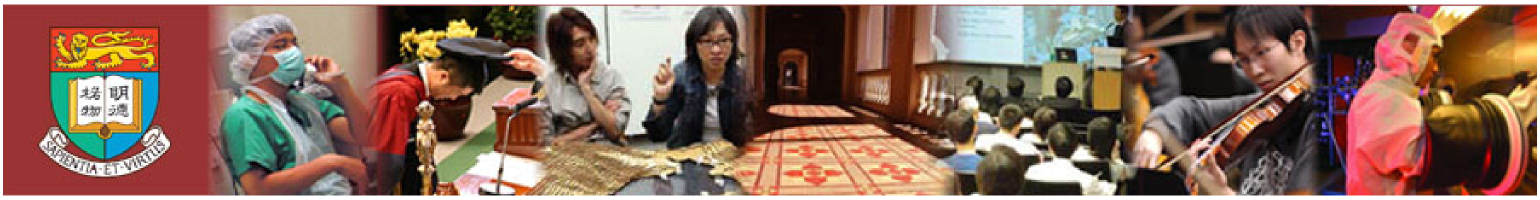

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Age Structure of the Workforce in Growing and Declining Industries: Evidence from Hong Kong*

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Age Structure of the Workforce in Growing and Declining Industries: Evidence from Hong Kong

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Abstract. Industry-specific human capital reduces the incentive for older workers to leave declining industries and raises the incentive for younger workers to join growing industries. Using the industry restructuring experience of Hong Kong, we find that a one percent increase in employment share of an industry is associated with a 0.60 year decrease in the average age of its workforce. The relationship is more pronounced among less educated workers, who have less general human capital, and male workers, who are more committed to the labor force, than among well educated workers and female workers.

JEL classification. J10, J23, J24

Keywords. Industry-specific human capital, industry upgrading, sectoral shifts

1. Introduction

A stereotypical worker in the information technology sector is one in his twenties or thirties, while the rural agricultural economy is usually depicted to be populated by older folks. Such stylized characterizations are not a pure fiction: there are indeed large and systematic variations in the age structure of the workforce across different industries. In Hong Kong, the average age of agricultural workers is 15.5 years older than that of workers in the communications industry (49.4 and 33.9 years, respectively).[1] More interestingly, we find that the age structure of the workforce in an industry is not invariant to changes in the economic environment. Growing industries tend to be populated by younger workers, while older workers stay in declining industries. Take the apparel and textile industry in Hong Kong for example. The industry was a main engine of the early economic growth of Hong Kong (Chen 1979), employing 26.3 percent of the total workforce in 1976. The average worker in that industry then (31.3 years) was 3.8 years younger than the representative worker. With the outsourcing of manufacturing work to mainland China and the restructuring of the Hong Kong economy toward the service industries (see, for example, Suen 1995; Hsieh and Woo 2005), apparels and textiles have steadily lost employment share in the 1980s and 1990s. In 2001 its employment share had shrunk to 3.4 percent. Meanwhile the average age of a textile worker had risen to 42.1 years, which was 3.9 years higher than the economy-wide average. Our paper is an attempt to document and understand these changes in age structure across industries in the context of industrial upgrading in Hong Kong. We believe that our findings are not unique to the local experience.

A key to understanding the relationship between sectoral shifts and variations in age structure across industries is the concept of industry-specific human capital. The

[1]Figures reported in this paragraph are based on authors' calculations using records from the Hong Kong population censuses and by-censuses. See Section 2 below for more details of the data.

industry-specific human capital that a worker has accumulated is more productive when the worker stays in the same industry than when he moves to a different industry. Since Derek Neal (1995) introduced this concept to the literature, much of the research has focused on the effect of exogenous job displacement on wages (Carrington 1993; Kletzer 1996; Kim 1998), or on the effect of low-frequency demand shifts on the wage structure (Weinberg 2001; Devereux 2005a, 2005b). But industry-specific human capital also affects young workers and old workers differently because of the different amounts of capital they have accumulated and because of their different incentives to engage in further investments. Our paper emphasizes this differential impact to study the implications for the age structure of growing and declining industries.[2]

It is well known that specific human capital is a significant factor in the determination of labor market turnover (Becker 1964; Parsons 1972). By driving a wedge between what a worker can produce in his current economic sector and what he could otherwise produce in another sector, industry-specific human capital tends to reduce worker mobility across different industries. In their study of job mobility among young men in the United States, Topel and Ward (1992) find that a typical worker holds seven jobs in the first ten years in the labor market, about two-thirds of his career total. We expect young workers, who are relatively mobile, to have accumulated less industry-specific human capital than do old workers, who tend to have stayed in the same industry for a longer period of time. Suppose a negative demand shock hits a certain industry. Then, efficient separation implies that older workers, who have accumulated more industry-specific human capital, are less likely to switch to a different industry lest they lose the value of their human capital investment. Younger workers, on the other hand, are more eager to switch to a different industry

[2] See also MacDonald and Weisbach (2004) for a theoretical model of technology-specific human capital investment. They argue that technology change tends to depreciate older workers' skills and turn them into has-beens. The entry of younger workers, who can better grasp new technology, puts a downward pressure on the price of what older workers produce.

with better prospects because of their greater incentive to invest in a new type of industry-specific human capital. The greater incentive for older workers to stay in declining industries and the greater incentive for younger workers to join growing industries predict a negative relationship between the change in employment share of an industry and the average age of its workforce.

We do not claim that industry-specific human capital is the only explanation for the observed relationship between industrial shifts and the age structure of industries. It is possible that preference shifts among the younger cohorts drive systematic changes in industrial composition of the economy. Although we provide a descriptive analysis to argue that the industry upgrading of Hong Kong is likely driven by exogenous demand factors rather than a response to the changing composition of the workforce, a more direct identification strategy, if found, would make our informal argument more convincing. Moreover, part of the observed negative relationship between industry growth and the age of the workforce can be explained by other factors. For example, newly emerging firms with more advanced technolgoy may simply find it unprofitable to hire old workers with obsolete skills. Alternatively, older workers may be less mobile due to other reasons than industry-specific human capital. Until we can directly test the presence of industry-specific skills and link these skills with patterns of worker mobility, our explanation remain merely one of the potential factors behind the observed patterns. In the section on robustness checks, we provide some evidence regarding the timing of the relationship and some estimates that exclude entry-level and near-retirement workers to argue that differential mobility by age is not the entire story. The fact that the negative relationship between employment growth in an industry and the average age of its workforce is more pronounced for educated and male workers is also consistent with our interpretation. Our analysis does not pin down an exclusive factor that explains the observed relationship, but we interpret the evidence as suggesting that industry-specific human capital may be the more likely possibility.

