Who Benefits from Firm Growth? An Analysis of Technology Effects on Job Turnover

Jing Chen

Department of Economics

Florida International University

October 2007

Abstract. Motivated by the previous empirical finding that white-collar workers had higher turnover rates than blue-collar workers during firm expansion, this paper further examines job turnover among workers with or without specific skills when firm growth is driven by technology upgrading. To induce the intuition, I first present a simple search-matching model, which predicts that when firm growth is driven by technological advance, workers whose skills are specific to the obsolete technology show a higher tendency to separate from their jobs. This hypothesis is tested with an individual-level data set constructed from the Panel Study of Income Dynamics. There I find supportive evidence that in the context of industry-wide technological change, being on an occupation requiring specific skills, such as computer specialists, engineers, or professional workers, increases the odds of job separation by nearly eight percent.

JEL Classification codes: 24, 63

Keywords: **Technological change, turnover, specific skill**

***** Department of Economics, Florida International University, Miami, FL 33199. Email: jchen002@fiu.edu.

This paper is Chapter 2 of my dissertations. I am grateful to Peter Thompson for invaluable assistance and encouragement. I am also indebted to Jungmin Lee, Dmitriy Krichevskiy, and Travis Letellier for helpful discussions and editorial advice.

1. Introduction

A conventional wisdom regarding human capital and labor mobility suggests that high-level workers should have more stable employment. The reason is straightforward. High-level jobs are often thought to have more technology elements and higher requirement for (firm-) specific human capital. As articulated in human capital theory, workers acquire firm-specific human capital by investing in specific training on the job. They then earn higher wages than they could receive in any other firm because of greater productivity resulting from the stock of human capital. Meanwhile, their investment in firm-specific capital is of no use somewhere else. Considering these two aspects, a rational worker would be less likely to quit his job, the more firm-specific capital he has accumulated (Becker (1962), Moretensen (1978), Jovanovic (1979)). Empirical literature also provides supportive evidences. The most stylized fact is the negative relationship between job turnover and job tenure with the latter being positively related to the accumulation of specific human capital. Earlier studies also observe higher turnover rates for the low-level production workers (Jovanovic and Mincer (1978)). In addition, Topel and Ward (1992) document that worker-firm separation is less likely to occur on jobs with high wage-growth than on those with low-wage growth.

Regardless of these consistent findings, there are two exceptions in the recent studies. Dohmen and Pfann (2004) investigate a personnel dataset based on a Dutch aircraft firm and find that white-collar workers are more likely to quit jobs than their blue-collar counterparts during the demand-driven expansions of employment. A similar phenomenon, documented by Lazear (1999), is at play in a financial services company where higher level workers tend to separate from the firm more often. Both findings are at odds with the conventional view discussed above. This paper does not intend to generalize these results, for they may be specific to the individual firms. Instead, the purpose of this paper is to suggest some explanations on this atypical labor mobility pattern in the context of the existing human capital and search theories.

One essential element in this line of research is firm-specific human capital. It is accumulated through on-the-job-training and is only valuable within the firm. A direct result is that the worker's wage in the current firm, which is often equal to his marginal productivity, is an increasing function of the stock of firm-specific human capital. In contrast, the worker's outside offer has little to do with how much firm-specific human capital the worker accumulates in the current firm. Since separation occurs only if the value of the outside offer exceeds the value of the current job, it is easy to see that workers with more firm-specific capital are less likely to quit. Compared to firm-specific human capital, workers with general capital do not have such constraints. When outside wage rises, they have greater tendency to leave for another job because the human capital they have are equally valued elsewhere. In addition to firm-specific and general human capital, there is a third type of human capital in between. As Becker (1962) points out, some on-the-job-trainings are neither applicable in all firms nor exclusively useful in a single firm. Instead, they are specific to an industry or an occupation. Other studies also argue that few skills are really exclusively used in one specific firm and then become useless elsewhere. Most human capital and skills are occupation-specific (Kambourov and Manovskii 2005), task-specific (Gibbons and Waldman 2003), or industry-specific (Neal 1995). Following this idea, if a worker's skill is industry-specific, the amount of increase in the worker's marginal productivity due to the accumulation of specific capital is the same elsewhere in the industry. This new condition increases the worker's incentive to quit for two reasons: first, if he quits, he can find a similar job somewhere inside this industry without incurring any loss for the investment in human capital; second, he now has more bargaining powers on wage. If the current firm does not pay enough to the worker, there is always a chance for him to receive better payment somewhere else. In this sense, workers with specific human capital may have as high turnover rate as those with general capital. Relating this last point to high-level workers, we can show that high-level workers do not always have lower rate of separation as long as their human capital is not firm-specific. In reality, we see many cases in which specific skills are transferable across firms or even industries. A typical example is Silicon Valley. Saxenian (1994) document that job tenures for computer professionals in Silicon Valley is on average two or three years. Not only did these engineers moved frequently between firms, but some became venture capitalists, bringing their technical skills and experience to ventures they funded.

As we have seen so far, skill transfer alone is not sufficient enough to interpret why high-level workers may exhibit higher turnover rates. To see how this happens, we need another input, firm growth. Firm growth can be driven by two forces: demand expansion and technology advancement. In the first case, if demand increase is temporary, the firm needs to hire more low-level production workers just to meet the rising demand. Thus, there is really no incentive for either high-level or low-level workers to quit jobs, or for the firm to fire workers. If the increase is widespread in the whole industry, for example, a cyclical demand increase, the firm needs an expansion of employment of both types of workers. Intuitively, the demand for high-level workers (such as technical workers, professional managers) is particularly competitive because of the high productivity and the limited amount of supply. This may explain why Dohmen and Pfann (2004) find that white-collar workers in the Dutch aircraft firm are more likely to separate from their workplace in the period of employment expansion but less likely to leave during the following contraction.

In this paper, I only focus on technological change as the driving force of firm growth. For the help of intuition, let us first consider a simple story. There are two groups of workers in the firm: blue-collar workers and white-collar workers. Within both groups, workers differ in how specific their skills are to the technology used by the firm. For instance, both blue-collar technicians and white-collar engineers have skills specific to a certain technology currently adopted by the firm, though the degree of specificity may vary. In contrast, skills of low-level assemblers or office secretaries are more general and less attached to any specific technology. An important assumption here is that skills are specific at the industry level. This assumption has a direct implication. That is, if a worker who has the specific skill leaves the current firm, he can find a similar job somewhere else within the same industry. Job separation occurs if the outside offer exceeds the worker's current wage, which is assumed to be an increasing function of the worker-firm match. Here I follow Jovanovic (1996) and assume that technology upgrading in the firm has little impact on the match quality for workers with general skills, but it decreases the match quality for those with specific skills. The underlying reason is that general skills can be transferred freely from one technology grade to another, while specific skills do not have this flexibility. Therefore, the higher is the degree of specificity, the greater the loss in expertise and match quality. As a result, these workers will choose to leave and work for another firm in the same industry, where their skills are still valuable. Their positions in the old firm will then be replaced with those who are skilled at the latest technology. In contrast, workers whose jobs involve little specific skills would prefer to stay with the firm and benefit from its growth. Thus, the story predicts that workers with technology-specific skills have higher turnover rates in the presence of technological advancement. This hypothesis receives more support in the theoretical context of Chari and Hopenhayn (1991) and Jovanovic (1996). Both studies suggest that the worker will hardly switch to the new technology if he is very skilled at the old one.

