ABSTRACT

Title of dissertation: JOB COMPETITION OVER THE BUSINESS CYCLE

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My thesis explores the following question: how workers of different skill are allocated across jobs and unemployment over the business cycle. I am interested in understanding the "over-qualification" of workers that occurs during periods of high unemployment, as increased congestion in the labor market hinders workers from finding a suitable match. I focus on the skill mismatch that takes the form of high-skilled workers transitorily accepting low-skill jobs, thereby influencing the labor market prospects of low-skilled workers.

In the first chapter, I develop a business cycle matching model with heterogeneous workers and jobs, which helps understand the role of over-qualification on labor productivity and across-skill unemployment dynamics. I capture the across-skill search externalities and spillover effects that arise when low- and high-skilled workers compete for low-skill jobs, by relaxing the common assumption that all

workers qualify for any type of vacancy. I show that the skill mix of vacancies changes over the cycle, thus altering the allocation of workers of different skill across jobs and unemployment. In addition, my model explains observed differences in labor market outcomes of different skill groups, including the higher sensitivity of low-skilled unemployment to changes in economic activity.

In the second chapter, I test the empirical relevance of over-qualification. I ask whether the risk of unemployment induces high-skilled workers to accept transitorily low-skill jobs until a better job comes along. To this end, I study the mismatch rates and job level dynamics of high-skilled workers. Unlike existing studies that only examine how the business cycle affects job level probabilities, I adopt dynamic panel data estimation methods, in which the worker's lagged state (i.e., whether unemployed or mismatched) enters the model as an explanatory variable.

I find evidence suggestive of the existence of over-qualification. The mismatch rates of higher educational groups are higher and exhibit more cyclical variation. Moreover, I find that high-skilled workers are more likely to move into lower job levels when they are unemployed and the unemployment rate is high. In addition, my results point to the existence of an upgrading in the job levels of mismatched high-skilled workers when the unemployment rate is low.

JOB COMPETITION OVER THE BUSINESS CYCLE

by

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2005

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This dissertation is dedicated to my mother.

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Chapter 1

Job Competition Over the Business Cycle: Implications for Labor Productivity and Unemployment Rates by Skill

1.1 Introduction

An open theoretical question is how the quality of job-worker matches evolves over the business cycle. Evidence that matches created during recessions are of lower productivity and dissolve faster has increased attention on the role of search frictions in exacerbating skill-mismatches during recessions.[1]

This chapter focuses on the type of skill-mismatch that takes the form of high-skilled workers taking transitorily low-skill jobs, i.e., becoming "over-qualified", in order to avoid the distress of being unemployed, while continuing to search on the job for high-skill jobs. I analyze the implications of over-qualification for unemployment and labor productivity dynamics, by developing a business cycle matching model in which high-skilled workers can take both high- and low-skill jobs, whereas low-skilled workers can only take low-skilled jobs.

[1] For evidence on the procyclicality of match quality, see for example, Bowlus (1995), Davis, Haltiwanger, and Schuh (1996), Bils (1985), Shin (1994), Bowlus, Liu and Robinson (2002), and Liu (2003). Moreover, worker surveys indicate that workers are more likely to report being employed at jobs below their skill level during recessions (e.g., Akerlof Rose and Yellen, 1988; and Acemoglu, 1999).

The existing literature on the role of search frictions in exacerbating skill mismatch during recessions neglects the fact that workers face restrictions in the type of vacancies they can fill. Existing studies assume that all workers, independent of their skill level, qualify for any type of vacancy firms create. In reality, however, the matching technology is asymmetric: workers of high skill qualify for a wider range of job types, while jobs with low skill requirements can be filled by a wider range of worker types. Hence, when low-skilled workers compete with high-skilled workers for low-skilled jobs, the asymmetric nature of the matching technology entails search externalities and across-skill spillover effects that existing studies fail to incorporate. In turn, the job competition externalities that arise have important consequences for how workers of different skill are allocated across jobs and unemployment over the cycle.

Typically, workers of different skill experience different labor market outcomes on a variety of dimensions, which the assumption that all workers can be employed in any type of vacancies firms create (i.e., a single job-worker matching rate for all skill groups) cannot explain. Low-skilled workers have lower exit rates from unemployment and lower propensity to search on the job than high-skilled workers (e.g., Blau and Robins, 1990; Pissarides and Wadsworth, 1994; and Belzil, 1996). Moreover, low-skilled unemployment is higher and exhibits higher cyclical sensitivity than high-skilled unemployment (e.g., Topel, 1993). These differences in labor market outcomes for workers of different skill, are consistent with the existence of job competition externalities, as high-skilled workers take temporary jobs below their skill level, thereby affecting the labor market prospects of low-skilled workers.[2]

There is increasing interest in modeling over-qualification to explain why many EU countries in the recent decades have suffered an uneven increase in low-skilled unemployment relative to high-skilled unemployment (Albrecht and Vroman, 2002; Gautier, 2002; Dolado *et al.*, 2003). These studies focus on across-skill job competition externalities and investigate whether high-skilled workers "crowd-out" low-skilled workers as they compete for jobs. Since their goal is to explain long term uneven developments in unemployment rates, they only look at steady states.

The notion that search frictions exacerbate skill-mismatches during recessions has been formalized in Barlevy (2002), via a business cycle matching model with two-sided heterogeneity and on-the-job search. Prior to Barlevy, a series of theoretical papers argued that recessions promote efficient allocation of resources by "cleansing" out the less efficient production arrangements.[3] However, the "cleansing" view is at odds with the evidence that recessions encourage the creation of less productive matches. Barlevy (2002) is a first attempt at reconciling the theoretical literature on the "cleansing" effect of recessions with the evidence. In his model recessions kill marginal production arrangements, but also hinder the transition of mismatched workers into more productive uses (labeled as the "sullying" effect), because firms

[2] The findings of Bowlus (1995) that the quality of matches falls during recessions more evidently in white collar than blue collar activities gives additional support to this view.

[3] Examples are Hall (1991, 2000), Mortensen and Pissarides (1994), Caballero and Hammour (1994, 1996) and Gomes, Greenwood, and Rebelo (1999). These studies have been inspired by the work of Davis and Haltiwanger (1992), who argue that recessions are associated with increased job reallocation in the manufacturing sector.

create fewer vacancies per job seeker. The latter effect dominates, and accounts for the lower match quality observed during recessions. Barlevy's model adopts a symmetric framework (i.e., firms create equal amounts of each type of vacancy and all workers can be employed in any type of vacancy firms open), making the role of aggregate shocks more transparent. However, a symmetric framework implies identical unemployment rates across skill groups, and therefore cannot account for the observed uneven cyclical fluctuations in unemployment rates of different skill cohorts. More importantly, it ignores the externalities and spillover effects across skill groups arising from job competition.

In this paper, I relax the symmetry assumption and incorporate both business cycle fluctuations and job competition externalities into the model, thus bringing the two strands of literature together. I investigate the dynamic effects on unemployment of two types of shocks: an exogenous shock to productivity that affects output of all matches and shock to the rate at which matches dissolve. Given the asymmetric nature of the matching technology, changes in the skill composition of vacancies alter the way high- and low-skilled workers are allocated across types of jobs and unemployment.

I show that the skill composition of vacancies changes over the cycle, as firms respond to changes in the relative value of opening high- and low-skill vacancies. My model delivers the conventional result that in periods of low aggregate productivity workers have greater difficulty escaping unemployment, as firms create fewer vacancies per job seeker, but it also shows that downturns generate two countervailing effects. On the one hand, an exogenous reduction in aggregate productivity raises the relative value of opening high-skill vacancies and encourages firms to upgrade the skill composition of vacancies. In turn, the skill upgrading in the vacancy mix facilitates the transition of both unemployed and overqualified (i.e., in low-skill jobs) high-skilled workers into high-skill jobs, increasing average match productivity. On the other hand, a rise in exogenous job separation rates induces firms to downgrade the skill composition of vacancies: since low-skill jobs can be filled by both types of workers, their relative profitability increases when matches dissolve faster and thus is a greater supply of job seekers. The skill downgrading, together with the increase in the number of unemployed high-skilled workers, enhances the likelihood that unemployed high-skilled workers take low-skill jobs, while stifling the transition into high-skill jobs. The net effect on the degree of over-qualification and thus average match productivity depends on the relative importance of exogenous aggregate productivity and separation rate shocks over the business cycle.

Once I allow for the skill composition of vacancies to vary over the cycle, Barlevy's (2002) result that recessions stifle the transition of mismatched workers into appropriate jobs no longer holds unless the fall in aggregate productivity is accompanied by a sufficiently high increase in job separation. Further, contrary to the "cleansing" view, under which higher job separation during recessions eliminates marginally productive arrangements, higher job separation in this paper actually exacerbates over-qualification and lowers average match productivity. Hence, my model gives a view of skill-mismatch over the cycle that puts more emphasis on job separation rather than aggregate productivity fluctuations, and calls for further investigation on the link between the two impulses.

In addition, by relaxing the common assumption of a single matching rate for all skill groups, my model allows for the unemployment rate not only to vary over the cycle, but across skill groups as well. Therefore, my model allows for an examination of why low-skilled unemployment is more sensitive to slowdowns in economic activity than high-skilled unemployment, and whether this is due to intensified job competition between high- and low-skilled workers. Consistent with the evidence, I find that low-skilled unemployment is higher and more volatile than high-skilled unemployment. However, contrary to the common belief, the main reason is not that high-skilled workers crowd out low-skilled ones when competing for jobs; instead, high-skilled workers are eligible for both high- and low-skill jobs and are therefore less vulnerable to the changes in the skill composition of vacancies that occur over the cycle. As it turns out, regardless of whether or not over-qualification and job competition externalities increase during recessions, the low-skilled unemployment rate still rises relatively more.

The rest of the paper is organized as follows. Section 1.2 is devoted to the description of related literature. Section 1.3 describes worker and firm behavior and the labor market mechanisms (matching process, wage bargaining). In sections 1.4 and 1.5, I examine the properties of the model through comparative statics and dynamic simulation exercises, by considering separately the effects of aggregate productivity and separation rate fluctuations. Finally, in section 1.6, I conclude with a few remarks and discuss how future research will build upon this contribution.

1.2 Related Literature

Several modifications to the conventional search equilibrium model have been made to incorporate the significance of skill mismatches which occur during periods of high congestion in the labor market, mainly by allowing for some heterogeneity in job productivities and/or workers skills. The literature on matching models with heterogeneous agents dates back to the contribution by Pissarides (1994), where one-sided heterogeneity is assumed: there are two types of jobs (good and bad jobs) but workers are homogeneous. Workers who take bad jobs stay in them as their wages increase with job tenure, so that employment in good jobs is no longer attractive to them.[4]

The more recent contributions of Acemoglu (1999) and Mortensen and Pissarides (1999) set up the foundations of the role of search frictions in matching models with skill heterogeneity. Assuming a constant contact rate between unemployed workers and vacancies, thus eliminating any possible interactions between workers with different skills, Acemoglu (1999) offers a theory of how the unemployment rates of high- and low-skilled workers and between-group wage dispersion change endogenously depending on the vacancy creation strategy of firms. In particular, firms find it profitable to either create only low-skill jobs or to create both low-skill and high-skill jobs and search for the appropriate candidates. Similarly, in Mortensen and Pissarides (1999), the distribution of workers over a continuum of skill levels is exogenous, whereas the distribution of job types is endogenous. They examine the

[4]A relevant contribution in this line of research is also McKenna (1996).

consequences of skilled-biased technological change on unemployment rates across skill groups. However, they do not deal with across skill search externalities and spillover effects associated with skill-mismatches, because in their model there is a perfect match between workers skills and firms skill requirements.

Similar models have also been considered in studies that investigate the role of unemployment risk in how efficiently workers are allocated across jobs, and the corresponding welfare implications of unemployment insurance policy. In Acemoglu (2001), workers are identical and only job productivities are heterogeneous. Similarly, Acemoglu and Shimer (1999) assume that workers are identical in terms of their skills, while jobs are heterogeneous in terms of specificity with higher specificity jobs being more productive. Marimon and Zilibotti (1999) go one step further and allow for two-sided skill heterogeneity, thus capturing the negative impact that skill mismatch has on labor productivity. They model match productivity to be lower the higher the distance between the workers' skill level and the vacancies' required skill level. However, they impose a convenient symmetry in the production technology that is very restrictive: as long as the distance between the firms required skill level and the worker's skill level is the same, the productivity of the match will be equal. This implies that an overqualified worker can produce as much as an under-qualified worker (a nurse can do the job of a doctor as well as a doctor can do the job of a nurse).

Although the strands of literature described above set the foundations for studying search frictions in models with skill-heterogeneity, they do not deal with spillover effects of high-skilled workers onto the creation and filling of low-skill jobs and their connection to the observed differences in the labor market outcomes of different skill cohorts. Some of these papers assume perfectly segmented labor markets where job competition and interactions across skill groups are not possible. In other cases, markets are not segmented, but the type of heterogeneity assumed does not incorporate differences in the minimum skill requirements of jobs. That is, all types of workers are qualified to perform any type of job entrepreneurs create and thus have identical job finding rates. In such a set up, the matching behavior of different skill groups does not influence the ability of other skill groups to find a job. Hence, possible job competition and crowding out phenomena that may occur in periods of high congestion in the labor market, and their implications for unemployment rate differences across skill groups, are ignored.

The recent contributions by Albrecht and Vroman (2002), Gautier (2002) and Dolado *et al.* (2003) extend this type of model to include job competition and spillover effects across skill groups and address issues such as over-qualification and crowding-out more directly. In these studies, for simplicity, there are only two types of jobs (low-skill and high-skill) and only two skill groups (low-skilled and high-skilled workers). Both the distribution of skills and job destruction are exogenous, but the vacancy mix is endogenous and is determined by free entry conditions. The key feature of these models, first introduced by Albrecht and Vroman (2002), is the type of production technology assumed: low- and high-skill workers can be hired for low-skill jobs, whereas only the latter can perform high-skill jobs. In this context, high- and low-skill submarkets can endogenously segregate or merge depending on the matching behavior of workers. It may be worthwhile for unemployed high-skilled workers to mismatch, i.e., take low-skill jobs. If this is the case, job creation and unemployment in the low-skill market can affect job creation and unemployment in the high-skill market. Therefore, job competition takes place and crowding out may occur.[5]

Although these studies provide important insights into the externalities associated with searching and matching behavior of workers and shed some light on the implications of job competition for unemployment, they are limited in that they only perform comparative static exercises on the steady-state equilibrium, investigating

[5]The most notable differences between these three studies rest on their assumptions regarding the nature of job search. In both Gautier (2002) and Dolado *et al.* (2003) mismatched workers (high-skilled workers on low-skilled jobs) are allowed to search on-the-job and quit as soon as better jobs come along, while in the Albrecht and Vroman model, on-the-job search is not allowed. In the latter study, there are two main results. First, when high-skilled workers are willing to take low-skill jobs (cross-skill matching), unemployment duration among low-skilled workers is higher than among high-skilled workers, while the expected match duration is higher for high- than low-skill jobs. Second, in equilibria with cross-skill matching, high-skilled workers "crowd out", that is, take jobs away from low-skilled workers, but at the same time, their willingness to accept low-skill jobs leads to an overall expansion of low-skill vacancy supply. Therefore, the net impact on low-skilled unemployment depends on which of these effects is stronger. Gautier (2002) and Dolado *et al.* (2003) find that on-the-job search provides an additional mechanism through which the labor market position of low-skill workers is weakened when high-skilled workers move into low-skill jobs. In particular, the higher quit rate of mismatched workers exerts a negative externality on low-skill jobs, which lowers the value of posting a low-skill vacancy and thus, leads to lower low-skill vacancy creation. Gautier (2002) additionally argues that job competition may exert a positive externality on the profits of low-skill vacancies when high-skilled workers are more productive than low-skilled workers on low-skill jobs.

how the steady-state equilibrium unemployment rates of low- and high-skilled workers are affected by changes in the aggregate productivity level or the job separation rate, which represent changes in overall economic activity; changes in the relative productivity of high and low-skill jobs, which are interpreted as skill-biased technological shocks; and changes in the mass of high-skilled workers in the economy.[6]

Comparative static results do not provide insights into the dynamic impact of shocks. Therefore, the studies described above do not establish a clear connection between job competition and the observed differences in the cyclical patterns of unemployment across skill groups. To characterize the allocation of workers across different types of matches and unemployment over the business cycle, we need to allow for deviations from the steady state. Mortensen and Pissarides (1994) do precisely this in their model without heterogeneity and only off-the-job search, by allowing aggregate productivity to fluctuate over time. However, on-the-job search and heterogeneity make the transitional dynamics associated with deviations from the steady state difficult to characterize analytically. Barlevy (2002) incorporates both of these features but turns to a discrete-time version of the model and a collocation method to approximate the value function in order to analyze transitional dynamics. His study establishes that recessions exacerbate mismatch while booms

[6] More recently, Pierrard and Sneesens (2003) examine the dynamic adjustment process to a skill-bias shock and to skill upgrading by allowing for these changes to take place progressively over time. Their scope is to investigate how these changes in combination with job competition externalities affect the dispersion between the high- and low-skilled unemployment rates. However, they do not look at the cyclical implications of job competition for the across-skill unemployment dynamics.

promote allocative efficiency by allowing mismatched workers to quit and move into better jobs. The matching technology assumed in Barlevy, however, does not allow for the possibility of job competition and the resulting search externalities and spillover effects across skill groups.[7] Moreover, by assuming a symmetric equilibrium where firms create equal amounts of each type of vacancy, his model predicts that all types of workers face the same labor market prospects. This is inconsistent with the evidence that changes in aggregate economic conditions have different impacts on unemployment flows and rates of different skill groups.

In this paper, I unite the literature examining matching models with skill-mismatches and business cycles with the recent literature examining matching models of job competition. The section that follows gives a description of the model.

1.3 The Model

1.3.1 Main Assumptions

I assume that time is discrete. An exogenous fraction of workers δ is low-skilled (l), while the remaining fraction $(1-\delta)$ is high-skilled (h). Similarly, vacancies are high-skill (h) and low-skill (l). The distribution of skill requirement across vacancies is endogenous.

Interactions between high- and low-skilled submarkets are embedded into the model by incorporating heterogeneity in terms of jobs' minimum skill requirements. Both low- and high-skilled workers can be hired for low-skill jobs, but a high-skill job

[7] The matching technology in Barlevy is identical to that in Marimon and Zilibotti (1999).

can be filled only by a high-skilled worker. Consequently, workers of different skill not only have different productivity distributions across types of jobs but different job finding rates as well; high-skill workers have a higher job finding rate, while low-skill vacancies enjoy a higher arrival rate of workers than high-skill vacancies.

High- and low-skilled workers are assumed to be equally productive in low-skill jobs, but high-skilled workers are more productive when matched to a high-skill job. The flow output of each match is assumed to be the product of an aggregate component y, and a match specific component a_i^j, where i denotes the type of job and j the type of worker. More formally, let ya_i^j denote the flow of output of a job of type $i = (h, l)$ that is filled by a worker of type $j = (h, l)$. Then, the production technology assumptions can be summarized by $ya_h^h > ya_l^h = ya_l^l > ya_h^l = 0$.

Given that job-to-job movements represent a substantial fraction of worker flows (e.g., Gautier, 1998), I allow for on-the-job search. Mismatched high-skilled workers search on the job for high-skill jobs and quit as soon as they find one, while low-skilled workers have no reason to search on the job.

Firms can open at most one job and the choice of type is irreversible. The mass of each type of vacancy is determined endogenously by a free-entry condition. The exogenous component of job separation follows a Poisson process with arrival rate s. Although s is common to both types of job, the effective separation rate of low-skill jobs is higher due to on-the-job search by mismatched workers. Whenever a match is destroyed the job becomes vacant and bears a maintenance cost c, while the worker becomes unemployed and receives a flow of income b, which is to be interpreted as home production or leisure.