While the main objective of this paper is to use the demographic structure of industries to test the implications of industry-specific human capital, studying the age structure of the workforce in different industries has some independent interests. It is well-recognized that workers of different ages have different productivities because of their different experience in the labor market. Moreover, they are not perfect substitutes. Card and Lemieux (2001), for example, use a CES labor aggregator function to estimate the returns to skill for different age cohorts. Their work imply that heterogeneous workers cannot be aggregated simply by converting into efficiency units of labor: the composition of the workforce matters as well as the total quantity.[3] Human resources practitioners talk about maintaining an appropriate demographic mix within an organization, often justifying it on the grounds of succession planning and the intergenerational transmission of skills. Feyrer (2007) finds a significant correlation between the age structure of the workforce and aggregate productivity growth across countries. Although there is little research of this connection at an industry level, we expect that demographic structure may have an impact on productivity and productivity growth across industries as well.

To the best of our knowledge, this paper is among the first to explore the relationship between sectoral shifts and the age structure of the workforce across different industries. In a recent contribution, Autor and Dorn (2009) independently propose to use the average age of workers in an occupation to infer occupational opportunities. Like our work, they also resort to occupation-specific human capital to provide the linkage for the negative relationship between occupational growth and occupational age structure.

[3]See Suen (2000) for a similar approach applied to estimating the differential impacts of immigration.

The prior literature has mostly focused on the effect of changes in the industrial composition of demand on wages. Neal (1995) uses the Displaced Worker Surveys to show that displaced workers suffer large wage losses from switching industries. He also finds that the probability of switching industries upon displacement is decreasing in pre-displacement tenure and experience. Parent (2000) uses data from the National Longitudinal Survey of Youth and Panel Study of Income Dynamics to show that industry-specific human capital is more important than firm-specific skills in the determination of the wage profile. However, Weinberg (2001) uses the March Current Population Surveys to show that there is no significant relationship between industry-level wages and low-frequency changes in industry demand. He argues that the lack of a significant relationship can arise from the low cost of inter-industry mobility or from wage rigidity. Weinberg's results are disputed by Devereux (2005a). Devereux uses panel data to examine the relationship between long-term changes in industry wages and industry employment. After controlling for the composition of the workforce, he finds a higher positive relationship between wages and employment, which means that the composition of the workforce in these industries has changed: growing industries attract less skilled workers. In another paper, Devereux (2005b) examines the effect of industry growth and decline on wage changes. The main finding is that workers in expanding industries experience much faster wage growth than do other workers, suggesting that the supply of industry-specific human capital is not perfectly elastic.

The issue of cross-industry job mobility has been directly addressed in the literature as well. Kletzer (1996) studies the pattern of sectoral mobility following job displacement. McLaughlin and Bils (2001) find that high-wage industries usually have stronger employment fluctuations, and that positive self-selection can contribute to the cyclical upgrading of the quality of the workforce. Neal (1998) uses a model of training choice to show that able workers tend to choose highly specialized jobs, which is an important reason for the negative relationship between wage levels and turnover rates. Devereux and Hart (2006) examine the wage cyclicality of job stayers and job movers, and find that the wage cyclicality of within-company movers is 10–15 percent higher than that of stayers, and the wage cyclicality of between-company movers is 30–40 percent higher than that of stayers. These studies provide analysis on the relationship between wage and mobility, while our present study focuses on the implications of cross-industry mobility for the demographic characteristics of the workforce.

2. Industrial Restructuring in Hong Kong

The restructuring of industries in Hong Kong is an often-told story (see, for example, Greenwood 1990; Suen 1995; Berger and Lester 1997). The economic take-off of Hong Kong began in the 1960s and 1970s, when Hong Kong specialized in the manufacture of low-skilled, labor-intensive goods such as textiles, garments, and plastic products. The opening of China in 1978 offered an abundance of new business opportunities and necessitated a relocation of production according to comparative advantage. Manufacturing industries in Hong Kong began a long period of decline as production activities were outsourced to China. Meanwhile outsourcing-related business services such as transport, trade, and finance services grew to become the mainstay of the economy. In the early 1980s, Hong Kong's outward processing trade with China was almost non-existent. By the year 1997, Hong Kong was sending HK$ 245 billion and receiving HK$ 1087 billion worth of goods to and from China in connection with outward processing trade. To put these numbers in perspective, gross output from all domestic manufacturing establishments had declined from 157 billion to 82 billion (in 1997 Hong Kong Dollars) between 1982 and 1997 (Census and Statistics Department, various years). The shift in the manufacturing base was swift and unmistakable.

The opening policy in China since 1978 has not led to an abrupt reform, but a gradual economic transition. During this period, the transition from the centrally-planned to the market-oriented economy has been proceeded in a piecemeal manner. In the early 1990s when Chinese leader Deng Xiaoping conducted a tour to Shenzhen, a special economic zone neighboring to Hong Kong, the economic transition in China accelerated, and the relationship between the mainland and Hong Kong became much closer than ever. We find that the employment change in the textile industry has been more dramatic since the early 1990s, when most of this industry moved north to Guangdong province.

For the purpose of this study, we measure the changing demand for labor in different industries by the changes in their employment shares. As Hsieh and Woo (2005) point out, the Hong Kong experience is particularly interesting because the changes in employment shares are triggered by a largely exogenous event, namely, the opening of China. Thus, changes in employment shares arguably reflect demand factors rather than shifts in preferences or composition of the labor force. Moreover, the pace of sectoral shifts is greater in Hong Kong than in many other economies such as Singapore, Korea, Japan, or the United States (Suen 1995). Thus data from Hong Kong provide large variations in demand changes across industries, which help increase the precision of our estimates.

We calculate employment shares using random sub-samples of the Hong Kong population censuses and by-censuses of 1976, 1981, 1986, 1991, 1996, and 2001. The sample consists of all men and women who were aged 15 or above and who were employed, including employees, employers, the self-employed, and unpaid family workers.[4] Because the classification of industries has changed over the years, we recode

[4]Unpaid family workers refer to individuals who live with the family and do work (not domestic work) as part of the family enterprise in return for food and lodging. They are workers, and are different with home-makers. In any case, such workers represent a very small fraction of the total workforce.

the industry variable in order to keep the consistency and comparability of the definitions.[5] After dropping individuals whose industry is "unidentifiable or inadequately described" (they make up less than one percent of our sample), we assign workers to 25 different industries and calculate the average characteristics of the workforce in each industry. The result is a panel dataset of 25 industries with six observations for each industry.