In the second part of the paper, this hypothesis is tested with data from the Panel Study of Income Dynamics (PSID). The data set consists of 7285 household heads who were employed workers at the time of survey. The observation period spans 1981 to 1987. One problem with using the PSID is that there is no information on firms. Because of this data limitation, I am not able to observe technological change at firm level, and therefore cannot directly test whether or not workers with specific skills are more likely to separate from jobs when firms are experiencing technological change. A compromising way is to look at industry-level data. The idea is that given the industry is on average experiencing technological change, according to what the model predicts, we would expect to see higher rates of turnover among workers with specific capital who left the previous firms because of technology upgrading and moved to firms which have not caught up with the new technology. Thus, the main focus of this analysis is to see how technological change in industries affected these workers' employment choice. Especially, how these choices differ among workers with different types of skills? The dependent variable, which indicates a worker's employment choice in the current survey year, is constructed based on the PSID's employment history data. Depending on the certain regression, this variable is either a dummy variable which equals 1 if a worker quit previous job, or a categorical variable which takes the value of 1 if a worker stayed at the same job, 2 if he was laid off, and 3 if he quit the previous job. While there is no direct measure of skill specificity, I take the conventional approach by focusing on each individual's occupation. In the data set, a worker is defined as having skills specific to a certain technology if his occupation falls into one of the three categories: engineers and computer specialist, professional workers, or managers. Technological change is measured by productivity growth per production worker in each industry. The data come from the Bureau of Economic Analysis (BEA).

The analysis proceeds in three steps. First, I run a multinomial logit regression of employment choice on a dummy variable for being a worker with specific capital on the previous job, *specific*, and its interaction with productivity growth, *vaskill*. Observed heterogeneity such as demographic characteristics and previous industry categories are controlled in the regression. The results show that workers with specific skills in general have relatively stable employment, which is consistent with previous findings. However, when technological change is considered, workers with specific skills exhibit higher probability of quitting the jobs, which supports the prediction in the model. This result remains significant even after I control for the unobserved heterogeneity, which is approximated by the number of previous turnover.

Second, I run a conditional logit regression in order to control for individuals' fixed effects. The categorical dependent variable in the previous multinomial logit model is replaced with a dummy variable which equals one if a person quit the previous job. Both variables of interests (*specific* and *vaskill*) obtain expected signs, but the estimated coefficient on *vaskill* is not statistically significant. The most possible reason for obtaining the insignificant result is that 70 percent of total observations dropped in the conditional logit regression because of all positive or negative outcomes.

To avoid the problem of losing so many observations, the final analysis examines the linear probability model. With controls for individuals' observed and unobserved heterogeneity, the results again show that in the presence of technological change, being a worker with specific skills increases the chance of quitting by eight percent. The result is significant at 5 percent level.

The organization of the paper is as follows. Section 2 is the theoretical part of the paper. In this section, I present a simple match-searching model incorporated with technology upgrading, which generates some testable implications. Empirical tests on these implications are taken up in Sections 3 and 4, where I describe the data set and report the results from three main regression models. The final section concludes the paper.

2. The Model

All search and separations in the model are assumed to be initiated by the worker. The worker's wage at time t depends on the firm's technology level at that time (y_t) and his employment match with the firm in terms of skill. Define skill match as the difference between the worker's skill at job i (z_i) and the skill required on job i at time t (x_{it}). Thus, the wage function for job i at time t can be characterized as

$$w_{it} = y_t - (x_{it} - z_i)^2 \tag{1}$$

It is easily to see in equation (1) that on the one hand, the worker benefits from working for a firm at a higher technological level (w_{it} increases in y_t); on the other hand, his wage falls if his skill on the job does not match with the skill required by the firm. Mismatch happens in two cases: disqualified and overqualified. If a worker is disqualified, his skill level is below the required level. Conversely, an overqualified worker's skill is too advanced for the skill currently needed in the firm. Both of these cases would negatively affect his productivity on the job, therefore are treated equally in the model.

Firm's technological change follows

$$y_t = (1 + g_t)y_{t-1} \tag{2}$$

where the rate of change at time $t(g_t)$ is a serially correlated random variable, i.e. the change rate of technology in next period, g', is drawn form $F(g'|g)$, and $\partial F(g'|g)/\partial g \leq 0$.

Skill required on the job i in two consecutive years satisfies the following condition

$$x_{it} = x_{it-1} + \varepsilon_{it} \tag{3}$$

where $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2 g_t \alpha_i)$. According to equation (3), given the previous requirement of skill, the current requirement of skill is expected to be consistent with its previous level ($E(x_{it} \mid x_{it-1}) = x_{it-1}$). A deviation ($var(x_{it}|x_{it-1}) = \sigma_\varepsilon^2 g_t \alpha_i$) can be caused by the rate of technological change (g_t) or the variable $\alpha_i \in [0,1]$. α_i measures the responsiveness of skills required on job *i* to technological change. A higher value of α_i indicates a higher requirement for skill adaptation to new technology.

Consider a two-period model: t-1 and t. In period t-1, there is technological change occurring in the firm. As a result, the skill required on job *i* is upgraded to x_{t-1}, which, by assumption, is not observable to the worker until the end of this period.

At the end of period t-1, the worker needs to make a stay-or-leave decision, which would be based on the expected match between his skill and the skill required on the job in period t. Given the requirement in period t-1, x_{t-1}, we can rewrite wage function (1) as

$$w_{it} = y_t - E_{t-1}(x_{it} - z_i)^2, \tag{4}$$

where x_t denotes the skill required on job *i* in period t. Substituting (2) and (3) into (4) yields

$$w_{it} = (1 + g_t)y_{t-1} - \sigma_\varepsilon^2 g_t \alpha_i - x_{it-1}^2 + 2z_i x_{it-1} - z_i^2 \tag{5}$$

It is easy to see from equation (5) that if the worker maximizes his expected wage by improving his skill (z_i), he would improve it to x_{it-1}, the skill required by the firm in period t-1.[1]

In period t, if the worker stays at the firm, he would keep this skill level, x_{it-1}, over the period. This is because that he does not observe any change of skill requirement due to possible technological progress until the end of period t. Substituting $z_i^* = x_{it-1}$ into (5), we have

$$w_{it} = (1 + g_t)y_{t-1} - \sigma_\varepsilon^2 g_t \alpha_i$$

Differentiating both sides of the equation with respect to g_t gives

$$\frac{dw_{it}}{dg_t} = y_{t-1} - \sigma_\varepsilon^2 \alpha_i^2 \tag{6}$$

Proposition 1 *w_{it} is increasing in g_t if $\alpha_i < \frac{y_{t-1}}{\sigma_\varepsilon^2}$, and decreasing in g_t, if otherwise.*

Proposition 1 has an implication for two types of jobs: jobs employing specific technical skills and jobs using regular skills. Workers associated with the former type of job vary from production workers, technicians to R&D researchers. As the set of skills needed on these jobs is more responsive to technological change (higher α), there expects to be a larger variance between the skill required in period t-1 and that required in period t. We can easily see from equation (5) that this would increase the expected mismatch in period t, even if the worker improves his skill to x_{t-1} at the end of period t-1. In turn, the expected wage on these jobs decreases as technological change accelerates. Conversely, for workers associated with the latter type of job—ranging from unskilled blue-collar workers to low-level office workers, the rapid change of technology increases their wage for skills required on those jobs are hardly affected by new technology. There are two things worth noting. First, as a benchmark, technological change has no impact on wage if $\alpha_i = y_{t-1}/\sigma_\varepsilon^2$. The fact that the threshold value of α_i increases in y_{t-1} and the wage

---

[1] $w_t^* = \max(1 + g_t)\, y_{t-1} - \sigma_\varepsilon^2 g_t \alpha_i - x_{it-1}^2 + 2z_i x_{it-1} - z_i^2$. The first order condition gives $z_i^* = x_{it-1}$. Notice that If the worker is overqualified, he would choose to keep his original skill.

decreases in g_t if $\alpha_i > y_{t-1}/\sigma_\varepsilon^2$ implies that firms at lower technological level (y_{t-1}) have more jobs which are vulnerable to technological change.