I introduce productivity and separation rate fluctuations into the model by allowing aggregate labor productivity y and the separation rate s to follow a Markov process. Aggregate productivity takes the value of y_0 in recessions and $y_1 > y_0$ in booms, while the separation rate takes the value s_0 in recessions and $s_1 < s_0$ in booms. Both variables switch between the two levels with a transition probability p. At every point in time the current values of productivity and separation are common knowledge.

The condition that ensures a match is formed in equilibrium is simply that the flow of output generated from the match is higher than the unemployment benefit, i.e., $a_i^j > b$, $\forall i, j$. It is optimal for unemployed high-skilled workers to take low-skill jobs as long as their productivity is higher than the unemployment benefit, because they retain their chances of finding a high-skilled job by searching on the job.[8]

The meeting process is undirected in the sense that a low-skill worker encounters a high-skill vacancy (in which case a match is not formed) with a probability per unit of time that is proportional to the fraction of high-skill vacancies. Similarly, a high-skill worker encounters a low-skill vacancy with a probability per unit of time that is proportional to the fraction of low-skill vacancies.[9]

[8] Dolado et al. (2003) derive conditions that rule out a corner solution in which firms create only low-skill vacancies in a steady state equilibrium. They also derive the conditions under which a steady-state cross-skill matching equilibrium (i.e. an equilibrium in which high-skill workers take low-skill jobs) is unique.

[9] I assume the meeting process is undirected (i.e., workers cannot distinguish the vacancy type before applying) to capture the impact of changes in the skill mix of vacancies on the flow rates of different skill groups. In reality even if job seekers can distinguish the type of vacancy before they

The total number of matches between a worker and a firm is determined by a constant returns to scale function, $m\left[v_h+v_l, u_h+u_l+e_l^h(1-s)\right]$, where v_h and v_l denote the mass of high- and low-skill vacancies, u_h and u_l the mass of high- and low-skilled unemployed workers, and e_l^h(1-s) the number of high-skilled workers in low-skill jobs (which I label as mismatched henceforth) that survive separation. $m[\cdot,\cdot]$ is strictly increasing in both arguments. The "labor market tightness" is denoted by $\theta=\frac{v_h+v_l}{u_h+u_l+e_l^h(1-s)}$, so that in a tighter market there are more vacancies available per job seeker.

The pool of job seekers is composed of unemployed high- and low-skilled workers and mismatched workers. For convenience, I define the following shares:

$$\begin{aligned}\varphi &= \frac{u_l}{u_l+u_h}\\ \psi &= \frac{u_l+u_h}{u_l+u_h+e_l^h(1-s)}\end{aligned} \tag{1.1}$$

The rate at which firms meet a job seeker of any type is equal to $q(\theta)=m(1,\frac{1}{\theta})$, which is decreasing in θ and exhibits the standard properties of: $\lim_{\theta\to 0} q(\theta)=\lim_{\theta\to\infty}\theta q(\theta)=\infty$ and $\lim_{\theta\to\infty} q(\theta)=\lim_{\theta\to 0}\theta q(\theta)=0$. A mismatched high-skilled worker has no incentive to change employer unless the new employer offers him a high-skill job. Accordingly, some low-skill vacancies will meet mismatched workers who will refuse to match. Likewise, employers with high-skill jobs will not hire

apply there are still search frictions involved that prevent workers from finding the right match. For example, it is harder for a high-skilled worker to find a high-skill job if only 5% of the vacancies are high-skill than when 95% of the vacancies are high-skill, even if he/she can distinguish the vacancy type. This type of search friction is captured by assuming random instead of directed search.

the low-skilled workers they meet. Therefore, the effective matching rate of a low-skill vacancy with a low-skilled worker is given by $\psi\varphi q(\theta)$, while the corresponding rate with a high-skilled worker is $\psi\left(1-\varphi\right)q(\theta)$. High-skill vacancies match only with either mismatched or unemployed high-skilled workers, and thus their effective matching rate can be written as $\left(1-\psi\varphi\right)q(\theta)$. Assuming that $\eta=\frac{v_l}{v_l+v_h}$ denotes the fraction of low-skill vacancies, the effective matching rate of low-skilled workers is $\eta m(\theta)$, while mismatched high-skilled find a high-skill job with a rate $(1-\eta)m(\theta)$. Finally, unemployed high-skilled workers can take either a high- or a low-skill job and thus their effective matching rate is equal to $m(\theta)$ (i.e., $\eta m(\theta)+(1-\eta)m\left(\theta\right)$).

The asymmetric nature of the matching technology generates the following across-skill externalities and spillover effects:

i) *Vacancy Composition Effect* (VCE). An increase in the fraction of high-skill vacancies $(1-\eta)$ decreases the unemployment-to-employment flow probability of low-skilled workers, but also decreases the unemployment-to-mismatch flow probability of high-skilled workers;

ii) *Negative Quit Externality* (NQE). The higher quit rate of mismatched high-skilled workers lowers the profits of low-skill jobs. As a result, an increase in the fraction of high-skilled unemployed job seekers $\psi\left(1-\varphi\right)$, which in turn increases the likelihood of high-skilled workers taking low-skill jobs, lowers the profits of low-skill jobs. Hence, low-skill vacancy creation declines with higher fractions of unemployed high-skilled workers, making it harder for low-skill workers to find a job;

iii) *Negative Congestion Externality* (NCE henceforth).

High-skilled job seekers exert a negative externality on low-skilled employability by creating additional congestion in the market, thus making it harder for low-skilled workers to encounter a low-skill job, and for low-skill vacancies to encounter a low-skilled worker. To be more specific, an increase in the number of high-skilled job seekers $\left(e_l^h + u_h\right)$, lowers the probability that a low-skill worker will meet a low-skill vacancy, given by $\eta m(\theta)$, through a lower θ, and the probability that a low-skill vacancy will encounter a low-skilled worker, given by $\psi\varphi q(\theta)$, through a lower $\psi\varphi$.

In short, an increase in η implies a VCE that benefits low-skilled employability but at the same time facilitates the transition of high-skilled workers into low-skill jobs. An increase in the fraction of high-skilled job seekers (both unemployed and mismatched), given by $(1 - \psi\varphi)$, exacerbates both the NCE and NQE on low-skill employability.

1.3.2 Bargaining

In equilibrium there are three possible types of matches: (i) high-skilled workers in high-skill jobs, (ii) high-skilled workers in low-skill jobs and (iii) low-skilled workers in low-skill jobs. The surplus of each match is divided according to a Nash bargaining solution. The share of surplus that workers receive is exogenous and denoted by β. I adopt the following standard notation: U^j denotes the value of unemployment for a worker of type j, V_i denotes the value of a vacant job of type i, W_i^j denotes the value of employment for a worker of type j in a job of type i, and finally J_i^j denotes the value to the firm of filling a job of type i with a worker of type

j. Accordingly, the surplus of a match can be expressed as $S_i^j = W_i^j + J_i^j - U^j - V_i$ and the wage w_i^j satisfies

$$(1-\beta)\left[W_i^j - U^j\right] = \beta\left[J_i^j - V_i\right] \tag{1.2}$$

1.3.3 Timing and Flow Equations

Let $e = \left\{e_h^h, e_l^h, e_l^l\right\}$ be the mass of high-skilled workers in high-skill jobs, the mass of high-skilled workers in low-skill jobs and the mass of low-skilled workers in low-skill jobs, respectively, at the beginning of period t. At this stage, the Markov shock hits the economy and a new pair (y, s) arrives that is common knowledge to all agents in the economy. After $e = \left\{e_h^h, e_l^h, e_l^l\right\}$ and (y, s) are observed, production takes place, exogenous separations occur, and vacancies are posted by firms to insure zero profits. Search takes place and workers change jobs, leading to the following distribution of workers in the subsequent period:

$$e_l'^l = e_l^l(1-s) + \eta m(\theta)\left[\delta - e_l^l(1-s)\right] \tag{1.3}$$

$$e_h'^h = e_h^h(1-s) + (1-\eta)m(\theta)\left[(1-\delta - e_h^h(1-s)\right] \tag{1.4}$$

$$\begin{aligned} e_l'^h &= e_l^h(1-s) + \eta m(\theta)\left[1-\delta-(e_l^h+e_h^h)(1-s)\right] \\ &\quad -(1-\eta)m(\theta)e_l^h(1-s) \end{aligned} \tag{1.5}$$

1.3.4 Asset Values

Workers are risk neutral, time is discrete and the interest rate r is constant. The asset value of an unemployed low-skilled worker at aggregate state (y, s) and a given distribution of employment $e = \left\{e_h^h, e_l^h, e_l^l\right\}$ is denoted by $U^l(y,s,e)$ and satisfies

$$\begin{aligned} U^l(y,s,e) &= b + \frac{1}{(1+r)}[\eta m(\theta) E[W_l^l(y',s',e'/)/y,s,e] \\ &\quad + (1-\eta m(\theta)) E[U^l(y',s',e')/y,s,e] \end{aligned} \tag{1.6}$$

Equation (1.6) states that the value of an unemployed low-skilled worker is equal to his value of leisure b, plus the present value of the probability he finds a low-skill job times the resulting expected value conditional on the current state (y,s,e), given by $E[W_l^l(y',s',e')/y,s,e]$, plus the probability he does not find a job, times the expected value of staying unemployed given by $E[U^l(y',s',e')/y,s,e]$. (y',s') and $e' = \left\{e_h'^h, e_l'^h, e_l'^l\right\}$ denote the realization of aggregate shocks and the distribution of employment next period, respectively. Similarly, given that high-skilled workers accept both types of jobs, the corresponding value of unemployment for high-skilled workers, $U^h(y,s,e)$ satisfies

$$\begin{aligned} U^h(y,s,e) &= b + \frac{1}{(1+r)}[\eta m(\theta) E[W_l^h(y',s',e')/y,s,e] \\ &\quad + (1-\eta) m(\theta) E[W_h^h(y',s',e')/y,s,e] \\ &\quad + (1-m(\theta)) E[U^h(y',s',e')/y,s,e]] \end{aligned} \tag{1.7}$$

The rest of the asset values are similar. The asset values of high- and low-skilled workers in high- and low-skill jobs, respectively, satisfy

$$\begin{aligned} W_h^h(y,s,e) &= w_h^h(y',s',e') + \frac{1}{(1+r)}[s E[U^h(y',s',e')/y,s,e] \\ &\quad + (1-s) E[W_h^h(y',s',e')/y,s,e]] \end{aligned} \tag{1.8}$$

$$W_l^l(y,s,e) = w_l^l(y',s',e') + \frac{1}{(1+r)}[s E[U^l(y',s',e')/y,s,e]$$

$$+(1-s)E[W_l^l(y',s',e')/y,s,e]] \tag{1.9}$$

while the asset value of employment for mismatched high-skilled workers is given by

$$\begin{aligned} W_l^h(y,s,e) &= w_l^h(y',s',e') + \frac{1}{(1+r)}[sE[U^h(y',s',e')/y,s,e] \\ &\quad +(1-s)(1-\eta)m(\theta)E[W_h^h(y',s',e') - W_l^h(y',s',e')/y,s,e] \\ &\quad +(1-s)E[W_l^h(y',s',e')/y,s,e]] \end{aligned} \tag{1.10}$$

Mismatched high-skilled workers search on the job for high-skill jobs. Therefore, the last term in the above equation represents the value of on-the-job search: given that the match survives to the next period with a probability $(1-s)$ a mismatched high-skilled worker can find a high-skill job with a probability $(1-\eta)\,m(\theta)$, in which case he gains the expected capital gain from switching jobs, given by $E(W_h^h(y',s',e'/y,s,e) - W_l^h(y',s',e'/y,s,e))$. The values of opening high- and low-skill vacancies are given by

$$\begin{aligned} V_h(y,s,e) &= -c + \frac{1}{(1+r)}[(1-\psi\varphi)q(\theta)E[J_h^h(y',s',e')/y,s,e] \\ &\quad +(1-(1-\psi\varphi)q(\theta))E[V_h(y',s',e')/y,s,e]] \end{aligned} \tag{1.11}$$

$$\begin{aligned} V_l(y,s,e) &= -c + \frac{1}{(1+r)}[\psi\varphi q(\theta)E[J_l^l(y',s',e')/y,s,e] \\ &\quad +\psi(1-\varphi)q(\theta)E[J_l^h(y',s',e')/y,s,e] \\ &\quad +(1-\psi q(\theta))E[V_l(y',s',e')/y,s,e]] \end{aligned} \tag{1.12}$$

whereas the values to the employer of filling those vacancies satisfy

$$\begin{aligned} J_h^h(y,s,e) &= ya_h^h - w_h^h(y,s,e) + \frac{1}{(1+r)}[sE[V_h(y',s',e')/y,s,e] \\ &\quad +(1-s)E[J_h^h(y',s',e')/y,s,e]] \end{aligned} \tag{1.13}$$

$$J_l^l(y,s,e) = ya_l^l - w_l^l(y,s,e) + \frac{1}{(1+r)}[sE[V_l(y',s',e')/y,s,e]$$
$$(1-s)E[J_l^l(y',s',e')/y,s,e]] \qquad (1.14)$$

Finally, the value to a low-skill firm with a high-skilled worker is

$$\begin{aligned} J_l^h(y,s,e) &= ya_l^l - w_l^h(y,s,e) + \frac{1}{(1+r)}[sE[V_l(y',s',e')/y,s,e] \\ &+(1-s)E[J_l^h(y',s',e')/y,s,e] \\ &-(1-s)(1-\eta)m(\theta)E[(J_l^h(y',s',e') - V_l(y',s',e'))/y,s,e]] \end{aligned} \qquad (1.15)$$

where the last term represents the reduction in the value to the firm of hiring a high-skilled worker, as the latter searches on the job and thus will quit as soon as a high-skill job arrives.

1.3.5 Surpluses and Zero Profit Conditions

Using the Nash bargaining condition given by equation (1.2) and the asset value equations described above we can write the surplus functions as follows:

$$\begin{aligned} S_l^l(y,s,e) &= ya_l^l - b + \frac{1}{(1+r)}[(1-s)E[S_l^l(y',s',e')/y,s,e] \\ &-\beta\eta m(\theta)E[S_l^l(y',s',e')/y,s,e] \end{aligned} \qquad (1.16)$$

$$\begin{aligned} S_h^h(y,s,e) &= ya_h^h - b + \frac{1}{(1+r)}[(1-s)E[S_h^h(y',s',e')/y,s,e] \\ &-\beta(1-\eta)m(\theta))E[S_h^h(y',s',e')/y,s,e] \\ &-\beta\eta m(\theta)E[S_l^h(y',s',e')/y,s,e]] \end{aligned} \qquad (1.17)$$

$$
\begin{aligned}
S_l^h(y,s,e) \quad = \quad & ya_l^l - b + \frac{1}{(1+r)}[(1-s)E[S_l^h(y',s',e')/y,s,e] \\
& +(1-s)(1-\eta)m(\theta)E[(\beta S_h^h(y',s',e') - S_l^h(y',s',e'))/y,s,e] \\
& -\beta\eta m(\theta)E[S_l^h(y',s',e')/y,s,e] \\
& -\beta(1-\eta)m(\theta)E[S_h^h(y',s',e')/y,s,e]] \qquad (1.18)
\end{aligned}
$$

The surplus of a low-skill job filled by a low-skilled worker S_l^l, takes the standard form: the first term, gives the net flow of output the match generates; given that the match survives to the next period with a probability $(1-s)$, the second term gives the expected present value of future surplus; the last term reflects the workers' forgone search opportunity (i.e., their ability to search for a job) while employed, and is subtracted from the surplus.

The surplus of a filled high-skill job S_h^h, takes a similar form. The only difference is that once high-skilled workers find a job, they lose their opportunity to search for both high- and low-skill job jobs once employed. Hence, the surplus function changes accordingly. The surplus of a low-skill-job filled by a high-skill worker S_l^h, takes a slightly different form. When high-skilled workers take low-skill jobs, they can still search for high-skill jobs. The value of this option is added to the surplus and is given by the third term in the equation (1.18). Given that the match survives to the next period with a probability $(1-s)$, mismatched workers search on the job and with probability $(1-\eta)m(\theta)$ find high-skill jobs, in which case they gain a share β of $E[S_h^h(y',s',e')/y,s,e]$ while losing $E[S_l^h(y',s',e')/y,s,e]$.

After substituting the surplus expressions into the values of vacancies, given by equations (1.11) and (1.12), I define the following free entry conditions:

$$c = \frac{(1-\beta)q(\theta)}{(1+r)}\left[\psi\varphi ES_l^l(y',s',e') + \psi(1-\varphi)ES_l^h(y',s',e')\right] \tag{1.19}$$

$$c = \frac{(1-\beta)q(\theta)}{(1+r)}\left[(1-\psi\varphi)ES_h^h(y',s',e')\right] \tag{1.20}$$

These conditions imply that firms keep opening vacancies until the cost of keeping a vacancy unfilled c equals the expected future profits of a filled job. The conditions implicitly define $\theta_{y,s,e}$ and $\eta_{y,s,e}$ as a function of the current aggregate state (y,s) and the current distribution of employment across types of matches given by $e = \left\{e_h^h, e_l^h, e_l^l\right\}$.

1.3.6 Equilibrium

The equilibrium is given by a vector $\{\theta, \eta, \varphi, \psi, e\}$ that satisfies the following: (i) the three types of matches are formed voluntarily, i.e., $ya_i^j > b \; \forall i, j$ for which matches are formed; (ii) the two free entry conditions in (1.19) and (1.20), are satisfied so that the values of maintaining low- and high-skill vacancies are zero; and (iii) the state variables e_h^h, e_l^h, and e_l^l follow the flow equations (1.3) to (1.5) above.

1.4 Simulations

The purpose of this section is to gauge qualitatively the effects of business cycle fluctuations on job competition, skill mismatches, average match productivity and unemployment rates by skill group. I consider aggregate productivity and separation rate shocks separately in order to illustrate their individual effects and highlight their differences.

I turn to numerical techniques to analyze the model. I use the free entry conditions given by equations (1.19) and (1.20) above to find the state-contingent market tightness $\theta_{y,s,e}$ and fraction of low-skill vacancies $\eta_{y,s,e}$. I then simulate the model as follows: first, I generate a sequence of aggregate state (y, s) realizations; then, starting with the first realization of aggregate state, and an initial distribution of employment $e = \left\{e_h^h, e_l^h, e_l^l\right\}$I use the laws of motion given by equations (1.3) to (1.5) to compute the new distribution of employment at the beginning of the next period; and then I repeat. At the end of each period, I record the aggregate state and employment distribution and generate series of unemployment rates and labor productivity along a sequence of aggregate state realizations.

The exogenous variables are set at the following values: $\beta = .5$, $r = .03$, $c = .5$, $b = .1$, $\delta = .75$, $a_h^h = .8$ and $a_l^l = .45$. The matching function $m\left[\cdot,\cdot\right]$ is a Cobb Douglas function in which job seekers and vacancies are assumed to have equal elasticities of 0.5. In section 1.5.1, where I examine the effects of an aggregate productivity shock, I normalize the high value of aggregate productivity to $y_1 = 1$ and set the low value equal to $y_0 = .9$, while keeping the separation rate fixed at $s = .1$. In section 1.5.2, I keep aggregate productivity at its high level and let the separation rate fluctuate between $s_1 = .1$ and $s_0 = .11$. For the purpose of solving the free entry conditions to determine the state-contingent $\theta_{y,s,e}$ and $\eta_{y,s,e}$, the stochastic variable in each case follows a Markov process, with a transition probability .3. To compute impulse responses to each shock, I simulate the model assuming that once the shock arrives it follows a sample path in which it persists for 20 periods, although the agents believe that the shock persists only with probability 0.3 each period.

Since the purpose of this section is to illustrate qualitative implications the parameters have been chosen in a rather ad hoc manner. However, the results presented in this section are robust to changes in the underlying parameter configuration.