Since each industry is observed once every five years, the change in employment share of an industry over successive periods reflects relatively low-frequency changes in demand.

(Insert Table 1 here.)

In Table 1, we show these changes for each five-year period. This table indicates that the changes in the industrial composition of the economy has been quite continuous and uniform over time. If we aggregate these changes into two sub-periods (1976–1991 and 1991–2001) the coefficient of correlation between employment changes in these two sub-periods is 0.83.

For the purpose of understanding the nature of these low-frequency demand shocks arising from the industry upgrading, we take a closer look at some specific industries that have experienced great changes in employment share:

Agricultural Products. Hong Kong is a small region without much agriculture. In 1976, about 1.6 percent of all workers were engaged in this industry. Urbanization and the rising price of land has almost driven this industry into extinction, with its employment share reduced to 0.13 percent in 2001.

Manufacturing of Wearing Apparel, Leather and Textile Goods. This is the industry most affected by the economic restructuring process induced by the opening of the Chinese economy. At its peak, the textile industry employed more than a quarter of the Hong Kong workforce. Outsourcing of production into the neighboring Guang-

[5] Details of the recoding are shown in Appendix Table 1.

dong province has meant that the Hong Kong operation of textile firms are reduced to a management and control function, with a greatly diminished demand for labor (Suen 1995; Kwok and So 1995). Employment share in this industry was a mere 3.4 percent in 2001. Indeed, such a pattern of industry restructuring and the decline of manufacturing industries in general is not unique to Hong Kong. The other "dragon economies" of Taiwan, Singapore, and South Korea have experienced similar changes (Sung 1995).

Import/Export. We have already discussed the tremendous expansion of outward-processing trade in Hong Kong. Economic growth in China further fueled the expansion of trade-related services as Hong Kong served as an important port for the distribution of Chinese manufactured products to the rest of the world. Employment share in this sector increased from 2.8 percent in 1976 to 7.4 percent in 2001.

Real Estate, Rental, Surveying, and Miscellaneous Services. The sustained housing boom in Hong Kong has supported an ever growing fraction of the workforce engaged in this industry. Employment share in this industry has increased from 1.4 percent to 10.7 percent between 1976 and 2001. Again, the increase in employment is clearly due to demand rather than supply factors.

Although we do not have conclusive proof that the changes in industrial structure are driven by demand rather than supply factors, our knowledge about the development and the sources of comparative advantage of the Hong Kong economy leads to the belief that the changes in the industries described above are primarily driven by demand factors. Another corroborating piece of evidence is related to the demand and supply of female workers. In the beginning of our sample period, women workers were concentrated in the labor-intensive light manufacturing industries. In 1976, for example, 44 percent of all women workers were employed in the textile industry. The period 1976–2001 saw a increasing entry of women into the labor force. The employment rate of women aged over 15 rose from 40 percent in 1976 to 49 percent in 2001, while that of men fell from 74 percent to 67 percent. Yet the large increase in supply of female workers was associated with a decline of the female-intensive light manufacturing sector, casting doubt on the hypothesis that industry upgrading in Hong Kong was a response to changes in the composition of labor supply.

(Insert Table 2 here.)

Table 2 provides some further characteristics of the data. In the second column, we calculate the average absolute change in employment share for each of the five-year periods. The number in this column multiplied by 25 (25 industries) and divided by 2 (to avoid double counting) is a common measure of the degree of sectoral shifts. For example, the first row of this column suggests that at least 9.4 percent of the working population must have switched industries between 1976 and 1981. Column 2 of Table 2 shows that the magnitude of these shifts are quite sizable. Columns 3 and 4 further indicate that there are significant variations in employment growth and decline across different industries.

In Table 2, we also present summary statistics for the variations in age structure of the workforce across industries. Column 5 shows that there is a general rise in age of the workforce in Hong Kong, with an increase from 35.1 years to 38.2 years in the twenty-five period under study. This is in line with the aging trend in Hong Kong. However, the average age of the worker also shows significant variations across industries. The difference in average age between the industry with the oldest workers and the industry with the youngest workers is generally larger than ten years. It is to these variations in age structure that we now turn.

3. Sectoral Shifts and Worker Age Structure

To take a preliminary look at the data, we plot the average age of workers in 25 industries in 2001 against the 1996–2001 change in employment shares of these industries.

The fitted line in the figure is a weighted least-squares fit to the data, using 2001 employment shares as weights.

(Insert Figure 1 here.)

Consistent with the prediction based on industry-specific human capital, Figure 1 shows that there is a weak negative relationship between the growth or decline of an industry and the average age of its workers.

(Insert Table 3 here.)

Table 3 presents a more systematic look at the data using regression analysis. The basic equation we estimate is:

$$A_{it} = \alpha_i + \beta_t + \gamma \Delta E_{it} + \varepsilon_{it}.$$

where A_{it} is the average age of workers in industry i at year t, ΔE_{it} is the change in employment share of industry i from year $t-5$ to year t, and α_i and β_t are the industry and year fixed effects, respectively. Because of the possible correlation in age structure of an industry over time, we report robust standard errors clustered by industries.

In the first column of Table 3, panel A, we present the ordinary least squares estimate of γ without industry or year fixed effects. The regression coefficient is -0.56, indicating that an industry which expands its employment share by one percentage point over a period of five years will have a workforce that is about half a year younger than average. To control for the fact that workers of different age may have comparative advantage in different industries, column (2) includes industry fixed effects in the estimation. We find that these industry fixed effects can account for a substantial fraction of the overall variations in average age in our data. Industries such as "agricultural products" and "marine fishing and fishery products" tend to employ relatively old workers, while "communications" and "banking, finance, and investment companies" are dominated by younger workers. In column (3), we estimate the equation with year fixed effects but no industry fixed effects. The coefficients for the year dummy variables confirm the general aging trend of the Hong Kong workforce, but the estimated coefficient for the change in employment shares is not materially different from that in column (1) or (2). Column (4) of Table 3 shows the full specification with both industry and year fixed effects, and column (5) shows the weighted least squares estimate using employment shares as weights. The estimated size of γ is very consistent across all these specifications. The "between" and "within" estimates of the effect of employment growth on average age are virtually the same.