Second, the worker's skill, z_i, does not appear in equation (6). This implies that being overqualified on the job would not influence the worker's expectation of future match quality[2]. In the model, the only crucial factor that matters to the expected quality of future match is the responsive variable α_i. Therefore, technology growth may still cause a decrease in an overqualified worker's wage, in spite of the possibility that overqualified skills might become more valued during technological change.

Based on the above specification, let us now consider a simple search story. Firm growth is achieved by the adoption of new technology. Technological change in the firm affects the worker's wage through productivity growth (due to the adoption of new technology) and the change of employment match between the worker and the firm. Every period, the worker receives an offer outside the firm. The dynamic problem facing the worker is to decide whether to quit the job and accept the outside offer at the end of each period. If he stays, the value of working through the next period is $V(g')$ considering next period's technological change. Otherwise, he would earn Q by quitting. Since searching is random, it is convenient to assume that the value of quitting, Q, is constant for all new offers. Let $V(g)$ be the value of working in a firm where technology changes at the rate of g, then with a discount factor of β, the Bellman equation for the worker is

$$V(g) = w(g) + \beta \, Emax\,(V(g'), Q) \tag{7}$$

The existence of a unique solution $g*$ to equation (7) can be proved by following the standard way in the literature. The analysis below is broken down into two cases regarding the type of job.

2.1 Case 1: Jobs associated with specific technical skills

It is shown in the appendix that when w is decreasing in g, there is a unique solution to the optimal problem in (7), and $V(g)$ is strictly decreasing in g. This yields the following proposition:

Proposition 2 *The optimal stopping problem has a unique solution*, $g*$, and $V(g^*) = Q$. *In the case where* $w(g)$ *is decreasing in g*, *staying is preferable when* $g < g^*$ *and quitting is chosen when* $g \geq g^*$.

PROOF. See Appendix

The reservation equation is

$$Q = [1/(1-\beta)]w(g^*) - [\beta/(1-\beta)] \int_0^{g*} F(g'|g^*) V_{g'}(g') dg' \tag{8}$$

where $V_{g'}(g') < 0$. Differentiating equation (9) with respect to α gives

---

[2] As shown in equation (3), the expected requirement of skill in period t, x_t, given that in period t-1, x_{t-1}, is still x_{t-1}.

$$\left[y_{t-1} - \sigma_\varepsilon^2 \alpha - \beta \int_0^{g*} V_{g'}(g') \frac{\partial F(g'|g*)}{\partial g*} dg'\right] \frac{dg*}{d\alpha} = \sigma_\varepsilon^2 g^* \tag{9}$$

To see the first term on the LHS of equation (5) is negative, note that y_{t-1} is less than $\sigma_\varepsilon^2\alpha$ when $dw/dg < 0$. Moreover, $F(g'|g)$ and $V_{g'}(g')$ are decreasing in g' by assumption. Thus, $dg^*/d\alpha < 0$. Since $V(g)$ is decreasing in g, this result means a worker facing a higher α would choose to quit the job even at a low reservation growth rate (g^*). In this case, it indicates a higher probability of quitting for technology workers whose job are related to the latest technology, as they face a higher value of α. In this sense, workers who specialize in high-end production (the white-collars) tend to have a higher probability of quitting than those employed at low-end assembly work (the blue-collars). This leads to prediction 1.

Prediction 1. *During technological change, the more technology-intensive the worker's skill, the more likely he is to quit his jobs.*

2.2 Case 2: Jobs associated with nonspecific skills

Proposition 3 T*he optimal stopping problem has a unique solution,* g^*. *In the case where* $w(g)$ *is increasing in* g, *staying is preferable when* $g > g^*$ *and quitting is chosen when* $g \leq g^*$.

PROOF. See Appendix

It is shown in the appendix that when $w(g)$ is increasing in g, $V(g)$ is increasing in g as well. As specified in the model, if the worker chooses to stay in the firm for the current period, it implies that $V(g) > Q$. Since firm growth is characterized by the increasing rate of technological change, $V(g')$ is greater than Q as well. This indicates that workers with α lower than a threshold (*i.e.*,$y_{t-1}/\sigma_\varepsilon^2$) would always prefer to stay in a growing firm.

Prediction 2. *Workers with nonspecific skills prefer to stay in the firm with increasing technological growth.*

3. Data

3.1 Data Sources

The data are from the Panel Study of Income Dynamics (PSID), a longitudinal survey of a representative sample of U.S. individuals and their families. The advantage of using individual-level data is that it provides an opportunity to address the issue of labor turnover across different industries. It is reasonable to believe that a pattern prevalent in an industry can also be observed in individual firms.

Among the special public-release files in the PSID, the work-history file contains complete information for individuals about all of their spells of employment, including employment status, occupation, industry, etc. Combining these variables with a few identifiers allows us to track individuals' employment history.

Since primary data on technological change is not available, productivity growth per worker in each industry (*value-added GDP / number of production workers*) is used as a proxy for technological change. The Bureau of Economic Analysis (BEA) compiles industry economic accounts; from here I obtain the data needed for the above ratio.

One potential problem relating to the data is that it does not provide firm-specific but industry-specific information while the model develops a relationship between worker turnover and firm growth. However, this problem turns out to be harmless to the analysis. For instance, the turnover of white-collar workers can be observed in four scenarios: first, white-collar workers from firms at higher technological level leave for firms at low technological level; this flow can also be reversed for overqualified workers; third, workers left the industry; finally, both white-collar and blue-collar workers are forced to leave firms which are driven out of the market. The last scenario does not exist in the data, for observations of job separation due to firm closure is not considered as quit, and are removed from the dataset. Without firm-level data, an exact turnover pattern cannot be observed in a particular firm. However, with industry-level data, we can observe the turnover of white-collar workers in the industry, which is the overall flow of white-collar workers in this industry. Since the study is interested in the magnitude of turnover rather than the direction, industry-level data should be qualified for serving the purpose of this empirical test.

3.2. Data Construction

This section describes how the dataset is constructed to test the predictions of the model. One way to extract data from PSID is by selecting variables of interest for given years. There are two types of variables in PSID: family-level variables related to family records (along with other topical categories such as work history) and individual-level variables with information about individuals (such as age, gender, and educational attainment). Additional variables are also available for identifying each individual.

I first choose nine variables related to employment from the family-level variables. These include 1968 FAMILY ID, LOCATION, INDUSTRY OF PRESENT MAIN JOB, PRESENT OCCUPATON, COLLEGE DEGREE, HPND PREV JOB (HD-E), HPND LST JOB (H-U), EMPLMT STATUS, and MOS THIS JOB. Three other variables—1968 PERSON NUMBER, GENDER, and AGE—are selected from the individual-level variables. The combination of 1968 FAMILY ID and 1968 PERSON NUMBER constitutes the unique identifiers for individuals. The variables HPND PREV JOB (HD-E) and HPND LST JOB (H-U) are based on individuals' responses to the question about what had happened to their previous jobs. Eight possible categories for the response are created. The first variable is for household *heads* who were currently employed; for this, the data are available from 1968 to 1987. The second variable applies to household *heads* who were currently unemployed; these data span 1969 to 1993, and then every other year from 1999 to 2005. As data on most selected variables are only available after 1980, the whole sample with the selected ten variables was restricted to the period 1981 to 1987.

There is one concern with the dataset. The variables relating to employment have data only for household *heads* and *wives*. Other family members do not have their own records for these variables, instead they are automatically assigned the values belonging to the household *heads*.

An analysis based on this dataset will be prone to error since data applied to *heads* or *wives* would be mistaken if used for non-*head* individuals. To avoid this problem, I restrict the data sample to household *heads*.