1.4.1 Aggregate Productivity Fluctuations

In this section, I simulate the model allowing for aggregate productivity fluctuations. As already mentioned, the heart of the model is the skill composition of vacancies. Hence, I begin this section by characterizing the evolution of this skill composition. As we can see from Figure 1.1, the immediate effect of a negative productivity shock is to lower the fraction of low-skill vacancies (η).

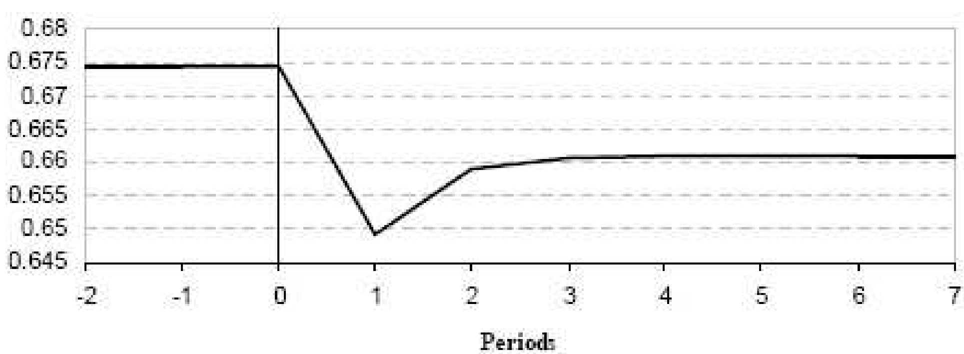

Figure 1.1: Effect of a Negative Productivity Shock on the Fraction of Low-skill Vacancies.

Over time, the initial decline is gradually partially reversed. The reason for the partial recovery is the increase in the fraction of low-skilled unemployed in the mass of jobs seekers immediately after the shock. In response to the increase in the fraction of high-skill vacancies following the fall in productivity, the fraction of unemployed low-skilled workers in the mass of job seekers increases, while the corresponding fraction of high-skilled (both unemployed and mismatched) workers decreases. These are illustrated in Figures 1.2 and 1.3, respectively. Firms with low-skill vacancies benefit from the increased fraction of low-skilled workers in the pool of searchers, because low-skilled workers do not search on the job and thus provide more surplus than mismatched high-skilled workers. Thus, the change in the skill composition of job seekers stimulates low-skill vacancy creation so that the fraction of low-skill vacancies partially recovers from the initial decline.

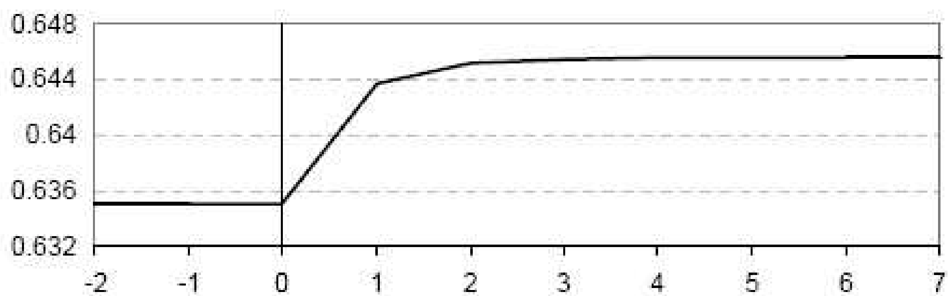

Figure 1.2: Effect of a Negative Productivity Shock on the Fraction of Low-skilled Workers in the Mass of Job Seekers.

The conventional result that periods of low productivity hurt the matching process is present in this model as well. This takes the standard form of a lower vacancy-job seeker ratio θ and thus a lower meeting rate $m(\theta)$ during downturns. As can be verified in Figure 1.4, the meeting rate follows a pattern similar to the

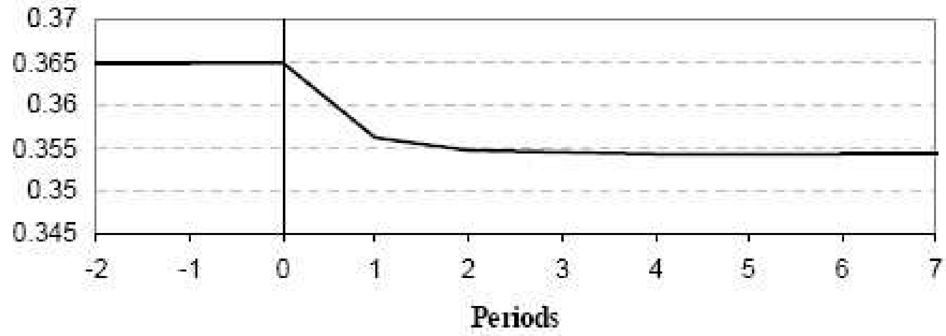

Figure 1.3: Effect of a Negative Productivity Shock on the Fraction of High-skilled Workers in the Mass of Job Seekers.

fraction of low-skill vacancies and for similar reasons: vacancy creation falls initially due to lower productivity and surplus, then gradually rises, as rising unemployment increases the worker arrival rate.

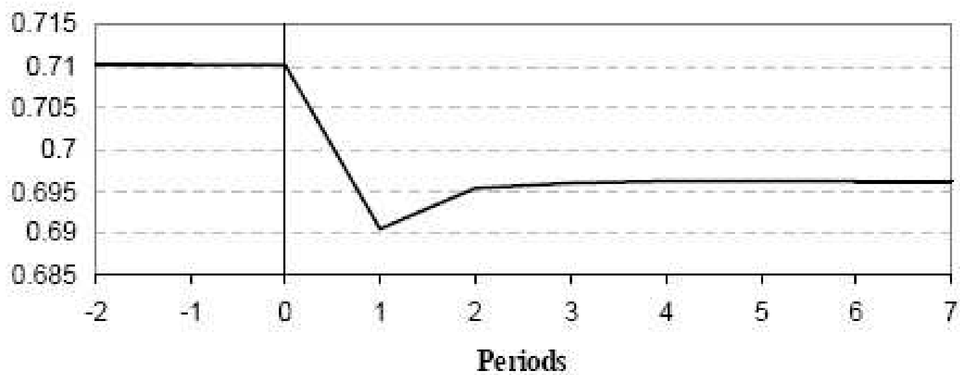

Figure 1.4: Effect of a Negative Productivity Shock on the Worker-Vacancy Meeting Rate.

Although the model delivers the conventional result of a lower vacancy-job seeker ratio (θ) during downturns, it does not replicate Barlevy's (2002) result that recessions stifle the transition of mismatched workers into the jobs they are best suited for, and therefore increase the degree of skill-mismatch in the market. Instead, the model suggests that economic slowdowns generate a reduction in the number of mismatched high-skilled workers.

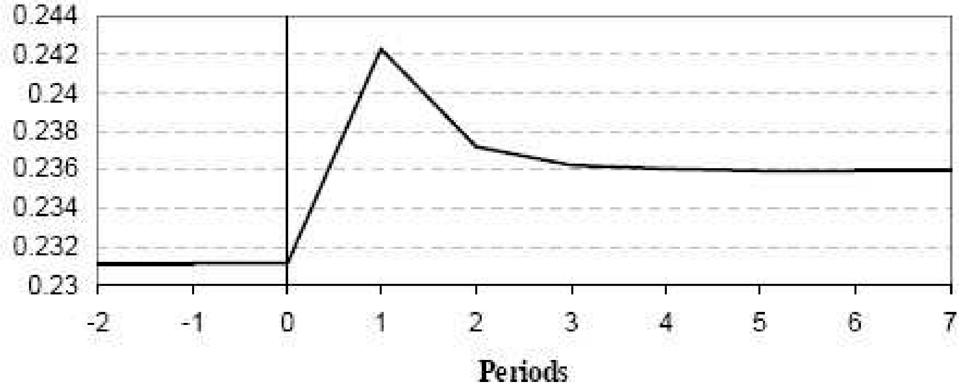

Figure 1.5: Effect of a Negative Productivity Shock on the Probability of Finding a High-Skill Job.

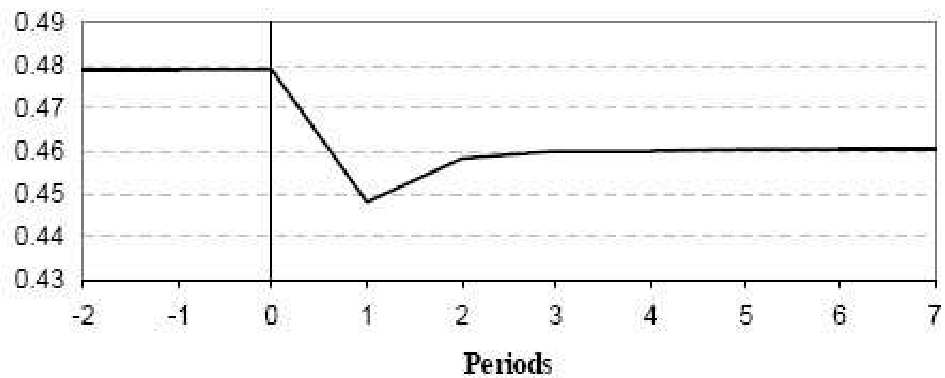

Figure 1.6: Effect of a Negative Productivity Shock on the Probability of Finding a Low-Skill Job.

The key to this novel result is the VCE described above, namely that periods of low productivity involve an upgrading in the skill composition of vacancies (i.e. an increase in $(1-\eta)$). More precisely, the VCE dominates the reduction in the meeting rate, so that the probability of finding a high-skill job $(1-\eta)\, m(\theta)$ increases, while the probability of finding a low-skill job $\eta m(\theta)$ decreases. The paths of these probabilities are illustrated in Figures 1.5 and 1.6, respectively. As soon as the shock arrives, the former increases, while the latter decreases, hindering the transition of unemployed high-skilled workers into low-skill jobs and facilitating the transition of both unemployed and mismatched high-skilled workers into high-skill jobs. Later on, these probabilities partially revert towards their initial values, reflecting the gradual recovery in the fraction of low-skill vacancies as firms try to take advantage of the higher arrival rate of low-skilled job seekers.

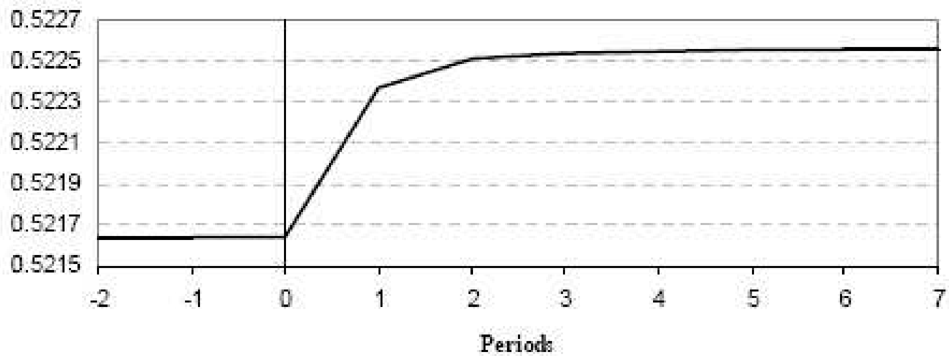

Figure 1.7: Effect of a Negative Productivity Shock on Average Match Productivity.

As illustrated in Figure 1.7, these changes in probabilities that occur during periods of low productivity shift the mass of the distribution of high-skilled workers towards high-skill jobs and therefore increase average match productivity (i.e. the average of a_i^j across all matches). This result is in line with previous work that argues that recessions should promote allocative efficiency (e.g. Hall 1991, 2000; Mortensen and Pissarides 1994; Caballero and Hammour 1994, 1996; and Gomes, Greenwood, and Rebelo 1999), but rests on a different mechanism: an upgrading in the skill composition of vacancies facilitates the transition of overqualified workers into the jobs for which they are best suited. This mechanism is new in the theoretical literature on business cycles and worker reallocation, because it results from asymmetries in the matching rates of different skill groups that have been neglected in previous research.

The notion that the lower meeting rate $m(\theta)$ during recessions stifles the transition of mismatched workers into the jobs they are best suited for has been labeled by Barlevy (2002) as the "sullying" effect of recessions. However, the "sullying" effect rests on the assumption of symmetry. To be more specific, Barlevy (2002) focuses only on equilibria in which the production technology is symmetric, the skill composition of the labor force is symmetric and firms create equal amounts of each type of vacancy.[10] Under these assumptions, neither the distribution of workers across match quality and unemployment nor the number of vacancies posted varies with skill type. Moreover, this type of framework implies that all workers are equally likely to form a match of any given quality. Hence, such framework leaves no room for search externalities and spillover effects across skill groups. Given that by assumption in equilibrium firms create equal amounts of each type of vacancy, the VCE that arises in my model during periods of low productivity is not present in Barlevy's model. The only effect of recessions in Barlevy is the lower meeting rate that impedes mismatched workers from reallocating into more efficient uses.

I next characterize the evolution of unemployment rates across skill groups.

[10]According to the production technology assumed in Barlevy the productivity of a match depends negatively on the distance between the worker's and job's skill level. However, an under-qualified worker is as productive as an over-qualified worker on a particular job, as long as the distance between the worker-job skill level is the same.

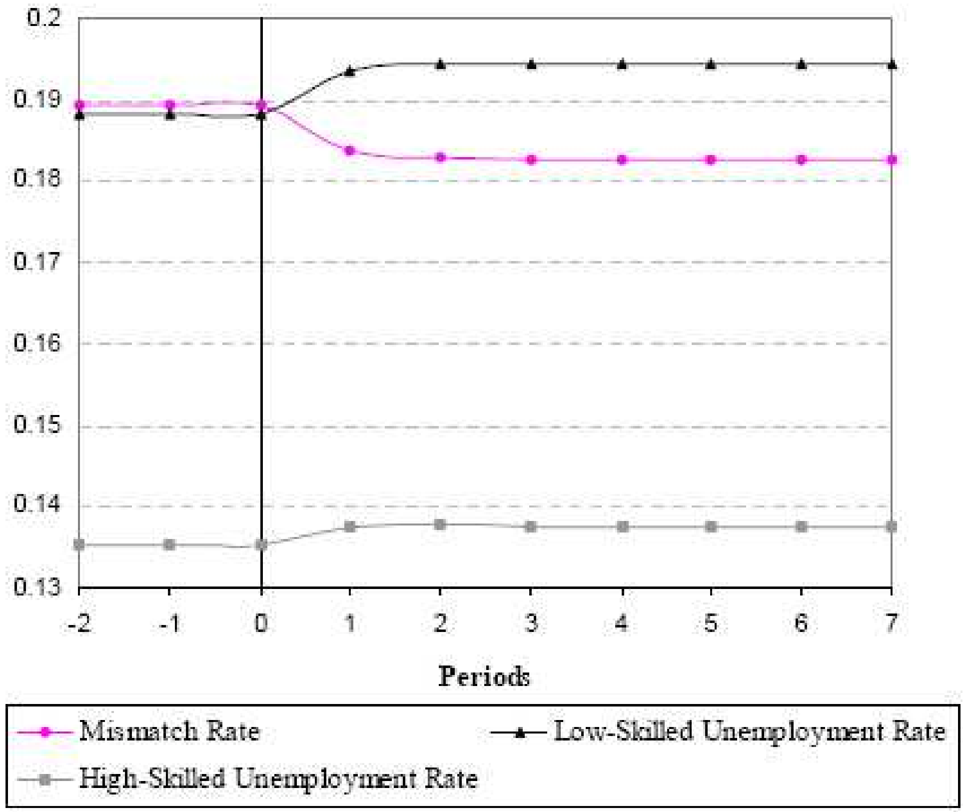

Figure 1.8: Effect of a Negative Productivity Shock on Unemployment and Mismatch Rates.

As mentioned in the introduction, the low-skilled unemployment rate is higher and more sensitive to changes in economic activity than the high-skilled unemployment rate. The model confirms this observation. Figure 1.8 illustrates the evolution of unemployment rates of the two skill groups and the evolution of the mismatch rate (defined as the fraction of high-skilled workers who are mismatched). Independent of the level of aggregate productivity, the low-skill unemployment rate is higher than the high-skilled one, because high-skilled workers qualify for both types of jobs and thus can find a job more easily. When aggregate productivity falls, mismatch in the form of high-skilled workers taking low-skill jobs declines, yet the low-skilled unemployment rate still rises more than the high-skilled unemployment rate. The latter converges to a level only 0.2 percentage points higher than the original, while the former converges to a level 0.6 percentage points higher than the original.

The explanation I offer for the higher sensitivity of the low-skilled unemployment rate to changes in economic activity is conceptually simple but contrary to the common belief that high-skilled workers "crowd-out" low-skilled workers in a competition for jobs.[11]

As illustrated above, periods of low aggregate productivity involve less job competition and fewer high-skilled workers taking low-skilled jobs. Instead, the model suggests that high-skilled employability is less sensitive to changes in economic

[11]Among the studies that investigate the implications of job competition externalities on low-skilled employability, only Gautier (2002) looks at the steady-state effects of changes in aggregate productivity. He confirms that low-skilled unemployment rises more than high-skilled unemployment when aggregate productivity falls, but suggests that this is due to high-skilled workers crowding out low-skilled workers. This result, however, rests on two assumptions. First he assumes that unemployment benefits are a fixed fraction of workers' productivity. Therefore, changes in economic activity do not alter the relative net productivities of high- and low-skill jobs, leaving the skill composition of vacancies unchanged. Second, he assumes that search is directed. Directed search implies that changes in the skill mix of vacancies do not affect workers probability of finding a job. Consequently, under directed search the VCE is no longer relevant. The only effect captured in Gautiers model is that high-skilled workers' exert a negative externality on low-skill job profitability because of their higher quit probability (NQE), so that when unemployment is higher and high-skilled workers' take low-skill jobs more frequently, low-skill vacancy creation declines. The validity of this result depends on the extend to which changes in the skill composition of vacancies do not affect workers' probabilities of finding a particular type of job.

activity because high-skilled workers can be employed in a wider range of job types and thus can more easily buffer against unfavorable changes in the skill composition of vacancies. High-skilled workers qualify for both types of jobs, which implies an effective unemployment-to-employment probability for high-skilled workers equal to $m(\theta)$, which depends only on market tightness (θ). Low-skilled workers, on the other hand, qualify for only low-skill jobs. Therefore, their effective matching rate is $\eta m(\theta)$ and fluctuates both with changes in market tightness and changes in the skill composition of vacancies. As a result, during periods of low productivity, low-skilled workers suffer both the consequences of a more sluggish labor market (lower θ) and skill upgrading in vacancy mix (lower η), whereas high-skilled workers suffer only the consequences of the former.

The reduction in the fraction of high-skilled job seekers (both unemployed and mismatched) implies a lower NCE and NQE on low-skilled employability. Given that there are relatively fewer high-skilled job seekers low-skill vacancies are more likely to encounter a low- than a high-skilled job seeker, and low-skilled workers suffer lower congestion from high-skilled workers. However, low-skill unemployment still rises more in response to the fall in productivity, indicating that the VCE dominates. Hence, what is hidden behind the higher sensitivity of low-skilled unemployment is not job competition externalities but the change in the skill composition of vacancies.

The finding that an upgrading in the skill composition of vacancies facilitates a more efficient allocation and improves average match productivity following a decline in aggregate productivity, does not square with empirical findings that match quality is procyclical. As will be explained in the next section, however, the model performs better along this dimension when periods of low productivity are driven by shocks to the separation rate and thus a high flow of workers into unemployment.

Before I proceed with characterizing the dynamic response to a separation rate shock, I discuss the robustness of the results presented so far to changes in the parameter configuration. The results are not sensitive to changes in the relative productivity of high- and low-skilled jobs or changes in the magnitude of the shock. A smaller productivity gap between skill types results in a smaller gap between high- and low-skilled unemployment rates, while larger shocks result in higher dispersion between high- and low-skilled unemployment rates. However, the implications of changes in aggregate productivity for unemployment and mismatch rates remain the same. I also examined changes in the skill composition of the labor force.[12] I find that the relevant variables follow the patterns described above independent of the skill composition of the labor force.