Because there is no prior work that estimates the effect of employment change on average worker age, we do not have a reliable benchmark to assess the magnitude of our estimated coefficient of -0.60 in the last column of Table 3. To put this number in perspective, consider the apparels and textiles industry again. This industry experienced a 7.3 point drop in employment share in 1986–1991. Our estimated model suggests that the average age of the industry would be 4.4 years older as a result. In comparison, the estimated year fixed effects of our model only predict that the average age of the workforce would rise by 0.6 year over that period. As another example, consider the real estates industry. Its employment share rose by 2.4 percentage points in 1996–2001, which translates into an estimated 1.4 year decrease in the average age of its workforce. This is more than enough to offset the estimated 1.0 year increase in age due to the general aging of the workforce during that period.

It may be argued that a one percentage point increase in employment share is more important in a small industry than in a large industry. For this reason, we re-estimate our basic regression equation by using $\Delta \log(E_{it})$ instead of ΔE_{it} as the independent variable. The results are shown in panel B of Table 3. This panel shows the same basic patterns as panel A, except that the coefficient on $\Delta \log(E_{it})$ in the specification of the last column (column 5) is statistically significant at only the ten percent level. Consider a "typical" industry with an employment share of 4 percent. According to the coefficient estimate of -3.53 means that a 25 percent increase (one percentage point increase) in employment share would lead to a -0.88 year decrease in the average age of the industry. This estimate is not very far from the original estimate of -0.60 year presented in panel A.

The theory of industry-specific human capital does not simply predict that the average age of the workforce of an industry increases when the industry experiences a negative shock. The age composition of the workforce is also expected to change. In particular, because the difference in accumulated industry-specific human capital and the difference in incentive to invest are largest between the oldest workers and youngest workers, the differential response to sectoral shifts is also expected to be largest between these two groups of workers.

(Insert Table 4 here.)

In Table 4, we replace the dependent variable A_{it} in our basic model equation by the proportion (in percentage) of workers in different age groups. The dependent variable for the six columns of this table correspond to the proportion of workers aged 15–25, 26–35, 36–45, 46–55, and over 55. We find that the proportion of workers in the youngest age group (15–25) has a positive and significant response to an increase in sectoral share. If the employment share of an industry increases by one percentage point, then the proportion of very young workers (aged 15–25) in that industry increases by 1.7 percentage points. The overall fraction of workers in this age group is 24.3 percent, so this increase represents a 7.4 percent rise in share. On the other hand, the proportion of workers in the older age groups (36–45, 46–55, and 55 plus) has a negative response to an increase in sectoral share. For example, if the employment share of an industry rises by one percentage point, then the proportion of its workers near retirement (aged over 55) falls by 0.67 percentage points. We do not find any significant effect of demand shifts on the proportion of workers aged 26–35 in the industry. This is consistent with our hypothesis that the differential response to demand shifts is largest among the youngest and oldest workers. Panel B of Table 4 repeats the exercise by replacing ΔE_{it} with $\Delta \log(E_{it})$ as the independent variable. The results are largely similar as those shown in panel A.

4. Robustness Checks

Because we do not have direct observation on industry-specific skills, our hypothesis that they are responsible for the negative relationship between industry growth and industry age structure remains one of several possible interpretations of the data. There can be other reasons for our finding, such as outliers, age differences in worker mobility, and supply factors (e.g., worker preferences). In this section we provide some robustness checks and additional analysis to show that, while we cannot complete exclude other possibilities, the industry-specific human capital interpretation may be the more plausible explanation.

Outliers. Figures 1 and 2 suggest that the estimated relationship between employment change and average age in an industry may be unduly influenced by a few outliers. We address this issue by excluding observations for which the variable ΔE_{it} or $\Delta \log(E_{it})$ lies outside the 5th and 95th percentile values. Re-estimating the regression model of Table 3 with these outliers removed (the number of observations is reduced from 125 to 113) produces regression coefficients of -0.836 (s.e. = 0.662, robust standard error) and -6.339 (s.e. = 1.910), respectively, corresponding to column 5 in Panel A and B of Table 3. If we exclude observations for which ΔE_{it} or $\Delta \log(E_{it})$ lies outside the 10th and 90th percentile values (reducing the number of observations from 125 to 101), the coefficients become -1.316 (s.e. = 0.957) and -6.873 (s.e. = 2.972), respectively. These estimates suggest that our main results are not simply driven by the presence of a few influential observations.

Entry-Level Adjustment and Retirement. An alternative explanation for the observed negative correlation between employment growth of an industry and average age of its workforce is that entry and exit of labor occurs at different points of the life cycle. Growing industries have more open positions to fill and younger workers are more likely to be applying to these jobs, if for no other reason than that younger workers are more likely to have just finished school. On the other hand, declining industries shrink via a combination of attrition through retirement, hiring freezes, and layoffs. To the extent that employers in declining industries encourage early retirement or lay off the senior workers, this will contribute to a younger workforce. But to the extent that employers stop hiring young workers or lay off their recent hires, this can contribute to an older workforce. In order to disentangle these effects of entry and exit from the effects of industry-specific human capital on job turnover, we can focus on workers who are not near schooling-leaving age or near retirement age.

(Insert Table 5 here.)

In Table 5, panel A, we re-estimate our basic regression after excluding workers aged 15–24 and workers aged 56 or above. The dependent variable A_{it} is the average age of the workforce among workers aged 25–55 (but the independent variable ΔE_{it} is still calculated by including all workers). In the weighted least squares specification with both industry effects and year effects (column 5), the estimated coefficient on ΔE_{it} is -0.23. This is smaller than the earlier estimate of -0.60, suggesting that entry-level adjustment and retirement are indeed conducive to the negative relationship between age structure and employment share. Nevertheless, the negative coefficient of -0.23 estimated for workers aged 25–55 also suggests that there is some differential job-switching induced by different degrees of industry-specific human capital between the young and old. In panel B of Table 5, we further restrict the focus to workers aged between 30 and 50. As is to be expected, the coefficient estimates are smaller than those shown in panel A. This is consistent with our findings in Table 4 that the youngest and oldest workers tend to be most affected by the industry upgrading. In sum, we find that entry-level adjustment and retirement also contribute to the negative relationship between age structure and employment, but job turnover related to the industry-specific human capital remains an important part of the observed negative correlation.