A. Selection of household *heads*

Table 1 illustrates how my dataset is generated. The original sample is composed of eight subsamples for each year from 1981 to 1987. PSID provides two individual-level variables that together indentify household *heads* in the current year. One variable is RELATIONSHIP TO HEAD, which describes the individual's relationship to the head of his family in a given wave. The household head from the current or previous year is coded "1" from 1981 to 1982, and it is coded as "10" since 1983. The other variable is SEQUENCE NUMBER, which identifies an individual's presence in each wave. An individual who was present in the family during the interviewing year is coded "1". In each sample, I use list-wise deletion to remove observations with a code not equal to "10" (or "1" for years 1981 and 1982) for the RELATIONSHIP TO HEAD variable, as well as observations with a code not equal to "1" for SEQUENCE NUMBER. This leaves a total sample of 9423 individuals who were current household *heads* in each wave.

B. Laid off and Quit

A job move is identified by the variable MOS THIS JOB, which represents the number of months an individual had been at his present job. The value of this variable is in the range of 0-999. A code of 0 refers to people who were not in the labor force (*i.e.*, unemployed, permanently disabled, retired, housewife, or student), and a code of 999 corresponds to data not being available. A person is identified as staying with the same job if MOS THIS JOB ≥ 12; MOS THIS JOB < 12 implies that at least one job change occurred during the year.[3]

To determine whether a job change occurred as a voluntary quit or a lay-off, I use the variable HPND PREV JOB for currently employed household *heads* and HPND LST JOB for currently unemployed household *heads*. Among the eight possible categories, category 3 refers to lay-offs, and category 4 includes voluntary quits, resignations, retirements, and other various types of separations.

In this paper, quit is defined as leaving for another job. This implies that a person would still be working after he quits his previous job. Under this definition, the entire sub-sample of unemployed household *heads* does not qualify to be included in my analysis of quits. This exclusion does not apply in the analysis of lay-offs. However, in PSID, there are no industry or occupation data available for the unemployed. Given these constraints, I choose to focus on

[3] • PSID data collection for a given wave starts from March through September. So it's quite possible that the person who had the present job for less than 12 months actually changed his last job in a year before. To avoid the confusion, this job change would still be accounted as change happening in the present interview year. As the data collection procedure is the same for each year, the consistency can be reserved.

• Since PSID data collection process is conducted only once in a year, there is no variable in PSID that can record all job changes that an individual had in each wave. Therefore, if an individual had changed more than one jobs in one year, the current dataset can only capture the last one.

currently employed household *heads*, and I exclude the sub-sample of unemployed from the empirical analysis.

As discussed above, category 4 alone cannot be used to identify the occurrence of a quit. Therefore, I use the variable EMPLMT STATUS to preclude the other reasons for turnover listed in category 4, as well as to ensure that people who quit were currently working. Observations on people who voluntarily quit their previous jobs but were currently unemployed were removed from the sample. Analogously, the observations on people who did not quit (but were neither currently working nor temporarily unemployed) were also eliminated. In the end, I am left with a sample of 7285 currently employed household *heads*.

Finally, the dependent variable CHOICE equals 1 if a person stayed with the same job, 2 if he was laid off from the previous job, and 3 if he quit his last job.

C. Industry and Occupation Dummies

Variables on industry and occupation for present jobs are selected from the PSID family-level set. These two variables are coded using the 3-digit code of industry and occupation from the 1970 Census of Population. A categorical variable with thirteen values is generated for the industries[4]. Industries such as agriculture forestry, fishery, and public administration were excluded from the analysis because of their weak linkage to firm growth and technical change. From the remaining industries, eleven dummy variables (indy1-11) were generated. Analogously, for the occupation data, a categorical variable consisting of nine values was created[5]. Nine occupation dummy variables (ocp1-9) were thus obtained. Observations with undefined industry or occupation were removed from the sample. The final sample consists of 6700 individuals.

Table 2 provides demographic statistics for the sample. Seventy-four percent of the sample is male, 50% is under 35 and about 20% has a college degree. Among the observations for males, 52% percent reported no change in jobs, contrasted with 38% for female. This difference is consistent with the stylized facts in the literature that women tend to have more unstable employment than men. However, this variation can also be attributed to the larger proportion of missing values of employment choice among female workers. The data also show that turnover rates are decreasing in age. Of the sample aged 55 years and above, 86% percent chose to stay at their current employment, compared to only 77% of the sample under age 35. On the contrary, merely 4% of the over-55 sample quit jobs; that number increases to 17% for the under-35 sample. Eighty-six percent of the sample that reported having a college education stayed with the same jobs, implying that people with a college education generally have more stable employment.

---

[4] These values refer to agriculture, forestry, and fishery; mining; construction; manufacturing; transportation and warehousing; information; utilities; wholesale and retail trade; finance, insurance, and real estate; professional, business, education, and health services; entertainment and recreation; other services including repair, personal services, membership association; and public administration.

[5] These include computer specialists and engineers; professional and kindred workers; managers and administrators; sales workers, clerical, and kindred workers; craftsman and kindred workers; operatives, laborers, and farmers; and service and private household workers.

Table 3 presents summary statistics about the industries and occupations included in the sample. Half of the sample is from industries such as manufacturing; professional business, education, and health services; as well as wholesale and retail trade. The other half is distributed among the other eight industries.

Most of the high-rank technical or managerial occupations are embodied in categories 1, 2, or 3, which account for 30% of the sample. These three occupations are then combined into one single variable, *specific*. This variable takes on the value of 1 if the occupation observation falls into one of these categories; it is zero otherwise.[6]

4. Results

4.1 The Multinomial model

Greene (2002) and Kennedy (2003) discuss two different logit models for multiple choices: the multinomial logit and the conditional logit. The former is used if the data have information on characteristics of individuals while the latter is preferred if the data have choice-specific attributes which are identical to all individuals. As put forth in the data description section, most variables in the dataset are individual-specific (such as age, gender, education, and occupation). An exception is the variable on the growth rate of industry. However, since it is used to interact with an individual's occupation variable, the interaction variable is still individual-specific. Thus, the multinomial logit model is chosen for the regression on the three employment choices: staying, being laid off, and quitting. A Hausman test shows that these three choices are not close substitutes, which ensures that the assumption of independence of irrelevant alternatives (IIA) holds.

In order to capture the interaction effect between technological growth and specific technical skills, an interaction variable (*vaskill*=*VA***specific*) is generated. Another interaction between technological change and college education (*vacolg*=*VA***COLG*) is generated in the similar way. The collinearity between these two interaction variables could be a concern. As the majority of workers associated with technology-specific jobs may have college degrees, these two variables are likely to be positively correlated. To examine how serious this problem could be, I first test the collinearity between *vaskill* and *vacolg* through correlation coefficients. The correlation coefficient between the two variables is -0.34 for the choice of being laid off and -0.45 for the choice of quitting. Kennedy (2003) suggests that a correlation coefficient of 0.8 – 0.9 in absolute value indicates a high correlation between two independent variables. Compared to this threshold, the correlation coefficients between the *vaskill* and *vacolg* are quite low.

The multicollinearity between all independent variables in the model—except dummy variables for industries and years—is examined through the use of the correlation matrix in the linear

[6] The final variable (*VA*) in the analysis is a proxy for technological change, given by the growth of productivity per worker (from 1981-1987). Its construction is as follows. Productivity per worker is obtained by dividing annual value added GDP by the number of production workers in each industry.

regression model. According to the literature, muticollinearity exists if the largest variance inflation factor (*VIF*) is greater than ten, and the mean of all the *VIF*s is considerably larger than one. The result shows that the highest *VIF*, 6.7, is the one that is associated with the interaction variable *vacolg*. The mean of all the *VIF*s is 3.72, which is not considerably larger than one. Therefore, I speculate that multicollinearity need not be a concern in the present model.