1.4.2 Job Separation Fluctuations

In this section, I keep aggregate productivity fixed and allow the job separation rate to fluctuate over time. As illustrated in Figure 1.9, on impact of a negative separation rate shock, the fraction of low-skill vacancies increases as firms take advantage of the increase in their relative profitability. Over time, the fraction of

[12] This exercise was motivated by the work of Pierard and Sneezes (2003) and Dolado *et al.* (2003) that suggests the uneven increase in low-skilled unemployment, may be the result of an increase in the fraction of high-skilled workers in the labor force, which exacerbates job competition and crowding out of low-skilled workers.

low-skill vacancies gradually decreases, but remains higher than the original level.

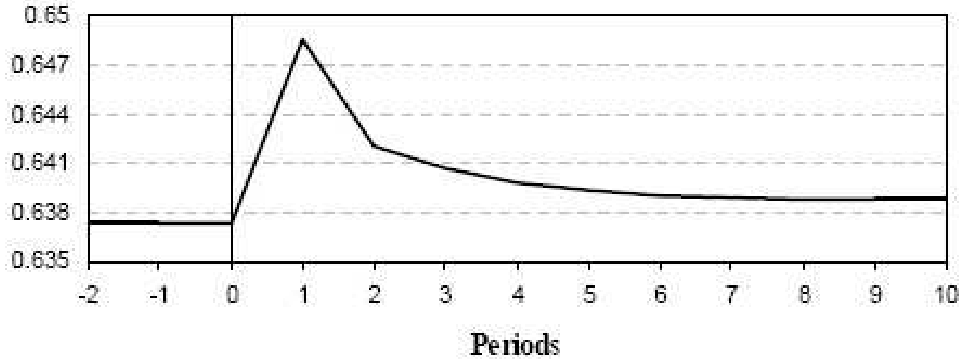

Figure 1.9: Effect of a Separation Rate Shock on the Fraction of Low-Skill Vacancies.

The gradual reversion is due to intensified negative quit externalities following the initial increase, which reduce low-skill job profitability and thus vacancy creation. The sharp initial increase in the fraction of low-skill vacancies, together with the sharp increase in high-skilled unemployment due to the separation rate shock, facilitate the transition of high-skilled workers into low-skill jobs while stifling transitions out of them, exacerbating negative quit externalities on low-skill job profitability. Figure 1.10 shows the evolution of the fraction of high-skilled job seekers (both unemployed and mismatched), which reflects the evolution of negative job competition externalities (NCE and NQE) on low-skilled employability. On impact, the fraction declines, reflecting the sharp increase in unemployment. Subsequently the fraction increases as more high-skilled workers move into low-skilled jobs. In turn, the rise in NCE and NQE results in a gradual reduction in the fraction of low-skill vacancies.

To clarify this further, I report the evolution of probabilities of finding a high- and a low-skill job in Figures 1.11 and 1.12, respectively. On impact of the shock, the

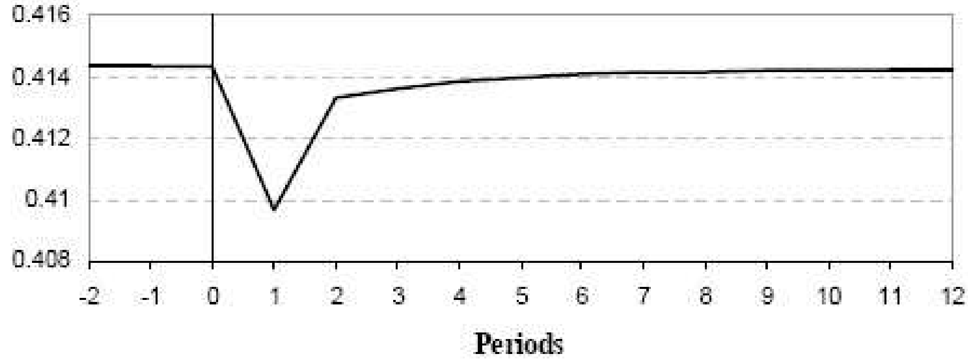

Figure 1.10: Effect of a Separation Rate Shock on the Fraction of High-skilled Job Seekers.

first decreases while the latter increases. Therefore, a higher mass of high-skilled workers is misallocated into low-skill jobs, while the lower probability of finding high-skill jobs implies that they remain overqualified for a longer period. Over time the resulting negative job competition externalities lower the probability of finding a low-skill job, while increasing the probability of finding a high-skill job.

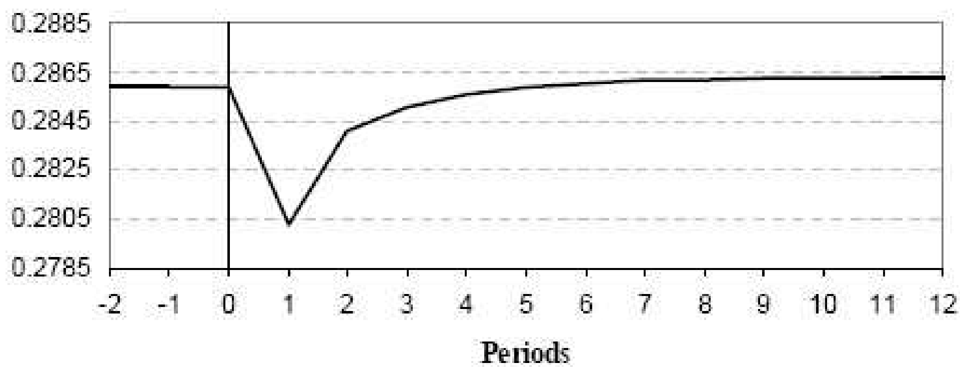

Figure 1.11: Effect of a Separation Rate Shock on the Probability of Finding a High-skill Job.

Given these changes in job probabilities in response to the increase in job separation, the model suggests that a higher degree of over-qualification during recessions is the result of an increase in job separation and flow of workers into unemployment.

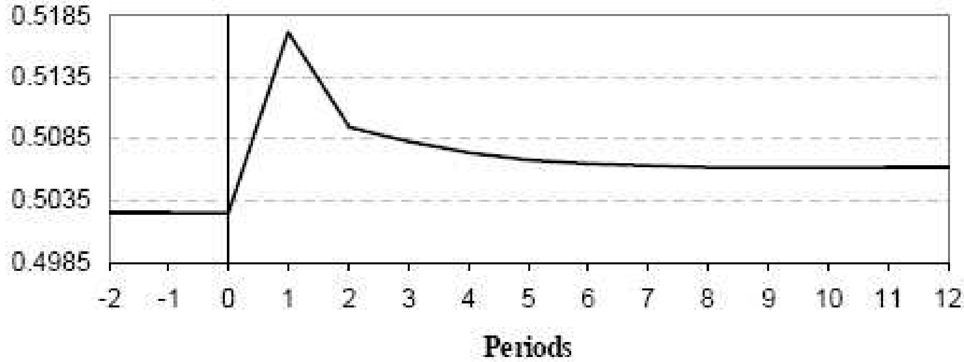

Figure 1.12: Effect of a Separation Rate Shock on the Probability of Finding a Low-skill Job.

If indeed recessions are characterized by sharp increases in job separation then the model can explain the observed procyclicality in match quality. As can be verified from Figure 1.13, in response to the separation rate shock, average match productivity decreases gradually, as more high-skilled workers become overqualified, and converges to a lower level.

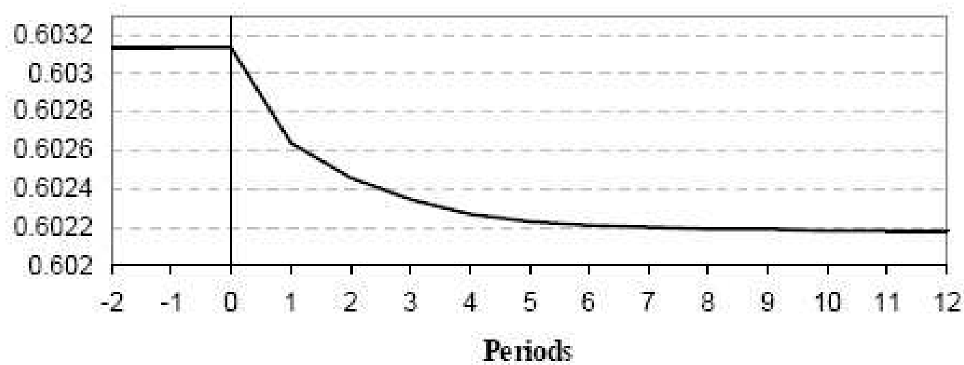

Figure 1.13: Effect of a Separation Rate Shock on Average Match Productivity.

The question that remains is whether separation rate fluctuations can also explain higher and more volatile low-skilled relative to high-skilled unemployment. One would expect that the shift in the vacancy mix towards low-skill vacancies in response to the shock, and the resulting higher probability of finding a low-skill job, would improve the position of low-skilled workers relative to high-skilled workers in the labor market. However, this is not the case. The shift in the vacancy mix exerts a positive VCE on low-skilled employability, but at the cost of the strong negative job competition externalities that follow. The evolution of unemployment and mismatch is illustrated in Figure 1.14. Both unemployment rates increase in response to the shock, but the low-skilled unemployment rate continues to increase even further as the mismatch rate increases. Eventually, the low-skilled unemployment rate converges to a level 1.6 percentage points above the original, while the high-skilled unemployment rate converges to a level only 1.2 percentage points above the original.

As in the case of a negative productivity shock, the impact of a separation rate shock on unemployment and mismatch rates is not qualitatively sensitive to changes in parameters such as the relative productivity of high-skilled workers or the skill composition of the labor force. What drives the evolution of mismatch and unemployment rates in response to the separation rate shock is the increase in the fraction of low-skill vacancies, following the increase in the relative profitability of low-skill jobs. In turn, the increase in the relative profitability of low-skill jobs rests solely on the fact that low-skill vacancies can be re-filled faster once dissolved, because they can be filled by both types of workers. This advantage is never reversed, no matter the skill-composition of labor force or the productivity dispersion between high- and low-skill jobs.

I close this section by discussing the impact of job competition externalities

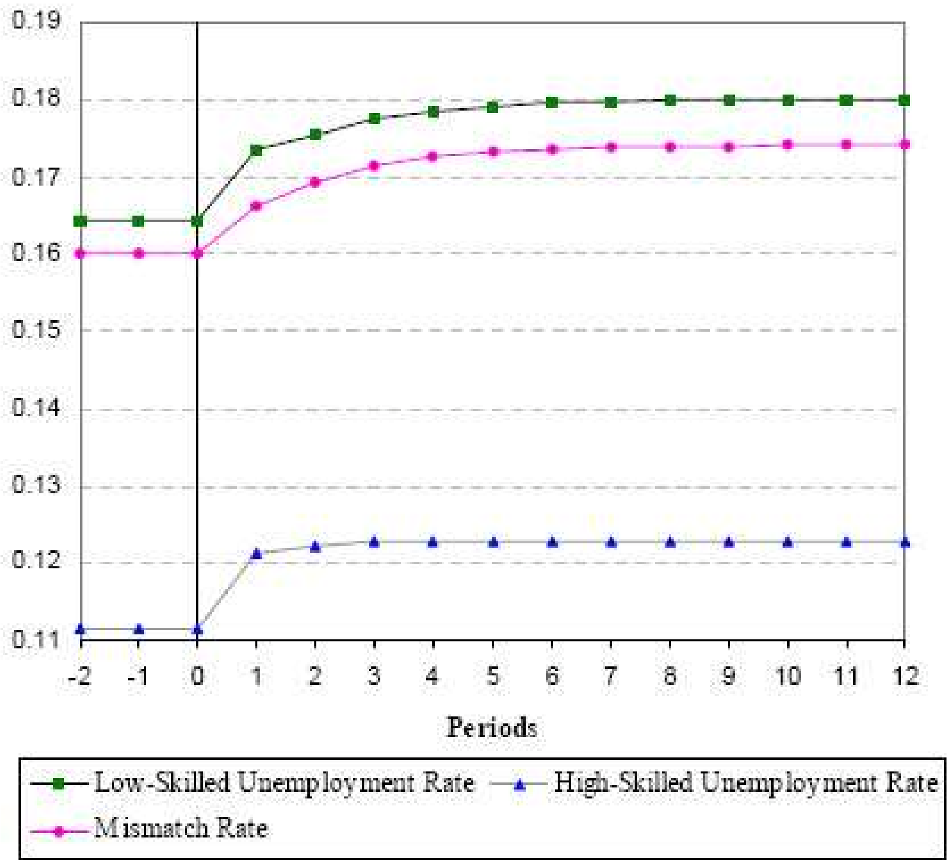

Figure 1.14: Effect of a Separation Rate Shock on Unemployment and Mismatch Rates.

on low-skilled employability. Unquestionably, the negative externalities arising from intensified job competition for low-skill jobs in response to the job separation shock harm low-skilled employability. However, the job competition externalities are not the only driving force behind the relatively higher sensitivity of low-skilled unemployment to cyclical fluctuations. The changes in the skill mix of vacancies that occur over the business cycle are also important, as low-skilled workers are more vulnerable to these changes than high-skilled workers. In response to a negative productivity shock, job competition externalities decline, but still low-skilled unemployment rises relatively more, because of the skill upgrading in the skill composition of vacancies that hurts low-skilled employability. On the other hand, a negative separation rate shock exacerbates the negative job competition externalities on low-skill employability, but only because low-skill vacancies become relatively more plentiful. Hence, regardless of the effect of the co-movement between aggregate productivity and job separation on competition for low-skill jobs, recessions hurt low-skilled employability relatively more.[13]

1.5 Conclusion

In this paper I develop a model that examines the impact of skill-mismatch, in the form of high-skilled workers taking temporarily low-skill jobs, on labor productivity and unemployment dynamics by skill. I capture negative job competition

[13] Job competition may actually benefit low-skilled employability by stimulating low-skill vacancy creation. I simulated the model assuming that searching on the job is costly enough that high-skilled workers are no longer willing to take low-skill jobs (i.e., separate markets). I found that unemployment for both types is higher when markets are separated than when cross-skill matching takes place. The high-skilled unemployment rate is higher in the absence of cross-skill matching for the obvious reason: given that they cannot take low-skill jobs they have a harder time escaping unemployment. What is somewhat surprising is that low-skilled unemployment is higher, but the explanation is also reasonable: when high-skilled workers are not willing to take low-skill jobs, the value of opening a low-skill vacancy is lower, as the option value of hiring a high-skilled worker is forgone, resulting in lower vacancy creation and higher unemployment in the low-skill market. This explanation does not contradict my previous argument that firms with low-skill vacancies prefer hiring low- instead of high-skilled workers. The intuition is that low-skill firms prefer hiring low- to high-skilled workers because the latter are likely to quit, but they are still better off having the option of hiring a high-skilled worker in case they meet one.

externalities on low-skilled employability, by incorporating into the model the fact that low-skilled workers qualify only for jobs with low skill requirements.

Previous work has argued that recessions hurt the matching process as firms post fewer vacancies per job seeker. As a result, mismatched workers who search on-the-job for better matches remain mismatched for a longer period, aggravating the allocation of workers into mediocre matches. However, as this paper illustrates, this is not the whole story. Recessions also involve an increase in the relative number of high-skill vacancies that facilitates the transition of high-skilled workers into high-skill jobs, thus bringing down the degree of over-qualification in the labor market. Accounting for the asymmetric nature of the matching technology, and the resulting job competition externalities, shows that recessions involve a higher degree of over-qualification only when associated with higher job turnover and flow of workers into unemployment. Hence, my model provides insights into skill-mismatch over the cycle that stress the role of increases in job separation when aggregate productivity is low. Further, my model explains observed differences in labor market outcomes of different skill cohorts. The asymmetry explains the relatively low exit rates of low-skilled workers from unemployment, and their relatively low propensity to search on the job. My model can also explain why low-skilled unemployment exhibits relatively higher cyclical sensitivity. The common belief is that, during recessions, high-skilled workers "crowd-out" low-skilled workers as they compete for jobs. However, in this paper I illustrate that the higher sensitivity of low-skill unemployment to changes in economic activity is not due to crowding out per se. Instead, the primary reason is that high-skilled workers qualify for both high- and low-skill jobs, and therefore are less vulnerable to changes in economic activity, because they are less vulnerable to the changes in the skill mix of vacancies that occur simultaneously.

By highlighting the vacancy composition effect of recessions, which has been overlooked in previous research, my model improves our understanding of how recessions affect the matching process and the employability of different skill cohorts, and suggests a closer look at the evolution of the skill mix of vacancies. In addition, by laying out the effects of aggregate productivity and job separation on the skill composition of vacancies, I stress the importance of understanding the relation between the two impulses. Modeling endogenous responses of the separation rate to changes in aggregate labor productivity as in Mortensen and Pissarides (1994), for instance, is therefore, the natural extension of the model. The nature of the model in this paper requires the endogenous variables to depend on the aggregate state and also on the distribution of workers across types of matches. Therefore, introducing aggregate productivity fluctuations alone is a significant contribution and makes the task of endogenizing job separation much more plausible. Future research will build upon this contribution by endogenizing separations.

Chapter 2

Cyclical Variation in Match Quality: The Role of Unemployment Risk

2.1 Introduction

Studies show that the unemployment rate of low-skilled workers is higher and more sensitive to changes in economic activity compared to that of high-skilled workers.[1] Some have suggested that this may in part be caused by "crowding out", i.e. the phenomenon in which high-skilled workers occupy simple jobs during recessions, thereby pushing low-skilled workers into unemployment, and move on to better jobs in booms.[2] Existing research has not yielded clear conclusions about the empirical relevance of such a cyclical pattern in the matching behavior of high-skilled workers. Hence, its empirical relevance remains a question, the answer of which forms the basic goal of this chapter.

To this end, I study the mismatch rates and job level dynamics using a panel of 15748 individuals constructed from the yearly family files of the Panel Study of

[1]For evidence on the cyclicality of low-skilled unemployment rate, see for example, van Ours and Ridder (1995). For evidence on the distribution of jobless time and unemployment being heavily concentrated among the least skilled individuals see e.g. Topel (1993); Bovengerg (1997) Ashenfelter and Ham (1979); Nickell (1979).

[2]See e.g., and Teulings and Koopmanschap (1989).

Income Dynamics (PSID), which covers the years from 1968 to 1993.[3] By job levels I refer to categories of occupations that differ in terms of skill requirements and prestige (i.e., high job levels are jobs that require more education and have higher prestige scores than low job levels).

First, to give a general idea of the cyclical patterns in match quality across different skill groups, I look at how mismatch rates vary over the business cycles and across workers with different education. Second, I use linear probability and Logit regression analysis to characterize how the probability of moving either to high- or low-skill jobs is affected by the overall unemployment rate and the education of the worker. Third, by adopting dynamic panel data estimation methods, I measure the effect of the workers' lagged state (i.e., whether unemployed or mismatched), as well as the effect of its interactions with overall the overall unemployment rate and workers' education level, on the probability of transitions to either high- or low-job levels. Finally, by modeling the dynamics of transitions as a first order Markov process, which is heterogeneous among individuals I investigate how workers' transitions between job levels vary with skill and over the business cycle. To characterize the transitions, I adopt a fixed effects multinomial Logit estimation procedure designed by Honoré and Kyriazidou (2000), which is based on conditional likelihood maximization (Chamberlain, 1984).

[3]Existing studies test for crowding out phenomena mainly in Europe. In the U.S. crowding out as an explanation for the high and more cyclical low-skill unemployment received less attention. To my knowledge, this is the first study that tests for crowding out phenomena using data from the U.S.