Identification Issues. In estimating the relationship between the change in employment share of an industry and the age structure of its workforce, our maintained assumption is that changes in employment share reflect low-frequency sectoral shifts in demand. We have justified this maintained assumption in Section 2 by appealing to a qualitative description of selected sectors of the Hong Kong economy. We argue that much of the employment changes in these sectors can be traced to clearly identifiable demand forces that are unrelated to worker preferences or worker age structure. In this subsection, we supplement our main argument with some quantitative evidence.

If industry growth and decline reflect a shift in worker preferences toward working in particular sectors (e.g., young workers brought up in urban lifestyles might dislike agricultural work) rather than demand-side factors, one would expect that declining industries are ones that face labor shortage while growing industries have a surplus of job applicants. Suen (1995), however, shows that growing industries tend to experience higher wage growth.[6] Our data also contain information on the industry of the previous job held by those unemployed in the years 1976, 1981, and 1986. We calculate the industry-specific unemployment rate as the number of unemployed from an industry divided by the sum of employed and unemployed from the same industry.

(Insert Figure 2 here.)

[6] This is consistent with Devereux's (2005a, 2005b) findings for the United States.

Figure 2 depicts the relationship between the employment growth of an industry from 1981 to 1986 and the industry-specific unemployment rate in 1986. The fitted least squares line slopes downward, with an estimated slope of -0.68 (s.e. = 0.24).[7] Since the measured industry-specific unemployment rate probably responds more to high-frequency changes in demand rather than to five-year shifts in employment shares, we do not expect the relationship between these variables to be very tight. At the very least, Figure 2 does not lend support to the hypothesis that changes in employment shares are driven by supply factors.

Another possible objection to the basic model we estimate is the reverse causality problem. One might conceivably argue, for example, that younger workers are more creative than older workers are, and therefore industries with more young workers grow faster than do other industries. We test this hypothesis by looking at the relative wages of young and old workers across industries. If younger workers are indeed more creative (and therefore more valuable) in growing industries, we would expect that their wages relative to older workers would be higher in these industries. In addition, the rising demand in growing industries can have a positive premium on wages of younger workers. Integrating these two effects would cause the premium to be much higher for younger workers in expanding industries. Based on the findings from Table 4, we measure the relative wage of young workers as the logarithm of the average wage of workers aged 15–35 minus that of workers aged over 35.

(Insert Table 6 here.)

Table 6 presents the regression results. In the first two columns, the dependent variable is the relative wage of young workers in industry i at year t. Both the weighted and unweighted estimates of the coefficient for ΔE_{it} are negative but not significant at conventional levels. In columns (3) and (4), the dependent variable is

[7]The estimated slope is -0.89 (s.e. = 0.44) when observations are weighted by their employment shares. The relationship between employment growth in 1976–1981 and industry-specific unemployment rate in 1981 is similar.

the relative wage of young workers in industry i at year t with education level j.[8] When we control for the education premium and changes in education premium over time, the estimated coefficients for ΔE_{it} are positive but statistically insignificant. In all four columns of the table, the magnitude of the effect of change in employment share on the relative wage of young workers is trivial. Given the analysis that there are two effects which would increase the wage premium for younger workers in expanding industries, the insignificant result can not verify the reverse causality story plausible.

Timing Issues. In the previous section, we focus on using employment change from year $t-5$ to year t to explain the age structure in year t. To the extent that individuals can forecast changes in industry structure of the economy, the same forces that cause young workers to choose growing industries and old workers to stay in declining industries will produce a negative relationship between future changes in employment shares and current age structure across industries. Recall that there is a high degree of persistence in the process of industrial restructuring in Hong Kong. Therefore, it is not unreasonable to believe that workers at least have some ability to predict low-frequency changes in demand across different sectors.

(Insert Table 7 here.)

Table 7, column (1), presents the estimation result of our basic equation using ΔE_{it+5} instead of ΔE_{it} as the explanatory variable. Even though the timing of the explanatory variable and the sample period are different, the estimated value of γ is not materially affected. The estimated γ is -0.59 under this specification, compared to the estimate of -0.60 in the previous section. In column (2), we include both ΔE_{it} and ΔE_{it+5} in the regression. The coefficient on the lagged change ΔE_{it} remains negative and significant, while the coefficient on lead change ΔE_{it+5} is negative but

[8] We classify workers into three education groups: primary and below, secondary, and college and above. The sample size is not three times as large as the sample size shown in columns (1) and (2), because some of the cells are too small to give a meaningful measure of the relative wage of young workers.

not significant. We also experiment with longer term demand changes by using $E_{it+5} - E_{it-5}$ to measure the change in employment share. As can be seen in column (3) of Table 7, the estimated response of average age in an industry to five-year changes in employment share or to ten-year changes share is quite similar.

Following a period of expansion, an industry will consist of many new workers who have come from other industries. If workers who have moved are predominantly young, then the average age of the workforce in an expanding industry will fall, with or without industry-specific human capital. We show in Table 7 that the workforce tends to be younger even for industries which are expected to expand (but have not experienced the actual expansion yet). Since such industries do not necessarily employ a disproportionate fraction of workers who have recently moved, our finding cannot be completely attributable to the selection effect due to differential mobility by age. We interpret our result as suggesting that, in order to preserve industry-specific human capital, younger workers have greater incentive to pursue their careers in industries which are expected to expand than industries which are expected to decline.

Columns (4) to (6) of Table 7 replicate the analysis using employment growth rates instead of changes in employment shares. We see that the estimated coefficients are all negative, though most are only significant at the ten percent level. The magnitudes of the estimated effect using the level specification and the log specification are comparable. For example, if an industry increases its employment share from four percent to five percent over a period of ten years, the model in column (6) suggests that average age in that industry will fall by 0.68 year.

Analysis by Sub-groups. Sectoral shifts in demand may affect the average age of workers in an industry through a composition effect. If growing industries also demand more educated workers or more female workers, and if educated workers or female workers tend to be relatively young, then the composition effect would reduce the average age of the workforce in growing industries. One way of controlling for these effects is to look at changes in average age for workers within a definite education of gender group.

(Insert Table 8 here.)

For example, in the first row of Table 8, we estimate the average age of workers with no schooling in industry i at year t as a function of ΔE_{it} and industry and year dummies. The estimated coefficient is negative but statistically insignificant. Comparing the estimation across different education groups, we find that less educated workers tend to be more responsive to industry growth and decline than are more educated workers. A possible reason for this observation is that industry-specific human capital may be relatively more important than general human capital for the less educated workers. Table 8 also shows that both the average age of male workers and the average age of female workers in an industry fall as the industry expands its employment share in the economy. In the case of female workers, however, the estimated response is not statistically significant. It is possible that the intermittent pattern of labor force participation reduces the importance of industry-specific human capital for female workers.