Table 4 reports the results from the multinomial logit regression. The dependent variable CHOICE equals 1 if a person remained at his job, 2 if he was laid off, and 3 if he quit. The choice of staying is used as the base alternative. The coefficients on the occupation dummy (*specific*) are negative and significant for choices 2 and 3. The computation of marginal effects indicates that compared to the choice of staying, having a technology-intensive job reduces the probability of being laid off by 4.1% and the probability of quitting by 3.7%. If productivity growth is considered, however, the technological intensity of a job becomes an irrelevant factor in determining whether a person would stay in the firm or be laid off (the result for the variable *vaskill* is insignificant). Intuitively, when the firm is going through a bad time, both skilled and unskilled workers face the possibility of being laid off. Analogously, when the firm is growing, the demand for both types of workers will increase.

Nonetheless, as for the choice of quitting, the degree of specificity in skills does seem to matter during technological change. As shown in the last column of Table 4, having a higher-rank technical or managerial job (*i.e.*, a job belonging to one of the first three occupation categories) increases the probability of quitting by 28%. This result supports the prediction of the model that during firm growth, white-collar workers whose jobs are associated with sophisticated technology (technology professionals in occupation categories 1 and 2) are more likely to quit than regular technical workers. It also indicates that even if the tasks performed by workers are not directly related to technology in production, higher-rank jobs are more susceptible to technical change. This explains why managers and administrators in category 3 show higher odds of quitting than lower-rank sales or clerical workers in categories 5 and 6.

Columns 1 and 2 in Table 5 present the results from the multinomial logit regression after controlling for individuals' observed heterogeneity—age, gender and education. In columns 3 and 4, an additional variable (number of previous turnovers) is added to control for the unobserved heterogeneity of individuals. It turns out that there are no substantial changes to the basic results even after controlling for the heterogeneity of individuals. In general, the technological intensity of a job does affect a worker's employment choice between staying or being laid off. But this factor becomes much less important in the presence of productivity growth. In contrast, during growth, the probability of voluntarily leaving a job increases by 31.8% if the job is technology-intensive. Age has negative effects on the probability of being laid off or quitting, which is consistent with the fact that older people or people with longer tenure prefer to have stable employment. Male workers have a stronger tendency to quit a job than female workers. People with college education are 1.7% less likely to be laid off, but 2.8% more likely to quit. Experiencing a previous turnover in a career increases the probability of being laid off by 1.1%, and the probability of quitting by 3.3%.

The results regarding education are more subtle. On the one hand, it shows that without growth, people with college education are 1.7% less likely to be laid off, but 2.8% more likely to quit. This should not be surprising since people with college education are expected to have more human capital. Conversely, when the variable of college education interacts with productivity growth, its effect on job turnover becomes insignificant. This implies that when firm growth is considered, whether or not an individual possesses a college degree does not affect his choice between staying and the other two alternatives. One possible interpretation is that in general, people with a college degree have more opportunities in the market. Therefore, they are less likely to be laid off; at the same time, they have more incentive to leave whenever they feel unsatisfied at the current job. If the firm experiences growth, then many of these workers will be better off. The benefits can come in the form of either a pay raise or a better work environment, both of which alleviate job dissatisfaction and reduce incentives to leave. As a result, in the context of firm growth, possession of a college degree becomes an irrelevant factor in determining an individual's employment choice.

Moreover, if there is a possibility that having technology-specific skills and having college education are correlated, we would expect the coefficients on both *vacolg* and *vaskill*—rather than just the coefficient on *vaskill*—to be positive and significant. However, it bears noting that 76% of the sample that had college education is also associated with occupations that are responsive to technological change (those occupations indexed by *specific*). The remaining 24% was employed as educators or doctors who had more stable employment and were less likely to change jobs even in the present of technological change. Differences in the nature of occupations may explain why I obtain opposite signs for the variables *vacolg* and *vaskill*, even if they seem to be positively correlated.

It is worth mentioning that for the group who quit jobs, the positive coefficient on *vaskill* is interpreted as the positive effect of technological growth on voluntary job separation among workers with specific skills. But the reverse could be true, *i.e.*, the positive sign reflects the situation where this group of people are less like to quit their jobs due to the decline of technological progress. To examine this possibility, I construct a dummy variable (*d*) that takes value of 1 if the rate of technological growth, *VA*, is positive and 0 if it is negative. This dummy is used to interact with variable *vaskill* and *vacolg* so that the modified regression model could distinguish the effect of increasing technological growth from that of decreasing technological growth. The results are provided in Table 5-1. For technological professionals, the effect of increasing technological growth is consistently positive and significant. By contrast, the effect of decreasing technological growth also appears to be positive, and the result is insignificant.

4.2 The Fixed-Effects Logit Model

In this section, I use the fixed-effects logit model in order to control for the fixed-effects of individuals. A binomial dependent variable is constructed to replace the categorical dependent variable from the multinomial logit regression.

Changes are made to the dataset to better accommodate the fixed-effects logit. First, I omit the option of being laid off and only study the two remaining options. The new sample has 6551 individuals who either stayed or voluntarily quit their jobs in each year. A dependent dummy variable (*quit*) is created. It takes on a value of one if a person quit his job and zero otherwise. All explanatory variables remain the same.

Tables 6 and 7 display summaries of demographic and industrial statistics for this new sample. They appear to be similar to the statistics for the previous sample.

One concern with using the fixed-effect logit is the incidental parameters problem. Katz (2001) suggests that when the period of observations is less than sixteen, the conditional estimators from a fixed-effects logit regression have a very small amount of bias (as compared to the unconditional estimators). Based on this argument, I choose the conditional fixed-effects logit model.

4.3 Results from the Conditional Fixed-Effects Logit Model

The first column in Table 8 reports the results from the conditional fixed-effects regression. Since the year and industry dummies are control variables, the estimated coefficients on these variables do not bear any economic implications. As shown in the previous multinomial model, educated workers tend to have a higher probability of turnover, except during firm growth. The estimated coefficient on *specific* is -0.537, indicating that workers associated with technology-specific jobs are less likely to leave their jobs. The estimated coefficient on *vaskill* is positive, as expected, but the result is insignificant.

The major drawback to using the conditional logit regression is that 17890 out of 25560 observations are dropped due to either all positive or negative outcomes. This loss of observations risks affecting the significance of the results. To avoid this problem, I employ the linear probability model. Another reason for using the linear probability model arises from the difficulty in computing marginal effects in the conditional fixed-effects logit. The problem can be easily solved in the linear probability model since its estimated coefficients are directly related to marginal effects. The results are displayed in the second column of Table 8. All the signs on the estimated coefficients remain the same as in the conditional fixed-effects logit. With technological change, having a technology-intensive job increases the chance of quitting by 8%. The result is significant at a 5% significance level.

One distinctive result is the significantly negative effect of the number of previous turnovers on the probability of quitting in the current period. This implies that a person is less likely to quit his job if he had quit many times before; this contradicts what we observe in the multinomial logit model. However, recall from the previous model that both lay-offs and quits are considered "turnovers". It is reasonable to speculate that being laid off several times is a signal of bad quality—indicative of more lay-offs in the future. In the fixed-effects model, though, only the occurrence of a quit is counted as a turnover. If it takes several job experiences for a person to learn his job type, a worker characterized by several previous turnovers would be more likely to have found his job match. Thus, he settles down with his current job.

Even though the analysis in this section is associated with voluntary job separation, we know that in some cases workers prefer to leave involuntarily. Doing so allows them to accrue the benefits gained from being laid off (*i.e.*, severance pay or unemployment benefits). Thus, they wait until being laid off and then go to another job. Here, the two actions (voluntary and involuntary job separations) generate the same results; thus, should be treated equally. In the next section, I modify my dataset by breaking down the quit term into voluntary and involuntary quits. A voluntary quit is recorded for each individual who reported quitting his previous job and moved to another job. Similarly, an involuntary quit refers to a person who was laid off from his previous job and then became employed elsewhere. Both of these behaviors are denoted by the variable *quit*.

Table 11 presents the results from both the conditional fixed-effects logit regression and the linear probability regression. The estimated coefficients on *specific* continue to be negative and economically significant in both models. The significant effect of having a college degree on the probability of job turnover vanishes in the presence of firm growth. A strong negative relationship remains between the likelihood of turnover and the number of previous turnovers.