The comparison of job level probabilities across groups of workers with different education years of high employment growth to those of low employment growth is a common methods of testing for cyclical variation in match quality. Such a comparison reveals whether workers with a given level of education achieve lower job levels in years with low employment growth, as the crowding out hypothesis assumes. Examples are Gautier, Pomp and Zijl (1997), and Gautier (1998) who separate workers into educational levels and estimate multinomial Logit models (one for each level of education).

Empirical tests also compare educational levels per job level. Teulings and Koopmanschap (1989), for example, explain regional changes in the distribution of educational levels per job level, using regional changes in unemployment rates. In a similar analysis, Hartog (1992) uses survey answers to questions regarding labor market tightness of the form: do people with your education, skills and age, in your area, easily find a job to match this? Others test the crowding out hypothesis by looking at the flows of filled vacancies. For example, van Ours and Ridder (1995) test whether lower stock of vacancies and higher number of unemployed job seekers at the beginning of the period, leads to higher flow of filled vacancies at lower levels. Their test of crowding out also involves estimating whether the correlation between the unemployment rate of higher educated workers and the flow of filled vacancies at lower job levels is positive and significant.

There are considerations, however, as to whether the empirical methodologies described above are accounting for the *cause* of the cyclical variation in match quality if such phenomenon exists. Higher probabilities, higher fractions of high-skilled workers, or higher flows of filled vacancies, at low job levels when employment growth is low, do not necessarily imply that the risk of unemployment induces workers to accept jobs below their skill level, as they can also be due to other reasons. For example, changes in the hiring and firing policies of firms (i.e., firms require more schooling at given job complexity during bad times), or higher turnover rates of low-skilled can also produce similar patterns.[4] Similarly, the opposite findings do not necessarily reject the existence of over-qualification. High-skilled workers may accept low-skill jobs to avoid the distress of being unemployed, but higher overall unemployment may not have the same effect on the behavior of high-skilled workers.

In order to account for this limitation, the main innovation of my empirical methodology is that it allows for job level probabilities to vary not only with overall economics activity, but with the workers' lagged state. In particular, I adopt dynamic panel data estimation methods, in which the worker's lagged state enters the model as an explanatory variable. By controlling for the lagged state I capture some

[4]Other explanations include skill-biased technological change, minimum wages, search frictions in combination with higher turnover rates of low-skilled workers, and incentive structures (e.g. high replacement rates, high reservation wages) that induce low-skilled workers to search less effectively. To my knowledge the only study that takes some of these considerations into account is Gautier *et al.* (2002). Unlike the studies mentioned above, which restrict crowding out to be an inflow phenomenon only, they allow for changes in the educational attainment per job level to be the result of a combination of inflow and outflow policies at the firm level. Hence, they observe whether upgrading at given job levels is associated with the outflow of relatively low educated workers or the inflow of relatively high educated workers. Nevertheless, this methodology does not distinguish crowding out from the rest of the possible explanations.

propensity to experience a certain job level, which has been previously unmeasured by focusing only on how overall economic conditions affect job level probabilities.[5] In particular, I am able to address whether *unemployed* high-skilled workers are more likely to move into low job levels, while *mismatched* workers are more likely to move into higher job levels when economic conditions improve.

Although existing studies reach mixed conclusions regarding the empirical relevance of cyclical variation in match quality of high-skilled workers, I find evidence highly suggestive of it. The mismatch rate of college graduates is higher and exhibits higher cyclical variation than the mismatch rate of workers without a college degree. Moreover, I find that in periods of high unemployment rate, the high-job-level probability of college graduates is lower, while the low-job-level probability is higher. The results of the dynamic panel data regression analysis show that when the origin state is unemployment, workers with a college degree are more likely to move into low-job-levels when the overall unemployment rate is high. Moreover, the results point to the existence of an upgrading in the job levels of mismatched college graduates when the unemployment rate is low.

Consistent with the crowding out hypothesis, the estimates of the Markov

[5] In a similar spirit, Teulings (1993) also accounts directly for the role of the risk of unemployment plays on job level transitions. He follows a different estimation procedure than the studies described above. On the basis of a number of job characteristics he ranks jobs from the most desirable to the least desirable and estimates whether higher expected search duration decreases the probability of finding an attractive job. His results confirm that this indeed the case, suggesting crowding out, but Teulings admits that other explanations may also be consistent with his findings.

Chain Multinomial Logit model of job level transitions suggest that the odds of moving to a lower job level, as opposed to a higher job level, are larger when the lagged state is unemployment and vice versa. Moreover, I find that the negative impact of higher unemployment rate on each job level probability declines with education and more evidently for "mediocre" job levels. Thus, I conclude that workers of higher education are more likely to accept jobs below their skill level than become unemployed.

The rest of the chapter is organized as follows. In section 2.2, I describe the data set. Following this, in section 2.3, by grouping occupations into categories using prestige scores and information on educational attainment, I show how mismatch rates vary over the business cycle and across different education groups. Sections 2.4 to 2.6, describe the empirical models, estimation methodologies, and results. Finally, in section 2.7, I conclude this chapter with some remarks.

2.2 Data

Each year the Panel Study of Income Dynamics (PSID) asks the head of each family participating in the study to report his/her employment status, i.e. whether unemployed, employed or out of the labor force and their occupation. Occupations are reported using the 3-digits code from 1970 Census of Population. I use the PSID family files to construct an unbalanced panel of 15748 heads who have been in the labor force for at least one year. The panel covers the years from 1968 to 1993. I consider individuals who report being students, retired, or keeping a house, to be out of the labor force. Since I am only interested in analyzing movements across occupational categories and unemployment, I am not considering transitions in and out of the labor force. Hence, these transitions are excluded from the sample.

Responders also report their years of schooling, which can be used as proxy for their skill level. A better approximation of skill would be a combination of education and work experience. Unfortunately, the questions regarding experience and job training asked in the PSID vary from year to year. I can only use both education and work experience as a proxy for workers' skill level, if I concentrate on a smaller subperiod, in which case, the sample size declines considerably.

To capture the effect of aggregate economic activity on job level transitions, I use the yearly average unemployment rate as a time varying covariate in the estimation procedures. I construct the time series of yearly average unemployment rates, using the seasonally adjusted monthly unemployment rates for the years 1968 to 1993, available from the Current Population Survey (CPS).

I separate occupations into categories (job levels) based on the Hodge-Siegel-Rossi (HSR) prestige scores, which are conveniently assigned to the 3-digit U.S Census of Population classification.[6] Table A.1 in Appendix A gives a detailed description of the scores.

[6]One could argue that the use of the term "job level" is misleading, because I am essentially referring to occupation and not job categories. It may be the case that workers with the same occupation perform jobs or tasks of different complexity. Hence, there may be variation in skill requirements within occupations. The reason I am using occupation and not job categories is simply the lack of such information.

The problem with prestige scores is that they do not necessarily measure the complexity of the jobs or the skill level required to do the job. Ideally, occupations would be categorized based on their skill requirements rather than their socioeconomic status. Such a ranking could be constructed by measuring workers' qualification in each occupation. However, the PSID is a relatively small data set and the number of workers within each occupation is sometimes too small to obtain accurate estimates of skill requirements.[7] Although no information regarding educational attainment was used to derive these scores, this caveat is partly surpassed by the fact that the scores are highly correlated with the level of educational attainment of the workers in each occupation. Occupations with high prestige scores are occupations that employ workers with high levels of education.

Table 2.1 illustrates the resulting job levels using prestige scores. Some additional descriptive statistics of are in Table 2.2. On average, 5% of the individuals is unemployed and the majority of employed individuals is found in job levels 1 and 2. Only 14% of the employed is found in the lowest job level and only 4% in the highest.

2.3 Mismatch Rates Over the Business Cycle

The hypothesis discussed in the introduction, and investigated theoretically in the first chapter of my thesis, is that mismatch rates increase during recessions

[7] An alternative methodology would be to rank occupations into skill categories using residual wages. I could regress real wages on education, experience, and other individual characteristics like and create a ranking based on the average residual wage of workers in each occupation.

when there is greater congestion in the labor market, and especially among the more educated who are qualified for a greater variety of jobs. Here I test this hypothesis by looking at how mismatch rates vary over the business cycles and across workers with different education.

As already mentioned, in the absence of information on the skill requirements of each occupation, I group occupations as low-skill and high-skill based on educational attainment and prestige scores. First, I consider as high-skill, occupations with prestige score 37 and above, and low-skill occupations with prestige score below 37. Based on this cutoff point, on average, 90% of college graduates in each year are in high-skill occupations. Then, I consider a lower prestige score cutoff point, 21, which results in an average of 95% of college graduates being in high-skill occupations each year. The lower the prestige score cutoff point that divides occupations between high- and low-skill, the higher the "degree" of mismatch of college graduates who happen to be in low-skill occupations.

Figure 2.1 shows the fraction of mismatched college graduates (i.e., in low-skill occupations) using the 90% cutoff prestige point. There is an obvious upward trend. This may reflect the introduction of new technologies so that traditionally simple or "low-specialization" tasks now require more knowledge and training. We also observe cyclical variation in the fraction of mismatched workers. There was a recession starting at the end of 1973 and ending at the beginning of 1975. As we can see from the graph, the mismatch rate increases in 74. From 1980 to 1982, there were two recessions, one shorter, beginning in 1980 and ending half year later, and one beginning in the middle of 1981 until the end of 1982. The mismatch rate obviously

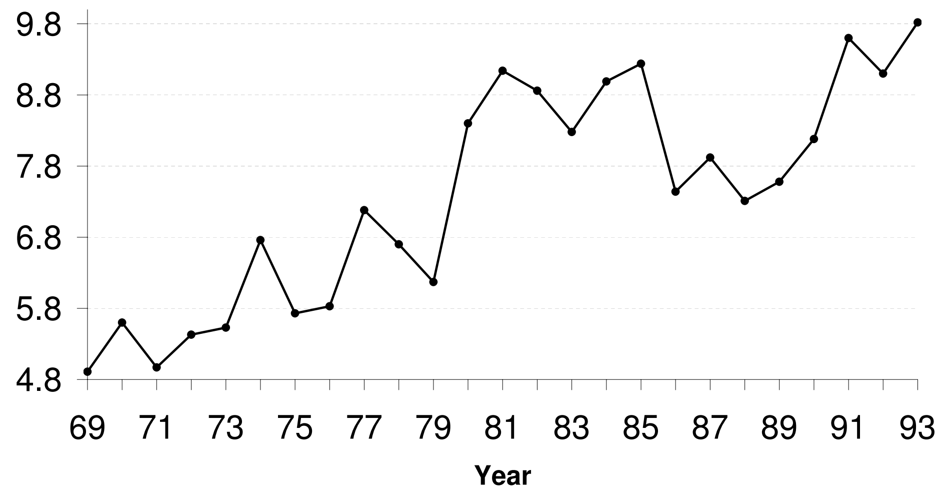

Figure 2.1: Mismatch Rate of College Graduates (90% cutoff point)

increases during that period. It decreases in subsequent years and increases again in the years 90 and 91 reflecting the July 90-March 91 recession.

As expected, when a lower cutoff prestige score is used the mismatch rate is lower. Figure 2.2 shows the fraction of workers with a college degree that are in jobs below the 95% percent cutoff prestige score. Both the upward trend and the relationship between business cycles and the mismatch rate are less clear in this case, but we still observe an increase in the mismatch rate around the years 74, 80 to 82 and 91.

The main assumption of the model in the first chapter of my thesis, upon which the crowding out hypothesis rests, is that there is asymmetric matching: while high-skilled workers can be employed in both high- and low-skill jobs, low-skilled workers

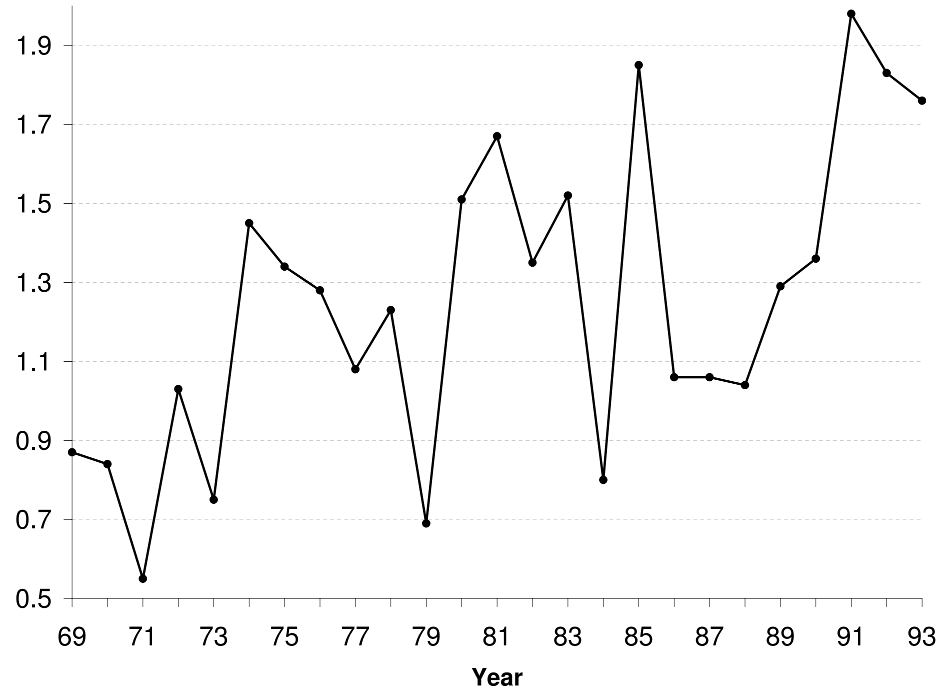

Figure 2.2: Mismatch Rate of College Graduates (95% cutoff point)

do not qualify for high-skill jobs. This is a realistic assumption given that in reality jobs have minimum skill requirements that some workers satisfy, but some others do not. However, asymmetric matching does not automatically imply that mismatch rates increase with education as possible "scarring" effects or career considerations may prevent high-skilled workers from taking low-skill jobs. If this was the case, then we should observe similar levels and patterns in the mismatch rates across workers with different education.

To test this, I compare the mismatch rates of workers with a college degree to those without a college degree. I measure the mismatch rates of workers without college degree in a similar fashion. I find the cutoff prestige score that implies on average 90% of workers without a college degree each year are in occupations

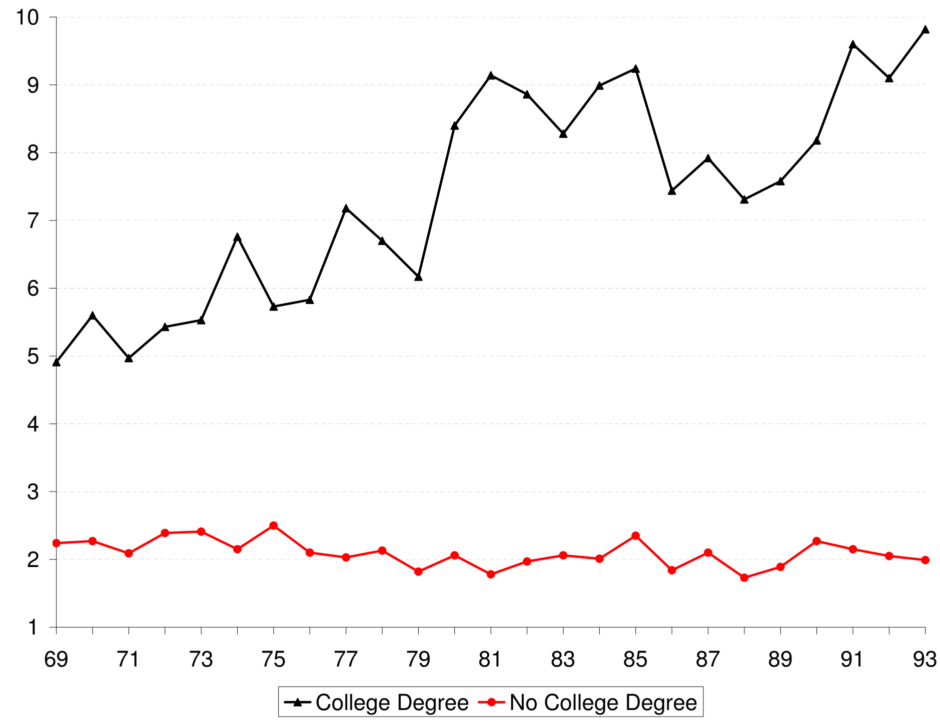

Figure 2.3: Mismatch Rates by Education (90% prestige cutoff point)

above the cutoff prestige point. The mismatch rates for the 90% cutoff prestige score for workers with and without a college degree, respectively are in Figure 2.3. The mismatch rate of workers without a college degree is much lower overall and relatively constant over time. One the other hand, the mismatch rate of college graduates is much higher, has an upward trend and exhibits cyclical variation.

If high-skilled workers are eligible for more types of jobs and hence, as shown above are more likely to mismatch during recessions, the question that follows naturally is whether the fraction of unemployed workers decreases with education and exhibits more cyclical variation. Is it the case that high-skilled workers, as opposed to low-skilled workers, mismatch and search on the job instead of staying or becoming unemployed during recessions? Figure 2.4 shows the fraction of workers with

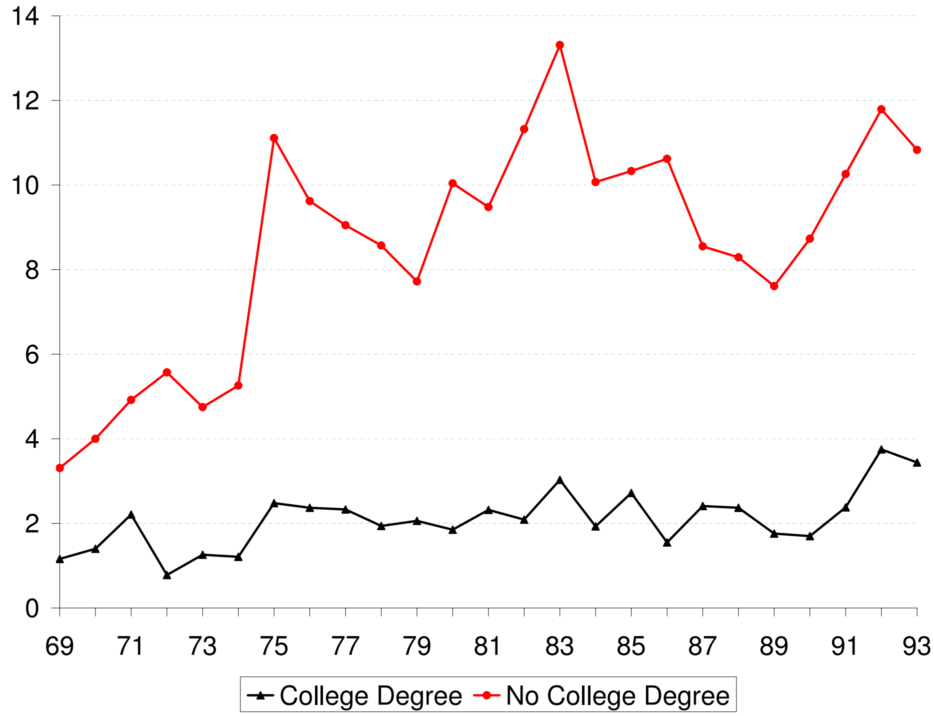

Figure 2.4: Fraction of Unemployed by Education

and without a college degree reporting unemployed each year. The fraction is always higher for workers without a college degree. In addition, it exhibits higher cyclical variation. While both fractions follow a similar pattern, the fraction for workers without a college degree increases more evidently in recessions (around 74-75, 80-82 and 90-91).

Another interesting question that arises is whether the higher mismatch rates in recessions are due to workers moving into "stop-gap" jobs as opposed to a general type of mismatch. Stop-gap jobs are considered to be part-time jobs and temporary arrangements in low-paying industries. A more general type of mismatch occurs when workers simply lower their standards when finding a suitable job is difficult, and accept jobs of slightly lower level, but not necessarily stop-gap jobs. If what observed is a stop-gap phenomenon we should expect a higher fraction of mismatched workers to be concentrated in jobs with very low prestige scores.