Industry-Occupation Mix. The process of industry restructuring is often associated with within-industry changes in the structure of occupations.[9] In practice, the distinction between industry-specific human capital and occupation-specific human capital may not be very clear. We therefore supplement our analysis by investigating the effect of changes in occupation structure as well as changes in industry structure.

To this end, we recode the occupation variable into 26 two-digit groups so as to maintain consistency across census years. We then regress the average age of workers in an occupation on the change in employment share of that occupation. The result

[9]Evans (1999) analyzes the cyclical structure of occupational upgrading and downgrading.

is displayed in column (1) of Table 9.

(Insert Table 9 here.)

We find that the demographic response to occupation demand shocks is still significantly negative, with an estimated coefficient of -0.22, though it is smaller in magnitude than the response of worker average age to industry demand shocks. In columns (2) through (6) of the table, we construct industry-occupation cells and use the average age of workers in each industry-occupation cell as the dependent variable. Many of these cells are quite small if we maintain the 25 industries by 26 occupations classification. So we change the level of aggregation to one-digit level, resulting in 56 industry-occupation cells.[10] For columns (2) and (3), we use the change in employment share of each industry-occupation cell as the independent variable. The difference between them lies in the different ways of controlling for fixed effects. Both specifications produce similar results: a one percentage point increase in cell employment share is associated with a 0.17 year fall in the average age of workers in that cell. We also experimented with using changes in occupation share (column 4), changes in industry share (column 5), and a combination of these two variables (column 6) as regressors. Our finding of a negative relationship between average worker age and employment share is robust to these alternative specifications.

5. Conclusion

This paper analyzes the response of industry demographic structure to industry upgrading in Hong Kong. In the period under study manufacturing industries have declined sharply in employment and production, while services industries have re-

[10] Although we have eight one-digit industries and ten one-digit occupations, the number of industry-occupation cells is not 80. Some occupations do not appear in all industries. For example, the occupation "market-oriented agricultural and fishery workers" only appears in agriculture-related industries. There are also some industry-occupation cells with very small cell size. The number of individuals in the data files working in the "agricultural products" industry with the occupation of "managers or professionals," for instance, is often below 10. We record the employment share of an industry-occupation cell in any one year as "missing" if there are less than 30 individuals in that cell.

placed manufacturing as the dominant sector of the economy. We find that these long-term demand shifts are associated with predictable effects on the average age of workers in different industries. Expanding industries tend to attract relatively young workers, while declining industries tend to be filled with older workers. The results show that the average age of workers in an industry is about 0.60 year younger when the employment share of that industry increases by one percentage point. We also find that the youngest and oldest workers are most responsive to changes in employment shares of their industries, whereas the proportion of workers aged 26–35 is not significantly associated with these demand shifts. Furthermore, less educated workers and male workers tend to be more responsive to demand shifts compared to more educated workers (who possess more general human capital) and female workers (who have lower attachment to the labor force). These broad patterns are generally consistent with the effects of industry-specific human capital on workers' mobility and entry decisions.

There exist several possible reasons for the finding, but our analyses seem to suggest that industry specific human capital may be the more likely possibility. One important limitation of this paper is that our data do not contain information on the industry tenure. As a result we do not have direct evidence on how industry-specific human capital affects labor mobility decisions. We can only establish an indirect linkage through the relationship between industry growth and the resulting age structure of the workforce. Our conclusions are subject to criticism regarding the direction of causality and alternative explanations such as the differential effects of age on labor mobility. We argue in Section 2 and in Section 4 that the industry upgrading of Hong Kong is likely driven by exogenous demand factors rather than a response to the changing composition of the workforce. A more direct identification strategy, if found, would make our informal argument more convincing. We also agree that part of the observed negative relationship between industry growth and the age of the workforce can be explained by the differential mobility of young and old workers. However, the evidence presented in Section 4 regarding timing of the relationship and the fact that the negative relationship is more pronounced for educated and male workers suggests that differential mobility by age is not the entire story. The broad pattern of our data suggests that forces due to industry-specific human capital are at work.

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Table 1. Changes in Industry Employment Shares

Industry	Employment Share 1976 (%)	Change in Employment Share 1976-1981 (%)	Change in Employment Share 1981-1986 (%)	Change in Employment Share 1986-1991 (%)	Change in Employment Share 1991-1996 (%)	Change in Employment Share 1996-2001 (%)	Change in Employment Share 1976-2001 (%)
Agricultural Products	1.55	-0.48	0.63	-1.14	-0.35	-0.08	-1.42
Marine Fishing & Fishery Products	0.26	-0.02	-0.11	0.32	-0.10	-0.10	0.00
Mining and Quarrying	0.06	0.01	-0.04	0.00	-0.01	-0.01	-0.05
Food, Beverage and Tobacco Industries	1.29	0.04	-0.23	-0.10	-0.12	-0.20	-0.61
Manufacturing of Wearing Apparel, Leather and Textile Goods	26.27	-3.99	-2.99	-7.33	-5.69	-2.85	-22.85
Manufacturing of Wood and Cork Products, Furniture and Fixtures	1.25	0.09	-0.46	-0.39	-0.26	-0.06	-1.08
Manufacturing of Paper and Paper Products, Printing, Publishing	2.13	-0.16	0.08	0.00	0.01	-0.03	-0.10
Manufacturing of Chemical Products, Coal and Plastic	2.26	-0.09	-0.35	3.09	-1.93	-0.96	-0.23
Manufacturing of Basic Metal Industries	4.56	0.85	-1.10	-1.80	-2.05	-0.26	-4.35
Manufacturing of Machinery, Equipments, Parts and Components	6.71	0.85	-1.03	-1.20	0.68	-2.09	-2.80
Electricity, Gas and Water	0.57	0.04	0.07	-0.01	0.00	-0.14	-0.05
Construction	5.96	1.90	-1.63	0.64	1.23	-0.60	1.55
Wholesale	0.77	0.70	0.68	-0.04	0.10	-0.04	1.40
Retail	11.56	-3.44	0.57	-0.52	0.54	0.07	-2.79
Import / Export	2.77	0.49	0.65	0.53	1.52	1.47	4.66
Restaurants and Hotels	5.84	1.10	0.68	0.44	-0.11	0.02	2.12