The estimated coefficient on *vaskill* turns out to be insignificantly different from zero in the conditional logit regression. In the linear probability model, it is positive and significant at a 10% significance level. This significance, however, is very sensitive to the specification of the model. It disappears once the interaction variable *vacolg* is omitted from the model. This may be caused by the existence of collinearity between the two variables. However, since the degree of collinearity is not substantially high, as shown above, there is no strong reason to remove *vacolg* from the model.

5. Discussions

This paper is the outgrowth of two unusual results on labor turnover from Dohmen and Pfann (2004) and Lazear (1999). It is commonly believed that firm growth spurs increasing demand for technology and skills. As a result, workers with specific skills should have more stable employment in a growing firm than workers with general or standardized skills. Paradoxically, their studies using firms' personnel data show that it is the workers from the relatively higher positions in a firm's hierarchy who tend to separate from their jobs.

To interpret the intuition behind their results, my model assumes that all skills are industry-specific, but there is variation of technological intensity amongst within-industry jobs. Jobs characterized by higher levels of technological intensity are associated with much stricter requirements to update skills. Therefore, these jobs are the most responsive to technological change. Taking this one step further, once a new technology is adopted, the demand for state-of-the-art skills arises. Conversely, jobs requiring a lower level of technology-based skills (the standardized skills) are less likely to be affected by technological change. As a result, the increased probability of quitting can be observed as we move up the technology-intensive hierarchy.

To test whether this turnover pattern predicted by the model is a general phenomenon, or if it is idiosyncratic to a specific firm, a panel dataset is constructed (again based on longitudinal data from the PSID). The dataset includes the employment history of 6700 individuals from 1981 to 1987, sampled from twelve industries and nine occupations.

Lacking firm growth, the results consistently support the generally shared thoughts of labor turnover. That is, since workers with technology-specific skills have more human capital and higher productivity, a higher compensation reduces their incentive to quit. However, when firm growth is considered (in the form of an increasing rate of technological change), high-rank technology professionals tend to show a higher probability of quitting than regular production workers with less specific skills.

One variable I am unable to construct concerns whether, after leaving the previous job, a person still worked at the same occupation or in the same industry. This variable would have served as a good indicator of industry-specific skills. In the model, all skills are assumed to be industry-specific. If a person's skill does not fit in one firm, he will still find it useful elsewhere in the same industry. In this sense, a job change within the same industry can be reasonably attributed to skill mismatch. However, if a person quits his previous job and begins to work in another industry, he may use the same type of skill or have to develop different skills. Therefore, it is hard to determine whether the quit is caused by the mismatch in skills or other reasons, *i.e.*, taste for variety (Astebro and Thompson (2007)). If these across-industry job changes happen often with technology professionals, the empirical results may overestimate the effect of technology-specific skills on a worker's job decision.

Appendix

1. PROOF OF PROPOSITIONS 2

Let $TV(g') = w(g) + \beta \int_0^\infty \max[V(g'), Q]\, dF(g'|g)$ denote the operator defined in (7). The contracting mapping of $TV(g')$ can be easily proved by following the standard way in the literature.

To show $V(g)$ is decreasing in g, let g^* be the value of g such that $V(g^*) = Q$. Assume $V(g')$ is decreasing in g', then

$$\int_0^{\bar{g}} \max[V(g'), Q]\, dF(g'|g) = \int_0^{g*} V(g') dF(g'|g) + \int_{g*}^{\bar{g}} Q dF(g'|g) \tag{A.1}$$

Integrating both terms in (A.1) by parts yields

$$Q - \int_0^{g*} F(g'|g) V_{g'}(g') dg' \tag{A.2}$$

Differentiating (A.2) with respect to g gives us$\int_0^{g*} F(g'|g) V_{g'}(g') dg'$

$$- \int_0^{g*} V_{g'}(g')\, [\partial F(g'|g)/\partial g]\, dg' \tag{A.3}$$

As $V_{g'}(g') < 0$ and $\partial F(g'|g)/\partial g < 0$ by assumption, equation (A.3) indicates that the second term in (7) is decreasing in g. As $w(g)$ is decreasing in g, we have shown that $V(g)$ is decreasing in g as well. Thus, quitting with value of Q is chosen when g is above g^*, while staying with $V(g')$ is preferable when g is below g^*.

2. PROOF OF PROPOSITIONS 3

Similar to the proof in part A, assume $V(g')$ is increasing in g'. Then

$$\int_0^{\bar{g}} \max[V(g'), Q]\, dF(g'|g) = \int_0^{g*} Q dF(g'|g) + \int_{g*}^{\bar{g}} V(g') dF(g'|g) \tag{A.4}$$

Integrating both terms in (A.4) by parts, we have

$$V(\bar{g}) - \int_0^{g*} F(g'|g)V_{g'}(g')dg' \quad \text{(A.5)}$$

Differentiating (A.5) with respect to y yields

$$-\int_{g*}^{\bar{g}} V_{g'}(g')\,[\partial F(g'|g)/\partial g]\,dg' \quad \text{(A.6)}$$

Since $V_{g'}(g') < 0$ and $w_g(g) > 0$, equation (A.6) implies that $V(g)$ is increasing in g. As the worker chooses to stay in the firm in the current period, these implies that $V(g) > Q$. If we only consider the case that firms' technological change rate, g, is increasing all the time, $V(g')$ should be greater than Q, which indicates that the workers with α lower than a certain threshold would always prefer to stay in a growing firm.

3. THE RESERVATION EQUATION

When $V(g)$ is decreasing in g, by using (A.2), equation (7) can be rewritten as

$$V(g) = w(g) + \beta[Q - \int_0^{g*} V_{g'}(g')F(g'|g)dg'] \quad \text{(A.7)}$$

Substituting g^* into (A.7) and rearranging it gives the reservation equation

$$Q = \frac{1}{1-\beta}w(g^*) - \frac{\beta}{1-\beta}\int_0^{g*} V_{g'}(g')F(g'|g^*)dg'.$$

When $V(g)$ is increasing in g, equation (7) can be expressed as

$$V(g) = w(g) + \beta\{Q + \int_{g*}^{\bar{g}}[V(g') - Q]dF(g'|g)\} \quad \text{(A.8)}$$

Replacing g with g^* in (A.8), the reservation equation is obtained as

$$Q = \frac{1}{1-\beta}w(g^*) + \frac{\beta}{1-\beta}\int_{g*}^{\bar{g}}[V(g') - Q]dF(g'|g^*)$$

References

Acemoglu, Daron (1999): "Changes in Unemployment and Wage Inequality: An Alternative Theory and Some Evidence." *American Economic Review*, 89(5): 1259-1278.

Astebro, Thomas, and Thompson, Peter (2007): "Entrepreneurs: Jacks of All Trades or Hobos?" Working paper.

Chin, Aimee, Juhn, Chinhui, and Thompson, Peter (2006): "Technical Change and the Demand for Skills during the Second Industrial Revolution: Evidence from the Merchant Marine, 1891-1912." *Review of Economics and Statistics*, 88(3): 572-578.

Dohmen, Thomas J., and Pfann, Gerard A. (2004): "Worker separations in a nonstationary corporate environment." *European Economic Review*, 48(3): 645-663.

Gibbons, Robert, and Waldman, Michael (2003): "Enriching a Theory of Wage and Promotion Dynamics Inside Firms." NBER Working paper No.9849.

Greene, William H. (2002): "Econometric Analysis." Prentice Hall, NJ.

Hill, Martha S. (1992): "The Panel Study of Income Dynamics: A User's Guide." SAGE Publications, Newbury Park, CA.

Jovanovic, Boyan (1979): “Firm-Specific Capital and Turnover.” *Journal of Political Economy*, 87(6): 1246-1260.