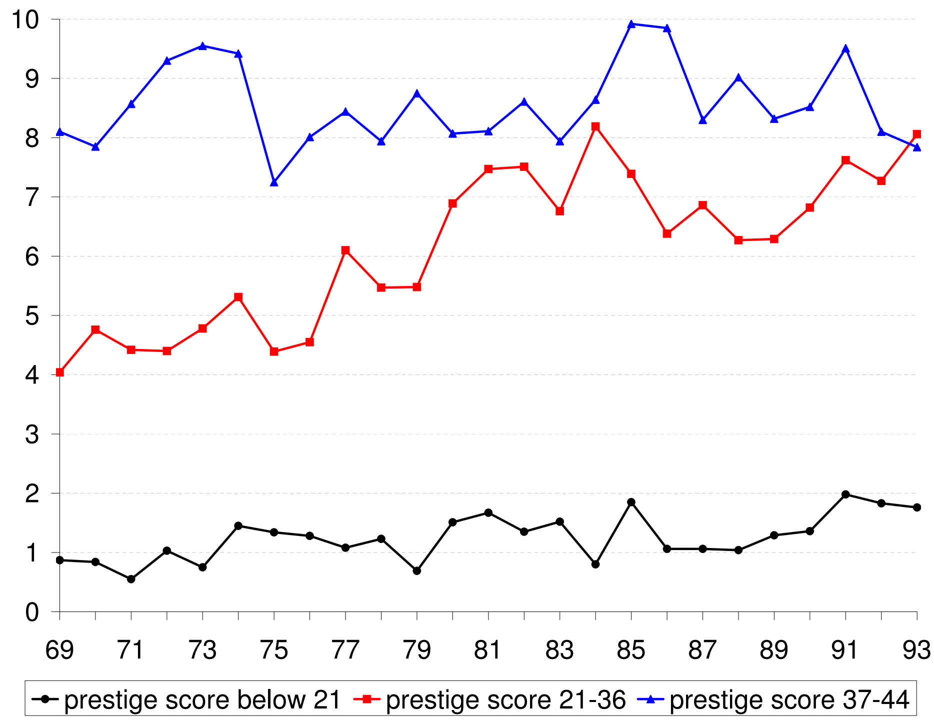

Figure 2.5: Degrees of Mismatch: College Graduates

In Figure 2.5, I compare the fraction of college graduates in jobs with lower prestige scores to that in jobs with higher prestige scores. As we can see from the figure, the fraction of college graduates in jobs with prestige scores 37-44 is higher than the fraction in jobs with prestige scores 21-36. Moreover, the latter is higher than the fraction of college graduates in jobs with prestige score below 20. In addition, the fraction of college graduates in middle prestige category (21-36) follows the business cycle most closely (i.e., it increases in recessions and decreases in booms). This indicates that workers are mainly taking "mediocre" jobs to avoid unemployment rather than stop-gap jobs.

2.4 Linear Probability and Logit Models

In this section, I estimate linear probability (LP) and Logit models to characterize how the probability of moving to either high or low job levels is affected by the overall unemployment level and the education level of the worker. I consider as high job levels, occupations above the 90% prestige score cutoff point. Low jobs levels are occupations below this cutoff point. Moreover, throughout the analysis, I consider as high-skilled workers who hold a college degree. The model to be estimated is the following:

$$y_{it} = \beta_1 UNE_{i,t-1} + \beta_2 EDU_{i,t-1} + \beta_3 (UNE * EDU)_{i,t-1} + \epsilon_{it} \tag{2.1}$$

The latent variable y_{it} describes the propensity to be either in high or low job levels, depending on the question of interest. The variable UNE is a dummy that takes the value of 1 when the unemployment rate is above 6%, and EDU is a dummy that takes the value of 1 when the worker has a college degree and zero otherwise. The EDU*UNE variable is an interaction term that takes the value of 1 when both the unemployment rate is high and the worker has a college degree.[8] The subscript

[8]I model the unemployment rate as a dummy instead of a continuous variable because it makes it easier to interpret the marginal effects of the unemployment rates and its interaction with the education dummy on the probability. Moreover, in the sections that follow, I estimate dynamic models where whether the worker is mismatched or not, enters as an explanatory variable. By modeling the unemployment rate as a dummy allows me to ask what is the effect on the probability of high job levels when the worker is mismatched and the unemployment rate is low (i.e., is below 6%). Hence, I model the unemployment rate in the same fashion here to be able to compare the estimates. However, the reader should know that the results that follow do not change when a

i is for individual and t is for time. I model individual effects as fixed. Hausman tests show that fixed effects are more appropriate, but the results are similar in both cases.

2.4.1 The Effect of Business Cycle and Education on High- Job-Level Probability

The results in the first two columns of Table 2.3 show the marginal effects estimates of the LP and Logit model, respectively, when the interaction term between education and unemployment is not included in the set of regressors. As expected, education has a positive and significant effect on the probability of high job levels. The unemployment dummy, on the other hand, has no significant effect on the probability. However, the question of most interest is not how higher unemployment in general affects the probability, but whether higher unemployment reduces the probability *high-skilled* workers move into high job levels. To address this question we need to look at the interaction between the education and the unemployment dummy.

The 3rd and 4th columns show the results when this interaction term is included. The interaction has a negative and significant marginal effect in both cases. The LP model suggests that when overall unemployment is high the probability workers with a college degree will be in a high job level next period is approximately 1.5% lower, while the Logit model suggests that the probability is approximately

continuous variable is used.

5.5% lower. According to the likelihood ratio test chi-squared statistic, which is statistically significant at the 5% level, the model with the interaction term is superior to the partial model.

The results are consistent with the view that in periods of high unemployment high-skilled workers have a more difficulty moving into the jobs they are best suited for. Although having a college degree increases the probability of moving into high job levels, when unemployment is high, the effect of education on the probability is lower.

2.4.2 The Effect of Business Cycle and Education on Low- Job-Level Probability

The results above suggest that in periods of high unemployment high-skilled workers have more difficulty moving into the jobs they are best suited for. However, this does not necessarily imply that high-skilled workers take jobs below their skill instead. It may be the case they just become or stay unemployed. To clarify this I also estimate the effects of overall unemployment, education and their interaction on low-job-level probability.

The results are in Table 2.4. I find that when the unemployment rate is high, workers with a college degree are more likely to be in low job levels next period. Having a college degree has a negative and significant effect on the probability. The effect of unemployment rate, on the other hand, although quite small, is negative and significant. Again, the question of interest it is whether *high-skilled* workers are more likely to move into low job levels when the unemployment rate is high. Hence to address this question we need to look at the effect of the interaction between UNE and EDU.

The interaction of the two has a positive and significant effect. The negative impact of overall unemployment on the probability of moving into low-job levels is lower when the worker is high-skilled. Equivalently, the negative impact of having a college degree on low job levels probability is lower when overall unemployment is high. The LP model suggests that is approximately 2% lower, while the Logit model suggests is approximately 7% lower. Moreover, the likelihood ratio test statistic, which is statistically significant at the 5% level indicates that the interacted model is superior to the model without interaction term.

2.5 Dynamic Panel Data Models

Individuals' decisions on whether or not to accept a particular job depend not only on the overall unemployment rate and their education level, but also on their state at the time the decision is made. In this section, account for this effect by including workers lagged state in the set of regressors. In particular, I consider the following model:

$$\begin{aligned} y_{itk} &= \beta_1 UNE_{i,t-1} + \beta_2 EDU_{i,t-1} + \beta_3 (UNE * EDU)_{i,t-1} + \gamma_1 \mathbf{1}\{y_{i,t-1} = j\} \\ &\quad + \gamma_2 [\mathbf{1}\{y_{i,t-1} = j\} * (UNE * EDU)_{i,t-1}] + \epsilon_{it} \qquad (2.2) \end{aligned}$$

where UNE and EDU are as defined above. The latent variable y_{itk} indicates the propensity the current state is k, while $y_{i,t-1}$ indicates the lagged state. There three possible states: high job level, low job level and unemployment. Depending on the question of interest, I model k to be either high or low job level and j to be unemployment. I divide occupations into low and high job levels using the 90% prestige score described above.

The possibility of unobserved unit effects, unfortunately makes the estimation of dynamic panel data models complicated. If a lagged depended variable model is estimated in the presence of unit effects, these effects are transferred to the disturbance term, violating the strict exogeneity assumption. I get around this problem by following 3 different estimation approaches.

First, I adopt the Anderson and Hsiao (1981) instrument al variables approach in the first differences of the model. According to this approach the coefficients can be estimated consistently by instrumenting the lagged depended variable. Anderson and Hsiao (A-H, henceforth) suggested using the second lag of the depended variable as instrument. Second, I use a generalized method of moment estimator proposed by Arellano and Bond (1991), which is based on the same idea. The Arellano-Bond (A-B) approach, first identifies how many lags of the dependent variables are valid instruments. Then, it combines these lagged levels and first differences of the strictly exogenous variables into an instrument matrix, and then, it derives the corresponding one-step and two-step GMM estimators.

Finally, I estimate a non-linear probability model by adopting Chamberlain's (1980) conditional MLE approach. Chamberlain proposed a procedure that specifies the density of $(y_{i1}, ...y_{iT})$ given y_{i0} and the vector of explanatory variables (x_i) for each i . What is convenient with this approach is that I can use standard random effects software to estimate the parameters. The only difference is that the list of explanatory variables is expanded to include the include y_{i0} and x_i in each period.

2.5.1 Are Unemployed High-Skilled Workers More Likely to Take Low-Skill Jobs in Recessions?

I begin with investigating the probability of low job levels. I model k to be high job levels and j the state of unemployment. With each of the estimation procedure described above I estimate three specifications. First, I estimate the main model in which the set of regressors contains only UNE, EDU and $\mathbf{1}\{y_{i,t-1} = j\}$. Then, I add the interaction term between UNE and EDU in the model. The third specification, which I call fully interacted model, includes in addition the three-way interaction term between UNE, EDU and $\mathbf{1}\{y_{i,t-1} = j\}$.

Table 2.5 summarizes the results in three panels, one for each estimation procedure. The result that education has a negative effect on the probability of low job levels is carried over in the dynamic model, but the results regarding the constituent effect of a UNE are mixed. It is insignificant according to the A-H and A-B procedure, but negative and significant according to the Chamberlain approach. Hence, we reach mixed conclusions regarding the impact of unemployment on low-job-level probability.

However, unemployment at the individual level seems to be important. With the exception of A-B procedure, where the effect of LAG is significant only in the fully interacted model, the other two approaches suggest that being unemployed has a negative impact on the probability of low job levels. This result does not represent rejection of the hypothesis that the risk of unemployment induces high-skilled workers to accept low job levels. To test this hypothesis, the variables of interest are the interaction terms.

When the interaction term between EDU and UNE is included in the set of regressors (second row of each panel) the rest of the coefficients retain their signs, but in contrast to the LP and Logit models presented above, the effect of this interaction here is not always positive. The A-H and A-B procedures reach similar conclusions regarding the impact of this interaction. While the constituent effect of higher unemployment rate is insignificant, its effect conditional on the worker having a college degree is negative (although, only marginally significant in the A-B procedure). Therefore, the results of these two procedures suggest that higher overall unemployment reduces the low job level probability of workers with a college degree even further.

In both cases, however, when this term is further interacted with the lagged unemployment dummy (third row of each panel) it becomes positive and significant, suggesting that college graduates are more likely to move into low job levels when they are unemployed and the unemployment rate is high. The results of both estimation procedures imply that the probability a worker with a college degree will be in a low job level next period is lower when overall unemployment is high, but conditional in addition on the worker being unemployed, the probability is higher. In both cases, the negative impact of education on low job level probability is weaker when unemployment is high and the worker is experiencing unemployment.

The results of the Chamberlain approach are most strongly supportive of the view that the risk of unemployment induces high-skilled workers to take low-skill jobs, especially in periods of high unemployment. Not only the three-way interaction term has a positive effect on the probability, but the two way interaction between unemployment and education has a positive effect on the probability as well.

The last row of the table contains the results of Logit estimates of the fully interacted model assuming no unobservable effects. The results are consistent with the Chamberlain results. Both the two-way and the three-way interaction terms are positive and significant, while the constituent effects of higher unemployment rate and having a college degree are negative and significant.

In sum, all estimation procedures suggest the negative effect of holding a college degree on the probability of low job levels is weaker when the origin state is unemployment and overall unemployment is high. Moreover, in comparison with the LP and Logit estimated presented earlier, the dynamic model puts more emphasis on the risk of unemployment at the individual level. The dynamic model suggests that what may induce high-skilled workers to accept jobs below their skill level is being unemployed while overall unemployment rate is high, rather than just the fact that the overall unemployment rate is high.

2.5.2 Are Unemployed High-Skilled Workers Less Likely to Take High-Skill Jobs in Recessions?

Here I investigate the impact of the same set of regressors and their interactions on the probability of moving into high job levels (i.e., k = high job level). The variation in the results across the different estimation procedures is higher in this case. While most procedures contribute to the conclusion that interactions between unemployment, either at the aggregate level or the individual level and education have a negative impact on the probability of high job levels, we cannot argue that this is certainly the case.

The results of the three estimation procedures are in Table 2.6. In accordance with the results so far, the A-H and A-B approach, show that the constituent effect of higher unemployment on high-job-level probability is insignificant. In the Chamberlain approach, however, the constituent effect of higher unemployment rate is insignificant, but when the interaction terms are included, it becomes positive and significant.

The constituent effect of the lagged unemployment dummy is in general insignificant. The only case this is negative and significant is in the Chamberlain approach. However, even in this case, it is significant only when the three-way interaction term is not included in the set of regressors. As can be verified from the third row of the bottom panel, when LAG is interacted with EDU and UNE, its constituent effect is no longer significant.

The conclusion that could be drawn from both the A-H and Chamberlain approach is that when the worker is unemployed, or when the unemployment rate is high, does not necessarily imply lower high-job-level probability, unless the worker has a college degree. In other words, those more likely to have a harder time moving into high-skill jobs when they are unemployed or when the unemployment rate is high, are those qualified for high-skilled jobs (i.e., those who hold a college degree).

In the A-H case, the only way higher unemployment rate affects negatively the high-job-level probability is when the worker both has a college degree and is experiencing unemployment. In fact, we get the counterintuitive result that the effect of the interaction between UNE and EDU, although quite small (approximately 1%) is positive and significant. The only way this results can be justified is if this interaction is actually picking up some of the effect of education. The constituent effect of having a college degree, as expected, and as the results indicate, is positive. Comparing the interacted model (row 2 and 3) to the constituent model (row 1) we can see that when the interaction between UNE and EDU is included the constituent effect of having a college degree declines by approximately 1 percentage point.

Similarly, in the Chamberlain approach, the thee-way interaction effect is negative, although only marginally significant at the 5% level, but in addition, the effect of the two-way interaction term between UNE and EDU on the probability is negative and significant. Thus, the positive impact of having a college degree on high-job-level probability is lower in periods of high unemployment.

The results of the A-B approach are different. The effect of the interaction between overall unemployment and education is very small and only marginally significant at the 5 % level in the fully interacted model. Moreover, the A-B approach gives the paradoxical result that when this term is further interacted with the lagged unemployment dummy it has a positive and significant effect on the probability of high job levels. This implies that in periods of high unemployment, workers who have a college degree, can more easily move into a high job level when unemployed than when employed. While the A-H results suggest that the positive impact of having a college degree on high-job-level probability is lower when overall unemployment rate is high and the worker is unemployed, the A-B approach contradicts this finding.

The strongest support for the hypothesis that unemployment both at the individual level and at the aggregate level reduces the probability of high-skilled (college graduates) workers finding an appropriate match can be found in the Chamberlain estimates. In this case, both when education is interacted with overall unemployment and when it is further interacted with the lagged unemployment dummy it has a negative and significant coefficient (although, the latter is only marginally significant at the 5% level).

Given the variation in the estimates across the different estimation procedures, it is useful to take a look at the estimates assuming no unobserved effects. These are given in the last row of the table. The only significant coefficients are those of EDU and UNE*EDU. The former is positive, while the latter is negative, confirming the LP and Logit estimates presented earlier. The estimates of the model with unobserved effects are also consisted with the Chamberlain estimates. They suggest that higher unemployment rate reduces the positive impact of having a college degree on high-job-level probability.

The overall conclusion from this analysis is that there some evidence suggestive of the hypothesis that high-skilled workers have more difficulty moving into high-skill jobs when unemployment is high. However, these evidence are not concrete.

2.5.3 Are Mismatched High-Skilled More Likely to Take High-Skill Jobs in Booms?

The results in section 2.5.1 suggested that college graduates are more likely to move into low job levels when unemployed, and overall unemployment is high. Hence, they support the view that the risk of unemployment induces workers to take jobs below their skill level. Here, I ask the question of whether this phenomenon is temporary or not. Do college graduates accept job below their skill level transitorily, until overall economic conditions improve, and a better job comes along?

To address this question I investigate how the unemployment rate affects the high-job-level probability of mismatched workers. I consider as mismatched workers who hold a college degree and are in low job levels (i.e., j = low job levels). As mentioned at the beginning of this section, this implies that they are in jobs the on average employ approximately only 10% college graduates each year. In addition, I model the overall unemployment rate dummy to be the reverse of the unemployment dummy in previous regressions. UNE takes the value of 1 when the unemployment rate is below 6% and 0 otherwise. Given this specification, the two-way interaction term between EDU and UNE, takes that value of 1 when unemployment is low and the workers has a college degree, while the three-way interaction term between EDU, UNE and LAG takes the value of 1, when in addition, the worker is in a low job level (i.e., mismatched).

The results are in Table 2.7. According to all three estimation procedures being in a low job level affects the high-job-level probability negatively. The coefficient of the lagged depended variable is negative and significant in all cases. This result is not surprising. One cannot argue that being in a low job level as opposed to a high job level increases your chances of being in a high job level next period.

For the hypothesis to be tested here, the interaction effects of overall unemployment and education with this dummy variable are of most interest. First, we are interested on whether when the unemployment rate is low workers with a college degree are more likely to be in high-skill jobs next period (i.e., the coefficient of EDU*UNE is positive). Second, we are interested to see whether mismatched college graduates are more likely to move into high job levels next period when the overall unemployment rate is low (i.e., the coefficient of UNE*EDU*LAG is positive).

Both the results of the A-H and A-B approach indicate that mismatched college graduates are more likely to move into high job levels when overall unemployment rate is high. In both cases, the three-way interaction term has a positive and significant coefficient. The two-way interaction term, however, has a negative coefficient in the first case and has an insignificant coefficient in the second. Hence, in both cases, a positive effect on high-job-level probability when overall unemployment rate is low, arises when then worker in addition to having a college degree, is mismatched.

The Chamberlain approach gives the opposite result. The coefficient of the two-way interaction term is positive and significant, suggesting that when overall unemployment is low, college graduates are more likely to move into high job levels, independent of their origin state. The coefficient of the three-way interaction term, on the other hand, is negative suggesting that conditional on a college graduate being mismatched, the positive impact of lower unemployment rate on high-job-level probability is lower.

The A-H and A-B results emphasize the tendency of mismatched college graduates to move into higher job levels when the overall unemployment rate is low, while the results of the chamberlain approach emphasize the positive effect of overall unemployment being low on the high-job-level probability of college graduates. Overall, we can conclude that the results of this regression analysis point to the existence of an upgrading in the job level of college graduates when the overall unemployment rate is low.