Transport and Supporting Services	6.61	-0.31	0.59	1.41	1.01	-0.12	2.57
Storage	0.28	0.02	-0.06	0.05	-0.09	-0.01	-0.09
Communications	0.61	0.14	0.11	0.28	0.33	0.31	1.17
Banking, Finance, and Investment Companies	2.00	0.83	0.06	0.80	0.59	-0.01	2.28
Insurance	0.23	0.09	0.10	0.39	0.20	0.25	1.03
Real Estate, Rental, Surveying, and Miscellaneous Services	1.41	0.43	1.29	2.93	2.19	2.40	9.24
Public, Sanitary, Education, Research, Health, Business, and Related Services	8.63	1.49	2.36	-0.54	1.11	1.69	6.12
Motion Pictures and Entertainment Services	0.89	0.37	0.23	0.13	0.21	0.00	0.94
Repair Services, Laundry and Miscellaneous Personal Services	5.52	-0.97	-0.11	2.09	0.97	1.33	3.31

Table 2. Data Characteristics of 25 Industries

Year	Change in Employment Share (%)			Average Age		
	Average of absolute value	Maximum	Minimum	Overall Average*	Maximum	Minimum
1976	N/A	N/A	N/A	35.17	47.41	27.35
1981	0.76	1.90	-3.99	35.06	48.45	28.72
1986	0.65	2.36	-2.99	35.61	41.50	30.72
1991	1.05	3.09	-7.33	36.33	47.82	31.13
1996	0.86	2.19	-5.69	37.21	50.57	32.87
2001	0.60	2.40	-2.85	38.24	49.37	33.86

Note: *The overall average age is calculated as the weighted average of industry ages, with the weights based on the employment share of each industry.

Table 3. Sectoral Shifts and Worker Average Age (Dependent variable: the average age of workers in industry i at year t)

	Panel A: Independent Variable is $\Delta E_{i\ t}$				
	(1)	(2)	(3)	(4)	(5)
$\Delta E_{i\ t}$	-0.564**	-0.578*	-0.564**	-0.578*	-0.600**
	(0.244)	(0.299)	(0.253)	(0.331)	(0.265)
Industry	No	Yes	No	Yes	Yes
Year	No	No	Yes	Yes	Yes
Weight	No	No	No	No	Yes

	Panel B: Independent Variable is $\Delta \log(E_{i\ t})$				
	(1)	(2)	(3)	(4)	(5)
$\Delta \log(E_{i\ t})$	-5.448***	-3.575***	-5.003***	-2.465***	-3.528*
	(1.321)	(0.773)	(1.397)	(0.847)	(1.883)
Industry	No	Yes	No	Yes	Yes
Year	No	No	Yes	Yes	Yes
Weight	No	No	No	No	Yes

Note: Robust standard errors in parentheses. The significance levels: * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4. Sectoral Shifts and Worker Age Composition (Dependent variable: share of each age group in industry i at year t, in percentage)

	(1)	(2)	(3)	(4)	(6)
Panel A: Independent Variable is $\Delta E_{i\ t}$					
	Age 15-25	Age 26-35	Age 36-45	Age 46-55	Age > 55
$\Delta E_{i\ t}$	1.768***	0.035	-0.344**	-0.789*	-0.670*
	(0.607)	(0.357)	(0.149)	(0.401)	(0.386)

	(1)	(2)	(3)	(4)	(6)
Panel B: Independent Variable is $\Delta\log(E_{i\ t})$					
	Age 15-25	Age 26-35	Age 36-45	Age 46-55	Age > 55
$\Delta\log(E_{i\ t})$	9.815**	0.523	-1.623	-4.066	-4.649*
	(4.230)	(2.540)	(0.960)	(2.832)	(2.682)

Note: We have used weighted least squares with weights based on the industry employment share. In addition, we have also controlled for industry and year fixed effects. Robust standard errors are in parentheses. The significance levels: * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5. Sectoral Shifts and Worker Average Age for age25-55 and 30-50 (Dependent variable: the average age of workers in industry i at year t; Independent variable: $\Delta E_{i\,t}$)

Panel A: Workers Aged 25-55

	(1)	(2)	(3)	(4)	(5)
$\Delta E_{i\,t}$	-0.450**	-0.246	-0.448**	-0.241	-0.230*
	(0.171)	(0.150)	(0.174)	(0.161)	(0.125)
Industry	No	Yes	No	Yes	Yes
Year	No	No	Yes	Yes	Yes
Weight	No	No	No	No	Yes

Panel B: Workers Aged 30-50

	(1)	(2)	(3)	(4)	(5)
$\Delta E_{i\,t}$	-0.242**	-0.108	-0.239***	-0.102	-0.097
	(0.089)	(0.095)	(0.082)	(0.080)	(0.062)
Industry	No	Yes	No	Yes	Yes
Year	No	No	Yes	Yes	Yes
Weight	No	No	No	No	Yes

Note: Robust standard errors in parentheses. The significance levels: * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6. Sectoral Shifts and the Relative Wage of Young Workers (Dependent variable: logarithm of the wage of workers aged 15-35 minus that of workers aged over 35 from industry i at year t)

	(1)	(2)	(3)	(4)
ΔEi t	-0.003	-0.001	0.007	0.002
	(0.013)	(0.007)	(0.008)	(0.004)
Industry effect	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	No	No
Interactions between year and education	No	No	Yes	Yes
weight	No	Yes	No	Yes
Observations	125	125	370	370
R-squared	0.66	0.80	0.44	0.84

Note: Robust standard errors are in parentheses. Weights are based on industry employment shares. The significance levels: * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7. Timing and Growth Rates (Dependent variable: average age of workers in industry i at year t)

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta E_{i\ t+5}$	-0.590**	-0.367				
	(0.278)	(0.224)				
$\Delta E_{i\ t}$		-0.658**				
		(0.264)				
$E_{i\ t}-E_{i\ t-10}$			-0.362**			
			(0.153)			
$\Delta\log(E_{i\ t})$					-3.054*	
					(1.573)	
$\Delta\log(E_{i\ t+5})$				-3.809*	-2.301*	
				(1.922)	(1.305)	
$\log(E_{i\ t+5})-\log(E_{i\ t-5})$						-2.718**
						(1.243)
Observations	125	100	100	125	100	100
R-squared	0.68	0.75	0.83	0.7	0.75	0.75

Note: We have used weighted least squares with weights based on the industry employment share. In addition, we have also controlled for industry and year fixed effects. Robust standard errors are in parentheses. The significance levels: * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8. Analysis by Sub-groups (Dependent variable: average age of workers in each sub-group in industry i at year t)