Kambourov, Gueorgui, and Manovskii Iourii (2005): “Occupational Specificity of Human Capital.” Society for Economic Dynamics, Meeting Paper 197

Katz, Ethan (2001): “Bias in Conditional and Unconditional Fixed Effects Logit Estimation.” *Political Analysis*, 9(4): 379-384.

Kennedy, Peter (2003): “A Guide to Econometrics.” The MIT Press, Cambridge, MA.

Lazear, Edward P. (1999): “Personnel Economics: Past Lessons and Future Directions.” NBER Working paper No.6957.

Neal, Derek (1995): “Industry-Specific Human Capital: Evidence from Displaced Workers.” *Journal of Labor Economics*, 13(4): 653-677.

Quintin, Erwan, and Stevens, John J. (2005a): “Growing Old Together: Firm Survival and Employee Turnover.” Finance and Economics Discussion Series No. 2005-22.

Quintin, Erwan, and Stevens, John J. (2005b): “Raising the Bar for Models of Turnover.” Finance and Economics Discussion Series No. 2005-23.

Rogerson, Richard, Shimer, Robert, and Wright, Randall (2004): “Search-Theoretic Models of the Labor Market: A Survey.” NBER Working paper No.10655.

Saxenian, Annalee (1994): “Regional Advantage: Culture and Competiton in Silicon Valley and Route 128, Cambridge.” Harvard University Press.

TABLE 1. Steps of Creating the Sample with Multiple Choices: Stay, Laidoff and Quit

Dataset 1

(Dependent Variable: CHOICE)

SAMPLES	SAMPLE SOURCE	NUMBER OF INDIVIDUALS
1	Individuals in 1981-1987	42970
2	Individuals in SAMPLE 1, whose 1. *RELATIONSHIP TO HEAD* = 1 or 10 (after 1982) 2. *SEQUENCE NUMBER* = 1	9423
3	Individuals in SAMPLE 3, whose 1. *MOS THIS JOB* ≥ 12, and *EMPLMT STATUS* = 1 or 2 *2.* *MOS THIS JOB* < 12 *HPND PREV JOB* (H-U)= 3, and *EMPLMT STATUS* = 1 *3.* *MOS THIS JOB* < 12 *HPND PREV JOB* (HD-E)= 4, and *EMPLMT STATUS* = 1	7285
4	Individuals in SAMPLE 4, whose value of 1. industry categorical variable is in the range from 2 to 12 2. occupation categorical variable is in the range from 1 to 9	6700

Notes:

SAMPLE	Includes:
1	7 separate subsamples for each year from 1981-1987. Each subsample was obtained after the selection of 7 family-level variables and 3 individual level variables.
2	7 separate subsamples, which only include current household *heads* in each dataset from SAMPLE 1.
3	7 separate subsamples based on SAMPLE 2, but each of them only includes currently-employed household heads who stayed with the jobs or were laid off or quit from last jobs.
4	7 separate subsamples based on SAMPLE 3, excluding individuals whose present occupation and industry couldn't be defined, or who worked in agriculture, forestry, fishery and public administration.

Numbers of individuals in column (3) were calculated after integrating the 7 separate subsamples into one big sample.

TABLE 2. Summary Statistics: Demographic Variables (3 groups)

Dependent Variable: CHOICE

	No. of Observation	Missed observations[7]	Fractions				
			Total	(1) People who stayed	(2) People who were fired	(3) People who quit	(4)[8] No observations on CHOICE
MALE	34573	0	0.74	0.52	0.03	0.06	0.40
FEMALE	12327	0	0.26	0.38	0.02	0.07	0.52
AGE	26770	20130					
<35	13358		0.50	0.77	0.07	0.17	0
35-44	6275		0.23	0.89	0.03	0.08	0
45-54	3834		0.14	0.92	0.02	0.05	0
>=55	3303		0.12	0.95	0.01	0.04	0
COLLEGE DEGREE	26770	20130					
YES	5667		0.21	0.86	0.02	0.12	0
NO	21103		0.79	0.84	0.05	0.11	0

---

7 For each individual-year dataset, there are no missing values for age, gender, college, or employment choice variable CHOICE. However, when all these seven datasets are merged together, individuals who exist in some years but no others would not have observations on age, college, and CHOICE in those years. An exception is the variable on gender. In the PSID, this variable is applied to all years. That is, once an individual had an observation on gender in one year, this value applies to all years from 1968 to 2005.

8 Based on the above reason, even if there are no observations on CHOICE because the individuals are absent in those years, there are still observations on gender, but not on age and college.

TABLE 3. Summary Statistics: Industry and Occupation (multinomial)

Industry	Fraction	Occupation	Fraction
Mining	0.01	Computer Specialists and Engineers	0.05
Construction	0.09	Professional and Kindred Workers	0.11
Manufacturing	0.28	Managers and Administrators	0.14
Transportation and Warehousing	0.06	Sales Workers	0.05
Information	0.02	Clerical and Kindred Workers	0.09
Utilities	0.03	Craftsman and Kindred Workers	0.19
Wholesale and Retail trade	0.18	Operatives	0.19
Finance, Insurance and Real Estate	0.05	Laborers and Farmers	0.05
Professional and Business Services; Educational and Health Services	0.19	Service Workers and Private Household Workers	0.12
Entertainment and Recreation	0.01		
Other services	0.08		
Total observations	26770	Total observations	26770

TABLE 4. Results in Multinomial Logit Model

	Dependent Variable: CHOICE			
	CHOICE=2 (laid off)	dy/dx	CHOICE=3 (quit)	dy/dx
Occupation dummy (*specific*)	-1.369 ***	-0.041	-0.455 ***	-0.037
	(0.207)		(0.097)	
Growth in value-added (*VA*)	1.502	0.047	1.991 **	0.188
	(1.488)		(1.026)	
Interaction between skill and growth (*VA*specific*)	2.414	0.077	2.976 **	0.280
	(2.893)		(1.405)	
Industry dummies				
Mining	-0.453 *	-0.016	-0.239	-0.021
	(0.27)		(0.198)	
Construction (dropped)	-			
Manufacturing	-0.812 ***	-0.027	-0.605 ***	-0.056
	(0.097)		(0.075)	
Transportation and Warehousing	-0.634 ***	-0.022	-0.321 ***	-0.029
	(0.144)		(0.107)	
Information	-1.738 ***	-0.062	-0.602 ***	-0.051
	(0.393)		(0.181)	
Utilities	-1.669 ***	-0.058	-0.785 ***	-0.070
	(0.287)		(0.156)	
Wholesale and Retail Trade	-0.201 **	-0.008	0.206 ***	0.021
	(0.099)		(0.074)	
Finance, Insurance and Real Estate	-0.659 ***	-0.026	0.293 ***	0.031
	(0.167)		(0.097)	
Professional, Business, Education and Health Services	-0.737 ***	-0.027	-0.078	-0.005
	(0.115)		(0.077)	
Entertainment and Recreation	-0.04	-0.003	0.405**	0.040
	(0.289)		(0.178)	
Other services (repair, personal services, etc.)	-0.431 ***	-0.016	0.058	0.007
	(0.125)		(0.089)	
Control for Year	Yes		Yes	
_Constant	-2.208 ***		-1.751 ***	
	(0.114)		(0.084)	
Observations	26770			
Log likelihood	-13907.599			