2.6 Markov Chain Multinomial Logit Model of Job level Transitions

2.6.1 The Model

The purpose of this section is to characterize job level transitions. To describe transitions between job levels, I adopt the latent propensity framework a la McFadden (1974). At each period, the latent variable y_{kit} describes the propensity level to be in state k out of states $0, ..., m$ for individual i at time t. States are unemployment $k = 0$ and five job levels $k = 1, ..., m$ with $m = 5$. Assuming N individuals i are observed at $T + 1$ points in time $t = 0, ..., T$, the propensity function is determined by

$$y_{kit} = x_{it}\beta_k + \sum_{j=0}^{m} \gamma_{jk}\mathbf{1}\{y_{i(t-1)} = j\} + \alpha_{ki} + \epsilon_{kit} \tag{2.3}$$

where x_{it} is a vector of observable covariates, $\mathbf{1}$ is the indicator function, $y_{i(t-1)}$ indicates the lagged state, $y_{i(t-1)} = j$ if the individual was in state j at time $t-1$, α_{ki} is an unobservable individual specific effect and ϵ_{kit} is an unobservable error term. This specification assumes that each individual has a specific propensity for each alternative depending on the lagged state.

The parameters $\beta = (\beta_0, ..., \beta_m)$ and $\gamma_j = (\gamma_{j0}, \gamma_{j1}, ..\gamma_{jm})\ \forall\ j = 0, ...m$ capture how the observed covariates and the lagged state, respectively, affect the propensity to be in each state. For example, the parameter β_k captures how the observed covariates influence the propensity of being in state k, while the parameter γ_{jk} captures the feedback effect when the state j at time $t-1$ is followed by the state k at time t. In total, there are m^2 feedback parameters γ to be estimated.

For the question of interest, the dependent variable y_{kit} is the propensity of individual i being in job level k at time t. I separate occupations 5 levels, from the lowest –job level 1– to the highest –job level 5– based on the HSR prestige scores. Table 2.1 shows the prestige scores corresponding to each job level. The vector of observable covariates x_{it} includes the education dummy and overall unemployment rate dummy, as defined in sections 2.5.1 and 2.5.2.

Assuming that the error terms ϵ_{kit} are independent across alternatives and over time conditional on (x_i, α_i, y_{i0}) and identically distributed according to the Type1 extreme value distribution, the probability of individual i of being in state k at time

t, is given by

$$P(y_{it} = k \setminus y_{i(t-1)} = j, x_i, a_i) = \frac{\mathtt{exp}(x_{it}\beta_k + \gamma_{jk} + \alpha_{ki})}{1 + \sum_{l=1}^{m} exp(x_{it}\beta_l + \gamma_{jl} + \alpha_{li})} \tag{2.4}$$

The parameters β and γ can be estimated based on a sequence of states where the individual switches alternatives at least once during periods 1 to $T-1$. Given that only $(m^2-(2m-1))$ feedback parameters can be identified, we need to impose some identification restriction. I follow Weber(2002) and assume that all parameters with respect to the reference state $k = 0$ are equal to zero. More specifically, I impose the following identification restrictions:

$$\begin{aligned} \beta_0 &= 0 \\ \gamma_0 &= (\gamma_{00}, ..., \gamma_{mo}) = 0 \\ \gamma_{0k} &= 0 \,\forall\, k = 1, ..., m \\ \alpha_{i0} &= 0 \,\forall\, i = 1, ..., N \end{aligned} \tag{2.5}$$

The problem with imposing parameter restrictions is that it complicates the interpretation of the parameters. For the purpose of the empirical analysis in this paper, it is convenient to choose unemployment as a reference state, as it makes the interpretation easier.

The advantages of this empirical methodology compared to the dynamic panel estimation procedures presented earlier are first, that it allows for the analysis of the impact of the covariates on multiple job level probabilities simultaneously. Second, it characterizes the effect of multiple lagged states on this probability simultaneously. Third, it allows us to compare not only the sign of the effect of the covariates on the probability of each job level, but also the magnitude of the effect across different job levels. For example, we are able to address a question of the following form: does a higher overall unemployment rate reduce the probability of higher job level more than it reduces the probability of lower job level? Forth, in a similar fashion, it allows us to compare the effect of different lagged states on the probability of a particular state. To give an example, we are able to address whether the effect of being in job level 1 as opposed to being in job level 2 on the probability of job level 3 is higher or not. Overall, this methodology allows for a more detailed description of job level transitions.

To clarify the advantages of this estimation methodology, let us interpret the parameters to be estimated. The odds ration of moving from state j to state k relative to a movement from the same origin to the reference state 0, which in our case is unemployment, is given by the following expression:

$$\frac{P(y_{it} = k \setminus y_{i(t-1)} = j, x_i, a_i)}{P(y_{it} = 0 \setminus y_{i(t-1)} = j, x_i, a_i)} = \mathtt{exp}(x_{it}\beta_k + \gamma_{jk} + \alpha_{ki}) \tag{2.6}$$

Therefore, a high value of α_{ki} implies a high propensity of moving to state k as opposed to unemployment conditional on any lagged state j. Hence, the parameter β_k represents the effect of the covariate x on the log odd's ratio.

$$\frac{\partial}{\partial x} \ln \frac{P(y_{it} = k \setminus y_{i(t-1)} = j, x_i, a_i)}{P(y_{it} = 0 \setminus y_{i(t-1)} = j, x_i, a_i)} = \beta_k \tag{2.7}$$

The difference $\beta_k - \beta_{k'}$ measures the effect of the covariate x on the log odd's ratio of moving from any state j to k relative to moving from any state j to k'. In order to interpret the parameter γ_{jk}, it is convenient to remove the individual specific effects by calculating the following ratio:

$$\frac{\frac{P(y_{it}=k \backslash y_{i(t-1)}=j, x_i, a_i)}{P(y_{it}=0 \backslash y_{i(t-1)}=j, x_i, a_i)}}{\frac{P(y_{it}=k \backslash y_{i(t-1)}=0, x_i, a_i)}{P(y_{it}=0 \backslash y_{i(t-1)}=0, x_i, a_i)}} = \texttt{exp}(\gamma_{jk}) \tag{2.8}$$

The above expression is identical across individuals and thus, it captures only the state dependence. According to the expression if γ_{jk} is positive, the odds of being in state k with respect to unemployment when the lagged state is j are larger than when the lagged state is unemployment. It is obvious that the effects of lagged states j and j' on the probability of moving to state k relative to unemployment can be measured by $\gamma_{jk} - \gamma_{j'k}$. More specifically,

$$\ln[\frac{P(y_{it} = k \setminus y_{i(t-1)} = j, x_i, a_i)}{P(y_{it} = 0 \setminus y_{i(t-1)} = j, x_i, a_i)}] - \ln[\frac{P(y_{it} = k \setminus y_{i(t-1)} = j', x_i, a_i)}{P(y_{it} = 0 \setminus y_{i(t-1)} = j', x_i, a_i)}] = \gamma_{jk} - \gamma_{j'k} \tag{2.9}$$

Moreover, by comparing the same origin feedback parameters γ_{jk} and $\gamma_{jk'}$, we can measure whether the odds of being in state k with respect to k' when the lagged state is j are larger or smaller than when the lagged state is unemployment. After some simple algebra we derive:

$$\ln[\frac{P(y_{it} = k' \setminus y_{i(t-1)} = j, x_i, a_i)}{P(y_{it} = k \setminus y_{i(t-1)} = j, x_i, a_i)}] - \ln[\frac{P(y_{it} = k' \setminus y_{i(t-1)} = 0, x_i, a_i)}{P(y_{it} = k \setminus y_{i(t-1)} = 0, x_i, a_i)}] = \gamma_{jk'} - \gamma_{jk} \tag{2.10}$$

2.6.2 Conditional Maximum Likelihood Estimation

I model individual effects as fixed, and pick up the method presented in Honoré and Kyriazidou (2000). The method concerns the estimation of panel data fixed effects discrete choice models when the explanatory variable set includes strictly exogenous variables, lags of the endogenous dependent variable as well as unobservable individual specific effects.[9] Based on the idea applied by Chamberlain (1984), Honoré and Kyriazidou (2000) provide conditions under which the probabilities of the events are independent of the individual effects. This approach allows for estimating the individual fixed effects parameters α_{ki} consistently. The conditions are also extended to the case of multinomial discrete choice variables, and therefore cover the model specified above.

The estimation of the β and γ parameters can be based on the maximization of a likelihood function, which regards events where the state variable y switches from say state k to state l or reverse between two points in time, say s and t with $1 \leq t < s \leq T-1$. Conditional on such a switch and on the constancy of the explanatory variables in the following periods $x_{i(t+1)} = x_{i(s+1)}$, the probabilities of the events are independent of the individual effects.[10] Defining the binary variable $y_{hit} = 1$ if the individual i is in state $h \in \{0, 1, ..., m\}$ in period t and $y_{hit} = 0$

[9] Whether individual effects should be modeled as random or fixed is an important issue in panel estimation. The latter is more common (Arellano and Honoré, 2001) even though the specification of the distribution function of random effects is difficult. In nonlinear models the numerical implementation of a random effects becomes even more difficult as multiple integrals need to be evaluated. For these reasons, I follow Weber (2002) and model individual effects as fixed.

[10] Given this condition, modeling the overall unemployment rate as a dummy instead of a continuous variable helps increase the number of observations that contribute to the likelihood. An alternative method to avoid this limitation would be to incorporate the unemployment rate as a continuous exogenous variable and replace the exact equality condition by weighting the differences with a Kernel function and giving the observations with smallest differences the highest weights.

otherwise, the maximum likelihood function takes the following form:

$$
\begin{aligned}
L = & \sum_{i=1}^{N} \sum_{1 \leq t < s \leq T-1} \sum_{k \neq l} \mathbf{1}\{y_{kit} + y_{kis} = 1\} \mathbf{1}\{y_{lit} + y_{lis} = 1\} \\
& \mathbf{1}\{x_{i(t+1)} = x_{i(s+1)}\} \mathtt{ln} \frac{\mathtt{exp}(D_1)}{1 + \mathtt{exp}(D_1)} \mathbf{1}\{s - t = 1\} \\
& \sum_{i=1}^{N} \sum_{1 \leq t < s \leq T-1} \sum_{k \neq l} \mathbf{1}\{y_{kit} + y_{kis} = 1\} \mathbf{1}\{y_{lit} + y_{lis} = 1\} \\
& \mathbf{1}\{x_{i(t+1)} = x_{i(s+1)}\} \mathtt{ln} \frac{\mathtt{exp}(D_2)}{1 + \mathtt{exp}(D_2)} \mathbf{1}\{s - t > 1\}
\end{aligned} \tag{2.11}
$$

where

$$
\begin{aligned}
D_1 = & (x_{it} - x_{is})(\beta_k - \beta_l) + \gamma_{y_{i(t-1)},k} + \gamma_{kl} + \gamma_{l,y_{i(s+1)}} \\
& -\gamma_{y_{i(t-1)},l} - \gamma_{lk} - \gamma_{k,y_{i(s+1)}}
\end{aligned} \tag{2.12}
$$

and

$$
\begin{aligned}
D_2 = & (x_{it} - x_{is})(\beta_k - \beta_l) + \gamma_{y_{i(t-1)},k} + \gamma_{k,y_{i(t+1)}} + \gamma_{l,y_{i(s+1)}} \\
& -\gamma_{y_{i(t-1)},l} - \gamma_{l,y_{i(t+1)}} - \gamma_{y_{i(s-1)},k} - \gamma_{k,y_{i(s+1)}}
\end{aligned} \tag{2.13}
$$

In the objective function above I impose the identification restrictions given in 2.3. For an observation to contribute to the likelihood at least four periods of observations are required and at least some variability in states in the periods between the dates 1 and $T - 1$.

2.6.3 Results

Estimation results are given for the whole sample and a sample that excludes individuals with no high-school degree in Tables 2.8 and 2.8, respectively. The analysis is conducted separately for those two samples to compare the parameter estimates and verify whether workers of higher education are more likely to move into lower levels than become unemployed during downturns.[11] The period in which transitions are observed is one year.

In both cases all the feedback parameters γ are positive, indicating that individuals are more likely to move to each of the job levels from employment, as opposed to unemployment. Moreover, the feedback parameters decline the further the origin state from the destination state. For example, $\gamma_{15} < \gamma_{25} < \gamma_{35} < \gamma_{45}$. Similarly, $\gamma_{51} < \gamma_{41} < \gamma_{31} < \gamma_{21}$, and so on. Hence, the odds ratio of moving to a particular job level with respect to unemployment are higher the closer the origin job level to the destination job level. In some cases, when the destination state is to far from the origin state the feedback parameter becomes insignificant indicating that this type of transitions are rare or impossible. For example, the feedback parameters when the origin state is job level 1 is positive and significant for destination states 2 and 3 but becomes insignificant for destination states 4 and 5.

The feedback parameters below the diagonal correspond to movements into job levels lower than the origin job level, while the parameters above the diagonal to movements into job levels higher than the origin job level. The parameters to

[11] Ideally I would like to compare the model estimated on a low-skill sample to one estimated on a high-skill sample. However, the full sample is too small to allow for meaningful estimates on high-skill and low-skill sub-samples. The majority of the workers in the sample have at most a high-school diploma. Focusing only on either college graduates or workers without a high-school diploma would imply a considerably smaller sample. This estimation methodology, in particular, requires a sufficient number of across state transitions for the estimates to be meaningful, making such a comparison even harder.

the left of the diagonal tend to be smaller than those to the right (i.e., $\gamma_{21} < \gamma_{23}$, $\gamma_{32} < \gamma_{34}$, $\gamma_{31} < \gamma_{35}$, etc.). This implies that workers are less likely to move from a higher job level to a lower one than from unemployment, and more likely to move from a lower job level to a higher one than from unemployment. In other words, the odds of moving into a lower job level as opposed to a higher job level are larger when the lagged state is unemployment and vice versa. This finding supports the hypothesis of interest as it indicates that workers experiencing unemployment are more likely to move into lower job levels.

The effect of higher unemployment on the odds ratio of moving to each of the job levels relative to moving into unemployment are given in the last row of each table. In both cases, higher unemployment rate reduces the probability of being in each of the alternatives relative to being unemployed. In other words, higher unemployment reduces the probability of employment, as one would expect. The crowding out hypothesis implies that workers of higher skill are more likely to move into lower job levels than become unemployed during periods of high unemployment compared to workers of lower skill. Hence, the negative impact of unemployment on the probabilities of being in low job levels should be lower for workers of higher skill.

Comparing the unemployment rate parameters for the sample that includes individuals with no high-school education to the one that excludes them, we note that this is indeed the case. The parameters are still negative in the second case, but lower in absolute value. Thus, for the more educated sample, higher unemployment reduces the odds of being employed as opposed to being unemployed next period but to a lower degree. In fact, the parameters corresponding to job levels 2 and 3 become insignificant. Hence, when workers with less than a high-school diploma are excluded from the sample higher unemployment does not reduce the odds of moving to job levels 2 or 3 as opposed to unemployment. This supports the view that when the unemployment rate is high, workers with higher education are more likely to move into "mediocre" occupations than become unemployed relative to workers with lower education. The parameter corresponding to job level 1 is smaller in absolute value, but to a lower degree (i.e., it is still significant). This is reasonable to expect, as the lower the level of the job the less willing one would be to accept it to avoid unemployment.

2.7 Conclusion

This chapter tests the hypothesis that high-skilled workers accept transitorily jobs below their skill level in order to escape unemployment, and move on to better jobs when times get better. The hypothesis is tested by studying the mismatch rates and job level dynamics using a panel sample of individuals constructed from the yearly family files of the Panel Study of Income Dynamics (PSID), which covers the years from 1968 to 1993.

My empirical methodology departs from existing studies that investigate the cyclical patterns of mismatch across different skill groups, in that it accounts for the effect of the workers' lagged state on the propensity of being in each of the occupational categories. While existing studies test the hypothesis by focusing only on the impact of economic activity on job level probabilities, I also incorporate the workers lagged state as an explanatory variable and use dynamic panel data estimation methodologies. Modeling state dependence captures some propensity to experience a certain job level, which has been previously unmeasured by focusing only on how overall economic conditions affect job level probabilities. I am able to capture directly the impact the risk of unemployment at the individual level, has on job level transitions.

I find evidence suggestive of the existence of a cyclical pattern in match behavior of high-skilled workers (college graduates). The mismatch rate of college graduates is higher and exhibits higher cyclical variation than the mismatch rate of workers without a college degree. Moreover, I find that the positive impact of having a college degree on the probability of achieving higher job levels is lower when the unemployment rate is high. Similarly, the negative impact of having a college degree on low-job-level probability is lower when the unemployment rate is high.

The results of the dynamic panel data regression analysis indicate that unemployed high-skilled workers are more likely to take low-skill jobs when the unemployment rate is high. In particular, the negative impact of holding a college degree on low-job-level probability is weaker when the origin state is unemployment and overall unemployment rate is high. In addition, the results point to the existence of an upgrading in the job levels of mismatched college graduates when the unemployment rate is low.

Finally, the estimates of a Markov Chain Multinomial Logit model of job level transitions suggest that the odds of moving to a lower job level as opposed to a higher job level are larger when the lagged state is unemployment and vice versa. In addition, the results suggest that higher unemployment rate reduces the probability of being in each job level relative to being unemployed. However, consistent with the crowding out hypothesis, the negative impact of higher unemployment rate on each job level probability declines with education and more evidently for "mediocre" job levels. Thus, I conclude that workers of higher education are more likely to accept jobs below their skill level than become unemployed.

Table 2.1: Job Levels Based on Prestige Scores

Job Level 1:	Prestige Scores 6-21
Job Level 2:	Prestige Scores 22-36
Job Level 3:	Prestige Scores 37-51
Job Level 4:	Prestige Scores 52-66
Job Level 5:	Prestige Scores 67-83

Table 2.2: Sample Descriptive Statistics

	Mean
Unemployed	0.05
Job Level 1	0.14
Job Level 2	0.36
Job Level 3	0.38
Job Level 4	0.08
Job Level 5	0.04
Observations	533908
Individuals	15748

Table 2.3: Linear Probability and Logistic Regression Results: High-Job-Level Probabilities

Depended Variable: High-job-level Probability

	LP	Logit	LP	Logit
Variable				
UNE	-.001	-.012	.001	.012
	(.001)	(.010)	(.001)	(.013)
EDU	**.062**	**.170**	**.071**	**.198**
	(.005)	**(.023)**	**(.005)**	**(.024)**
UNE*EDU			**-.014**	**-.054**
			(.003)	**(.019)**
Log-likelihood value		6804.4		-6804.6
LR Chi-squared		48.66		56.26
F-test	69.96		53.15	
R-squared	0.2711		0.2695	
LR test Chi-squared (significance of UNE*EDU)				7.6
Huasman test Chi-squared	2817.6	3067.14	2810.62	3062.19

Bolded coefficients are significant at the 5% level.

Table 2.4: Linear Probability and Logistic Regression Results: Low-Job-Level Probabilities

Depended Variable: Low-job-level Probability

	LP	Logit	LP	Logit
Variable				
UNE	-.003*	**-.013**	**-.007**	**-.029**
	(.002)	**(.006)**	**(.002)**	**(.008)**
EDU	**-.061**	**-.140**	**-.073**	**-.179**
	(.008)	**(.021)**	**(.008)**	**(.022)**
UNE*EDU			**.021**	**.071**
			(.005)	**(.016)**
Log-likelihood value		-14676.8		-14667
LR Chi-squared		42.44		62.00
F-test	32.32		28.35	
R-squared	.1526		.1508	
LR test Chi-squared (significance of UNE*EDU)			19.55	
Huasman test Chi-squared	906.30	603.77	909.45	628.74

Bolded coefficients are significant at the 5% level.

Starred coefficients are only marginally significant at the 5% level.