		$\Delta E_{i\ t}$	
		Coefficient	Standard error
(1) Education Groups	No schooling	-0.321	(0.34)
	Primary	-0.669**	(0.251)
	Lower secondary	-0.578**	(0.217)
	Upper secondary	-0.223	(0.154)
	Matriculation and non-degree	-0.192	(0.201)
	College and above	-0.386	(0.254)
(2) Gender	Male	-0.464***	(0.167)
	Female	-0.533	(0.365)

Note: We have used weighted least squares with weights based on the industry employment share. In addition, we have also controlled for industry and year fixed effects. Robust standard errors are in parentheses. The significance levels: * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9. Industry-Occupation Mix (Dependent variable: average age of workers in the relevant cell)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent	Age ($O_{j\,t}$)	Age ($IO_{i\,j\,t}$)	Age ($IO_{i\,j\,t}$)	Age ($IO_{i\,j\,t}$)	Age ($IO_{i\,j\,t}$)	Age ($IO_{i\,j\,t}$)
$\Delta O_{j\,t}$	-0.219***					
	(0.075)					
Industry-occupation cell $\Delta IO_{i\,j\,t}$		-0.166***	-0.173***			
		(0.032)	(0.048)			
$\Delta Ind_{i\,t}$				-0.383**		-0.334**
				(0.168)		(0.156)
$\Delta Occ_{j\,t}$					-0.105***	-0.078***
					(0.023)	(0.026)
Industry-occupation cell dummies	No	Yes	No	No	No	No
Industry dummies	No	No	Yes	Yes	Yes	Yes
Occupation dummies	Yes	No	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130	280	280	280	280	280
R-squared	0.88	0.89	0.79	0.79	0.79	0.80

Note: Weighted least squares estimation is used with the weights based on the employment share of each cell. Robust standard errors are in parentheses. The significance levels: * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix Table 1. Recoding the Industry Variables according to the Codebook of Census Data

industry	1976	1981	1986	1991	1996	2001
Agricultural Products	110-116	110-118	11-16,	1	110	110
Marine Fishing & Fishery Products	120-127	120-129	17	2	120	120
Mining and Quarrying	210-212	210-212	18	3	210	210
Food, Beverage and Tobacco Industries	310-315	310-315	21	31	310	310
Manufacturing of Wearing Apparel, Leather and Textile Goods	320-346	320-346	22-31	32-34	321	321
Manufacturing of Wood and Cork Products, Furniture and Fixtures	350-351	350-351	32	35	330	330
Manufacturing of Paper and Paper Products, Printing, Publishing	360-361	360-361	33	36	340	340
Manufacturing of Chemical Products, Coal and Plastic	390-392	390-393	39	37,38,41,42	350,360,390	350,360,390
Manufacturing of Basic Metal Industries	370-376	370-376	34	39	370	370
Manufacturing of Machinery, Equipments, Parts and Components	380-387	380-387	35-38	40	381	381
Electricity, Gas and Water	410-420	410-420	41	4	410	410
Construction	510-512	510-512	51-52	51	500-600	500-600
Wholesale	610	610	61	61	610	610
Retail	611-613	611	62-64,	62	620	620
Import / Export	614-615	612-613	65	63	630	630
Restaurants and Hotels	620-621	620-622	66-69	64	650	650
Transport and Supporting Services	710-716	710-719	71-76	71	710	710
Storage	720	720	77	72	720	720

Communications	721	721	78	73	730	730
Banking, Finance, and Investment Companies	810	810	81-82	81	810	810
Insurance	811	811	83	82	820	820
Real Estate, Rental, Surveying, and Miscellaneous Services	812-821	812-821	84-85	84	830	830
Public, Sanitary, Education, Research, Health, Business, and Related Services	910-914	910-917	90-95	91	910,920,930	910,920,930
Motion Pictures and Entertainment Services	920-923	920-923	96	94	941	941
Repair Services, Laundry and Miscellaneous Personal Services	930-935	930-936	97-98	95	950	950

Figure 1. Sectoral Shifts and the Age Structure of Workers

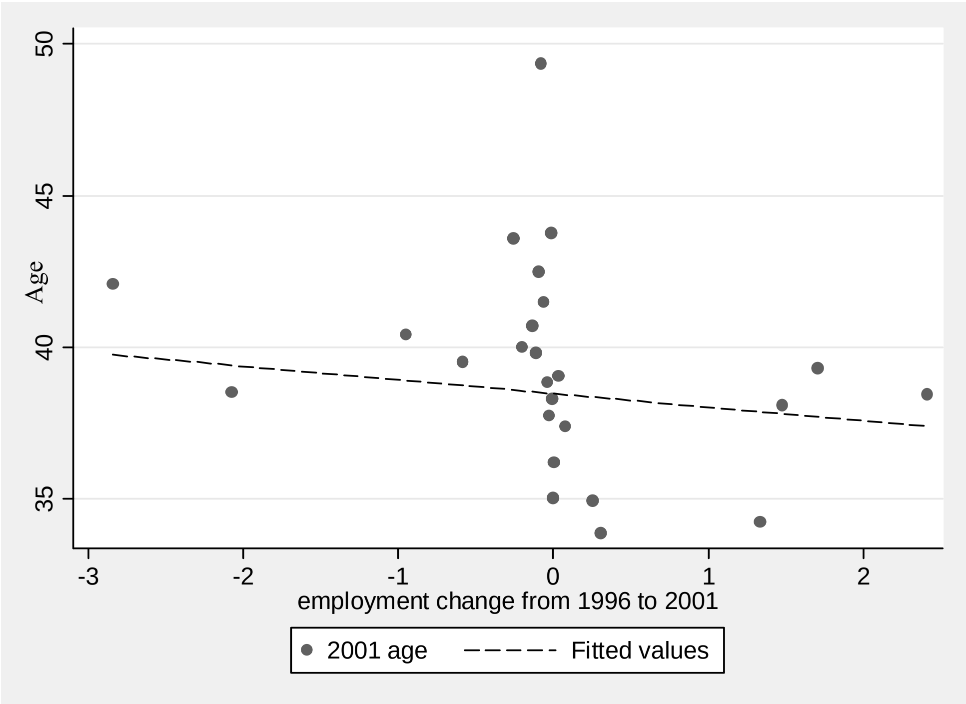

Figure 2. The Relationship between Industry Growth from 1981 to 1986 and the Consequent Unemployment Rate in 1986