TABLE 5. Multinomial Logit Model with Individual Heterogeneity Controlled

	Dependent Variable: CHOICE					
	CHOICE=2	CHOICE=3	CHOICE=2	dy/dx	CHOICE=3	dy/dx
Occupation dummy (*specific*)	-1.111 ***	-0.429 ***	-1.12 ***	-0.029	-0.442 ***	-0.031
	(0.217)	(0.109)	(0.217)		(0.11)	
Growth in value-added (*VA*)	1.313	2.062 **	1.144	0.030	1.877 *	0.151
	(1.512)	(1.057)	(1.506)		(1.055)	
Interaction between skill and growth (*VA*specific*)	2.391	3.697 **	2.647	0.070	3.965 ***	0.318
	(3.065)	(1.601)	(3.054)		(1.603)	
gender	0.02	0.419	0.033	0.000	0.432 ***	0.035
	(0.079)	(0.048) ***	(0.079)		(0.048)	
Age	-0.066***	-0.067 ***	-0.063 ***	-0.002	-0.065 ***	-0.005
	(0.003)	(0.002)	(0.003)		(0.002)	
College education dummy (*COLG*)	-0.502 **	0.359 ***	-0.533 **	-0.017	0.324 ***	0.028
	(0.247)	(0.118)	(0.247)		(0.118)	
Interaction between skill and college education (*VA*COLG*)	1.505	-1.99 ***	1.734	0.059	-1.676	-0.143
	(3.532)	(1.76)	(3.528)		(1.764)	
Number of previous turnover (laid off and quit)			0.395 ***	0.011	0.412 ***	0.033
			(0.044)		(0.029)	
Control for Industry	Yes	Yes	Yes		Yes	
Control for Year	Yes	Yes	Yes		Yes	
_Constant	0.015	0.056	-0.364 **		-0.349 ***	
	(0.176)	(0.122)	(0.183)		(0.127)	
Observations	26770		26770			
Log likelihood	-13083.629		-12962.041			

TABLE 5-1. Multinomial Logit Model:

Distinguishing Increasing Technological Growth from Decreasing Growth

	Dependent Variable: CHOICE	
	CHOICE=2	CHOICE=3
Occupation dummy (*specific*)	-1.124 ***	-0.446 ***
	(0.220)	(0.111)
Growth in value-added (*VA*)	1.180	1.926 *
	(1.510)	(1.062)
gender	0.033	0.432 ***
	(0.079)	(0.048)
Age	-0.063 ***	-0.065 ***
	(0.003)	(0.002)
College education dummy (*COLG*)	0.366	0.545 *
	(0.543)	(0.303)
*VA*specific*d*[9]	2.660	4.011 **
	(3.092)	(1.627)
*VA*specific*(1-d)*	4.437	3.144
	(22.934)	(8.908)
*COLG*VA*d*	-1.047 *	-0.253
	(0.599)	(0.320)
*COLG*VA*	3.647	-1.237
	(3.678)	(1.844)
Number of previous turnover (laid off and quit)	0.395 ***	0.412 ***
	(0.044)	(0.029)
Control for Industry	Yes	Yes
Control for Year	Yes	Yes
_Constant	-0.371	-0.352
	(0.183)	(0.127)
Observations	26770	
Log likelihood	-12960.541	

[9] *d* is a dummy variable which equals 1 if VA>0, and 0 if VA<0.

TABLE 6. Summary Statistics: Demographic Variables (quit)

			Fractions			
	No. of Observation	Missed Observation	Total	People who quit	People who didn't quit	Missing obs on quit
MALE	33838	0	0.74	0.06	0.53	0.41
FEMALE	12019	0	0.26	0.07	0.39	0.53
AGE	25560	20297				0
<35	12453		0.49	0.18	0.82	0
35-44	6098		0.24	0.08	0.92	0
45-54	3747		0.15	0.05	0.95	0
>=55	3262		0.13	0.04	0.96	0
COLLEGE DEGREE	25560	20297				
YES	5558		0.22	0.13	0.87	0
NO	20002		0.78	0.12	0.88	0

TABLE 7. Summary Statistics: Industry (quit)

	Fraction		Fraction
Industry		Occupation	
Mining	0.01	Computer Specialists and Engineers	0.06
Construction	0.09	Professional and Kindred Workers	0.11
Manufacturing	0.28	Managers and Administrators	0.15
Transportation and Warehousing	0.06	Sales Workers	0.05
Information	0.02	Clerical and Kindred Workers	0.09
Utilities	0.03	Craftsman and Kindred Workers	0.19
Wholesale and Retail trade	0.18	Operatives	0.19
Finance, Insurance and Real Estate	0.05	Laborers and Farmers	0.05
Professional and Business Services; Educational and Health Services	0.19	Service Workers and Private Household Workers	0.12
Entertainment and Recreation	0.01		
Other services	0.08		
Total observations	25560	Total observations	25560

TABLE 8. Conditional Fixed-Effects Model (quit only)

	Dependent Variable: QUIT	
	Conditional fixed-effects	Linear Probability
Occupation dummy (*specific*)	-0.537 ***	-0.033 ***
	(0.199)	(0.097)
Growth in value-added (*VA*)	3.574 **	0.208 ***
	(1.734)	(0.085)
Interaction between skill and growth (*VA**specific*)	1.951	0.08 **
	(2.749)	(0.131)
AGE	0.158	0.005
	(0.109)	(0.005)
College education dummy (*COLG*)	0.849***	0.07***
	(0.287)	(0.016)
Interaction between skill and college education (*COLG**VA*)	-6.329**	-0.346**
	(3.001)	(0.157)
Number of previous turnover	-4.48	-0.394***
	(0.134)	(0.005)
Control for Industry	Yes	Yes
Control for Year	Yes	Yes
_Constant	---	0.105
		(0.211)
Observations	7670	25560
Log likelihood	-1472.5191	

TABLE 9. Summary Statistics: Demographic Variables (quit and laid off)

	No. of Observation	Missed observations	Fractions			
			Total	People who quit or were laid off	People who stayed	Missing value for quit and laid off
MALE	34573	0	0.74	0.09	0.51	0.4
FEMALE	12327	0	0.26	0.09	0.38	0.52
AGE	26770	20130				
<35	13358		0.50	0.23	0.77	0
35-44	6275		0.23	0.11	0.89	0
45-54	3834		0.14	0.08	0.92	0
>=55	3303		0.12	0.05	0.95	0
COLLEGE DEGREE	26770	20130				
YES			0.21	0.14	0.86	0
NO			0.79	0.16	0.84	0

TABLE 10. Summary of Industry and Occupation (quit and laid off)

Industry	Fraction	Occupation	Fraction
Mining	0.01	Computer Specialists and Engineers	0.05
Construction	0.09	Professional and Kindred Workers	0.11
Manufacturing	0.28	Managers and Administrators	0.14
Transportation and Warehousing	0.06	Sales Workers	0.05
Information	0.02	Clerical and Kindred Workers	0.09
Utilities	0.03	Craftsman and Kindred Workers	0.19
Wholesale and Retail trade	0.18	Operatives	0.19
Finance, Insurance and Real Estate	0.05	Laborers and Farmers	0.05
Professional and Business Services; Educational and Health Services	0.19	Service Workers and Private Household Workers	0.12
Entertainment and Recreation	0.01		
Other services	0.08		
Total observations	26770	Total observations	26770

TABLE 11. Conditional Fixed-Effects Model (quit and laid off)

	Dependent Variable: QUIT	
	Conditional fixed-effects	Linear Probability
Occupation dummy (*specific*)	-0.639 ***	-0.054 ***
	(0.176)	(0.012)
Growth in value-added (*VA*)	2.24	0.149 ***
	(1.466)	(0.094)
Interaction between skill and growth (*VA*specific*)	2.539	0.25 *
	(2.446)	(0.146)
AGE	0.048	0.002
	(0.085)	(0.006)
College education dummy (*COLG*)	0.445*	0.041**
	(0.247)	(0.018)
Interaction between skill and college education (*COLG*VA*)	-4.299	-0.217
	(2.685)	(0.174)
Number of previous turnover	-3.846***	-0.352***
	(0.1)	(0.005)
Control for Industry	Yes	Yes
Control for Year	Yes	Yes
_Constant	---	0.329
		(0.229)
Observations	10051	26770
Log likelihood	-2157.5664	