Table 2.5: Dynamic Panel Data Models: unemployment to low-job-level transitions

Depended Variable: Low-job-level Probability

Variables	UNE	EDU	LAG	UNE*EDU	UNE*EDU*LAG
Anderson- Hsiao IV:	-.001	**-.044**	**-.074**		
	(.002)	**(.016)**	**(.010)**		
	.002	**-.036**	**-.074**	**-.016**	
	(.003)	**(.016)**	**(.010)**	**(.006)**	
	.002	**-.036**	**-.083**	**-.016**	**.168**
	(.003)	**(.016)**	**(.011)**	**(.006)**	**(.045)**
Arellano-Bond GMM:	-.001	**-.039**	-.029		
	(.002)	**(.016)**	(.046)		
	.000	**-.035**	-.025	-.011*	
	(.002)	**(.016)**	(.046)	(.006)	
	.001	**-.038**	**-.089**	-.009*	**.439**
	(.002)	**(.016)**	**(.043)**	(.006)	**(.099)**
Chamberlain CML:	**-.146**	**-.275**	**-.452**		
	(.027)	**(.099)**	**.051**		
	-.233	**-.469**	**-.439**	**.342**	
	(.031)	**(.104)**	**(.051)**	**(.062)**	
	-.230	**-.459**	**-.461**	**.333**	.384*
	(.031)	**(.104)**	**(.052)**	**(.062)**	(.235)
No Unobserved Effects:	**-.106**	**.926**	**-.260**	**.258**	**.443**
	(.031)	**(.100)**	**(.039)**	**(.063)**	**(.196)**

Bolded coefficients are significant at the 5% level.
Starred coefficients are only marginally significant at the 5% level

UNE: takes the value of 1 when the unemployment rate is above 6%
EDU: takes the value of 1 when the worker has a college degree
UNE*EDU: two-way interaction between UNE and EDU
LAG: takes the value of 1 when the worker was unemployed in the previous period
UNE*EDU*LAG: three-way interaction between UNE, EDU and LAG

Table 2.6: Dynamic Panel Data Models: unemployment to high-job-level transitions

Depended Variable: High-job-level probability

Variables	UNE	EDU	LAG	UNE*EDU	UNE*EDU*LAG
Anderson-Hsiao IV:	.001	**.066**	-.007		
	(.001)	**(.010)**	(.006)		
	-.001	**.060**	-.007	**.012**	
	(.001)	**(.010)**	(.006)	**(.004)**	
	-.001	**.060**	.001	**.011**	**-.146**
	(.002)	**(.010)**	(.007)	**(.004)**	**(.028)**
Arellano-Bond GMM:	-.002	**.047**	.005		
	(.002)	**(.010)**	(.019)		
	.003	**.053**	-.000	-.005	
	(.002)	**(.010)**	(.019)	(.004)	
	.003	**.053**	.007	-.006*	**.152**
	(.002)	**(.010)**	(.019)	(.004)	**(.059)**
Chamberlain CML:	.009	**.250**	-.310*		
	(.036)	**(.105)**	(.177)		
	.122	**.395**	**-.284**	**-.286**	
	(.046)	**(.111)**	**(.137)**	**(.074)**	
	.121	**.398**	-.173	**-.282**	-.517*
	(.047)	**(111)**	(.153)	**(.074)**	(.326)
No Unobserved Effects:	.067	**1.145**	-.182	**-.244**	-.389
	(.538)	**(.111)**	(.140)	**(.078)**	(.269)

Bolded coefficients are significant at the 5% level.
Starred coefficients are only marginally significant at the 5% level.

UNE: takes the value of 1 when the unemployment rate is above 6%
EDU: takes the value of 1 when the worker has a college degree
UNE*EDU: two-way interaction between UNE and EDU
LAG: takes the value of 1 when the worker was unemployed in the previous period
UNE*EDU*LAG: three-way interaction between UNE, EDU and LAG

Table 2.7: Dynamic Panel Data Models: low-job-level to high-job-level transitions

Depended Variable: High-job-level Probability

Variables	UNE	EDU	LAG	UNE*EDU	UNE*EDU*LAG
Anderson-Hsiao IV:	.001	**.065**	**-.015**		
	(.001)	**(.009)**	**(.005)**		
	.001	**.071**	**-.015**	**-.012**	
	(.001)	**(.009)**	**(.005)**	**(.004)**	
	.001	**.069**	**-.019**	**-.008**	**.046**
	(.001)	**(.009)**	**(.005)**	**(.003)**	**(.015)**
Arellano-Bond GMM:	**.003**	**.044**	**-.119**		
	(.001)	**(.010)**	**(.028)**		
	.002	**.045**	**-.110**	.003	
	(.002)	**(.010)**	**(.028)**	(.004)	
	.002	**.032**	**-.095**	-.001	.010*
	(.001)	**(.010)**	**(.026)**	(.003)	(.005)
Chamberlain CML:	-.037	.156*	**-1.330**		
	(.038)	(.117)	**(.043)**		
	-.021	.081	**-1.32**	**.159**	
	(.049)	(.123)	**(.043)**	**(.081)**	
	-.024	.125	**-1.258**	**.258**	**-.455**
	(.048)	(.123)	**(.045)**	**(.084)**	**(.099)**
No Unobserved Effects:	.056	**.739**	**-1.606**	-.001	-.008
	(.058)	**(.115)**	**(.044)**	(.088)	(.092)

Bolded coefficients are significant at the 5% level.
Starred coefficients are only marginally significant at the 5% level.

UNE: takes the value of 1 when the unemployment rate is below 6%
EDU: takes the value of 1 when the worker has a college degree
UNE*EDU: two-way interaction between UNE and EDU
LAG: takes the value of 1 when the worker was in a low job level in the previous period
UNE*EDU*LAG: three-way interaction between UNE, EDU and LAG

Table 2.8: Estimated parameters Markov Chain Multinomial Logit model, full sample, yearly transitions

Destination State	Job Level 1	Job Level 2	Job Level 3	Job Level 4	Job Level 5
Origin State					
Job Level 1	1.444	0.581	0.478	0.099	0.116
	(0.044)	(0.039)	(0.048)	(0.118)	(0.167)
Job Level 2	0.348	1.428	0.615	0.349	0.161
	(0.040)	(0.034)	(0.039)	(0.084)	(0.136)
Job Level 3	0.308	0.519	1.678	0.625	0.409
	(0.048)	(0.039)	(0.042)	(0.077)	(0.119)
Job Level 4	0.129	0.293	0.576	1.658	0.613
	(0.124)	(0.087)	(0.08)	(0.097)	(0.132)
Job Level 5	0.049	0.09	0.544	0.543	1.525
	(0.173)	(0.141)	(0.122)	(0.135)	(0.161)
Un. Rate> 6%	-0.151	-0.144	-0.158	-0.287	-0.238
	(0.038)	(0.032)	(0.033)	(0.051)	(0.064)

Mean log-likelihood: -0.268

Number of cases: 85481

Number of individuals 15748

Table 2.9: Estimated parameters Markov Chain Multinomial Logit model, high-school graduates, yearly transitions

Destination State	Job Level 1	Job Level 2	Job Level 3	Job Level 4	Job Level 5
Origin State					
Job Level 1	1.442	0.640	0.421	0.117	0.188
	(0.076)	(0.064)	(0.071)	(0.133)	(0.182)
Job Level 2	0.369	1.455	0.641	0.339	0.216
	(0.065)	(0.052)	(0.055)	(0.093)	(0.150)
Job Level 3	0.258	0.500	1.661	0.565	0.438
	(0.072)	(0.055)	(0.056)	(0.086)	(0.131)
Job Level 4	0.140	0.258	0.649	1.673	0.565
	(0.140)	(0.098)	(0.090)	(0.105)	(0.145)
Job Level 5	0.109	-0.007	0.503	0.609	1.520
	(0.192)	(0.157)	(0.135)	(0.148)	(0.175)
Un. Rate> 6%	-0.101	-0.0031	-0.082	-0.234	-0.103
	(0.056)	(0.045)	(0.045)	(0.059)	(0.072)

Mean log-likelihood: -0.26

Number of cases: 53507

Number of individuals 9441

Appendix A

Prestige Scores

Table A.1: Prestige Scores

	1970 Occupational Classification Codes	**Prestige Scores**
Physicians, including osteopaths	65	82
Agriculture teachers	102	78
Atmospheric, earth, marine, and space teachers	103	78
Biology teachers	104	78
Chemistry teachers	105	78
Physics teachers	110	78
Engineering teachers	111	78
Mathematics teachers	112	78
Health specialists teachers	113	78
Psychology teachers	114	78
Business and commerce teachers	115	78
Economics teachers	116	78
History teachers	120	78
Sociology teachers	121	78
Social science teachers, n.e.c.	122	78
Art, drama, and music teachers	123	78
Coaches and physical education teachers	124	78
Education teachers	125	78
English teachers	126	78
Foreign language teachers	130	78
Home economics teachers	131	78
Law teachers	132	78
Theology teachers	133	78
Trade, industrial, and technical teachers	134	78
Miscellaneous teachers, college and university	135	78

Teachers, college and university, subject not specified	140	78
Judges	30	76
Lawyers	31	76
Physicists and astronomers	53	74
Dentists	62	74
Bank officers and financial managers	202	72
Architects	2	71
Aeronautical astronautical engineers	6	71
Psychologists	93	71
Airplane pilots	163	70
Electrical and electronic engineers	12	69
Chemists	45	69
Clergymen	86	69
Civil engineers	11	68
Atmospheric and space scientists	43	68
Biological scientists	44	68
Marine scientists	52	68
Life and Physical scientists, n.e.c.	54	68
Chemical engineers	10	67
Petroleum engineers	21	67
Engineers, n.e.c.	23	67
Geologists	51	67
Archivists and curators	33	66
Political scientists	92	66
Sociologists	94	66
Urban and regional planners	95	66
Social scientists, n.e.c.	96	66
Mathematicians	35	65
Secondary school teachers	144	63
Mechanical engineers	14	62
Mining engineers	20	62
Optometrists	63	62
Registered nurses	75	62
Pharmacists	64	61
Clinical laboratory technologists and technicians	80	61
Dental hygienists	81	61
Health record technologists and technicians	82	61
Radiologic technologists and technicians	83	61
Assessors, controllers, and treasurers, local public administration	201	61
Health administrators	212	61

Officials and administrators; public administration, n.e.c.	222	61
School administrators, college	235	61
Chiropractors	61	60
Veterinarians	72	60
Elementary school teachers	142	60
Pre-kindergarten and kindergarten teachers	143	60
Authors	181	60
Officers, pilots, and pursers; ship	221	60
School administrators, elementary and secondary	240	60
Designers	183	58
Officials of lodges, societies, and unions	223	58
Postmasters and mail superintendents	224	58
Accountants	1	57
Economists	91	57
Public relations men and publicity writers	192	57
Metallurgical and materials engineers	15	56
Agricultural scientists	42	56
Personnel and labor relation workers	56	56
Religious workers, n.e.c.	90	56
Draftsmen	152	56
Painters and sculptors	190	56
Librarians	32	55
Actuaries	34	55
Statisticians	36	55
Actors	175	55
Sheriffs and bailiffs	965	55
Industrial engineers	13	54
Farm management advisers	24	54
Foresters and conservationists	25	54
Home management advisers	26	54
Surveyors	161	53
Dieticians	74	52
Social workers	100	52
Embalmers	165	52
Funeral directors	211	52
Computer programmers	3	51
Computer systems analysts	4	51
Computer specialists, n.e.c.	5	51
Sales engineers	22	51
Operations and systems researchers and analysts	55	51
Health practitioners, n.e.c.	73	51
Vocational and educational counselors	174	51
Athletes and kindred workers	180	51

Editors and reporters	184	51
Radio and television announcers	193	51
Writers, artists, and entertainers, n.e.c.	194	51
Research workers, not specified	195	51
Professional, technical, and kindred workers–allocated	196	51
Stocks and bonds salesmen	271	51
Locomotive engineers	455	51
Opticians, and lens grinders and polishers	506	51
Buyers, wholesale and retail trade	205	50
Office managers, n.e.c.	220	50
Sales managers and department heads, retail trade	231	50
Sales managers, except retail trade	233	50
Managers and administrators, n.e.c.	245	50
Managers and administrators, except farm–allocated	246	50
Bank tellers	301	50
Recreation workers	101	49
Credit Men	210	49
industries	281	49
Electricians	430	49
Purchasing agents and buyers, n.e.c	225	48
Bookkeepers	305	48
Insurance adjusters, examiners, and investigators	326	48
Job and die setters, metal	454	48
Machinists	461	48
Aircraft	471	48
Dental assistants	921	48
Health aides, except nursing	922	48
Policemen and detectives	964	48
Health technologists and technicians, n.e.c.	85	47
Agriculture and biological technicians, except health	150	47
Chemical technicians	151	47
Electrical and electronic engineering technicians	153	47
Industrial engineering technicians	154	47
Mechanical engineering technicians	155	47
Mathematical technicians	156	47
Flight engineers	170	47
Tool programmers, numerical control	172	47
Technicians, n.e.c.	173	47
Insurance agents, brokers, and underwriters	265	47
Automobile accessories installers	401	47
Carpet installers	420	47
Dental laboratory technicians	426	47

Craftsmen and kindred workers, n.e.c.	575	47
Former members of the Armed Forces	580	47
Craftsmen and kindred workers–allocated	586	47
Current members of the Armed Forces	590	47
Musicians and composers	185	46
Secretaries, legal	370	46
Secretaries, medical	371	46
Secretaries, n.e.c.	372	46
Marshals and constables	963	46
Billings clerks	303	45
Bookkeeping and billing machine operators	341	45
Calculating machine operator	342	45
Computer and peripheral equipment operators	343	45
Duplicating machine operators	344	45
Keypunch operators	345	45
Tabulating machine operators	350	45
Office machine operators, n.e.c.	355	45
Foremen, n.e.c.	441	45
Real estate agents and brokers	270	44
Telegraph operators	384	44
Farm managers	802	44
Firemen, fire protection	961	44
Adult education teachers	141	43
Teachers, except college and university, n.e.c.	145	43
Air traffic controllers	164	43
Radio operators	171	43
Postal clerks	361	43
Real estate appraisers	363	43
Stenographers	376	43
Advertising agents and salesmen	260	42
Mail carriers, post office	331	42
Tool and die makers	561	42
Practical nurses	926	42
Photographers	191	41
Buyers and shippers, farm products	203	41
Construction inspectors, public administration	213	41
Inspectors, except construction, public administration	215	41
Railroad conductors	226	41
Library attendants and assistants	330	41
Payroll and timekeeping clerks	360	41
Typists	391	41

Electrician apprentices	431	41
Engravers, except photoengravers	435	41
Machinist apprentices	462	41
Mechanic, except auto, apprentices	491	41
Plumber and pipe fitters	522	41
Plumber and pipe fitter apprentices	523	41
Tailors	551	41
Tool and die maker apprentices	562	41
Specified craft apprentices, n.e.c.	571	41
Not specified apprentices	572	41
Farmers (owners and tenants)	801	41
Farmers and farm managers–allocated	806	41
trade	282	40
Telephone operators	385	40
Carpenters	415	40
Carpenter apprentices	416	40
Printing trades apprentices, except pressmen	423	40
Floor layers, except tile setters	440	40
Millwrights	502	40
Photoengravers and lithographers	515	40
Pressmen and plate printers, printing	530	40
Pressmen apprentices	531	40
Welders and flame-cutters	680	40
Restaurant, cafeteria and bar managers	230	39
Receptionists	364	39
Cabinetmakers	413	39
Cranemen, derrickmen, and hoistmen	424	39
Electric power linemen and cablemen	433	39
Molders, metal	503	39
Molder, apprentices	504	39
Pattern and model makers, except paper	514	39
Power station operators	525	39
Telephone installers and repairmen	552	39
Telephone linemen and splicers	554	39
Chainmen, rodmen, and axmen; surveying	605	39
Dancers	182	38
Managers and superintendents, building	216	38
Compositors and typesetters	422	38
Electrotypers and stereotypers	434	38
Barbers	935	38
Podiatrists	71	37
Therapists	76	37
Therapy assistants	84	37

Decorators and window dressers	425	37
Jewelers and watchmakers	453	37
Air conditioning, heating, and refrigeration	470	37
Automobile body repairmen	472	37
Automobile mechanics	473	37
Automobile mechanic apprentices	474	37
Railroad and car shop	486	37
Sheetmetal workers and tinsmiths	535	37
Sheetmetal apprentices	536	37
Boatmen and canalmen	701	37
Clerical assistants, social welfare	311	36
Clerical supervisors, n.e.c	312	36
Counter clerks, except food	314	36
Enumerators and interviewers	320	36
Estimators and investigators, n.e.c.	321	36
Expediters and production controllers	323	36
Mailhandlers, except post office	332	36
Meter readers, utilities	334	36
Proofreaders	362	36
Statistical clerks	375	36
Teacher aides, except school monitors	382	36
Weighers	392	36
Miscellaneous clerical workers	394	36
Not specified clerical workers	395	36
Clerical and kindred workers–allocated	396	36
Blacksmiths	403	36
Brickmasons and stonemasons	410	36
Brickmasons and stonemasons, apprentices	411	36
Forgemen and hammermen	442	36
Heat treaters, annealers, and temperers	446	36
Locomotive firemen	456	36
Rollers and finishers, metal	533	36
Shipfitters	540	36
Structural metal craftsmen	550	36
Tile setters	560	36
Checkers, examiners, and inspectors; manufacturing	610	36
Photographic process workers	645	36
Health trainees	923	36
Nursing aides, orderlies, and attendants	925	36
Airline stewardesses	931	36
Housekeepers, except private households	950	36
Ticket, station, and express agents	390	35
Furriers	444	35

Radio and television	485	35
Miscellaneous mechanics and repairmen	492	35
Not specified mechanics and repairmen	495	35
Stationary engineers	545	35
Railroad brakemen	712	35
Farm foremen	821	35
Salesmen and sales clerks, n.e.c.	280	34
Salesmen of services and construction	285	34
Sales workers–allocated	296	34
Dispatchers and starters, vehicle	315	34
Bakers	402	34
Data processing machine repairmen	475	34
Office machines	484	34
Motion picture projectionists	505	34
Sailors and deckhands	661	34
Bulldozer operators	412	33
Excavating, grading and road machine operators, except bulldozer	436	33
Farm implements	480	33
Heavy equipment mechanics, including diesel	481	33
Household appliance and accessory installers and mechanics	482	33
Plasterers	520	33
Plasterer apprentices	521	33
Shoe repairmen	542	33
Stone cutters and stone carvers	546	33
Furnacemen, smeltermen, and pourers	622	33
Graders and sorters, manufacturing	624	33
Heaters, metal	626	33
Milliners	636	33
Stationary firemen	666	33
Railroad switchmen	713	33
Hairdressers and cosmetologists	944	33
Auctioneers	261	32
Cement and concrete finishers	421	32
Piano and organ tuners and repairmen	516	32
Blasters and powdermen	603	32
Dressmakers and seamstresses, except factory	613	32
Meat cutters and butchers, except manufacturing	631	32
Shoemaking machine operatives	664	32
Machine operatives, miscellaneous specified	690	32
Machine operatives, not specified	692	32
Miscellaneous operatives	694	32

Not specified operatives	695	32
Operatives, except transport–allocated	696	32
Bus drivers	703	32
Truck drivers	715	32
Cashiers	310	31
Boilermakers	404	31
Bookbinders	405	31
Inspectors, scalers, and graders	450	31
Inspectors, n.e.c.	452	31
Roofers and slaters	534	31
File clerks	325	30
Telegraph messengers	383	30
Loom fixers	483	30
Painters, construction and maintenance	510	30
Painter apprentices	511	30
Sign painters and letterers	543	30
Upholsterers	563	30
Fishermen and oystermen	752	30
Sales clerks, retail trade	283	29
Salesmen, retail trade	284	29
Shipping and receiving clerks	374	29
Furniture and wood finishers	443	29
Metal platers	635	29
Mixing operatives	641	29
Painters, manufactured articles	644	29
Drill press operatives	650	29
Grinding machine operatives	651	29
Lathe and milling machine operatives	652	29
Precision machine operatives, n.e.c	653	29
Punch and stamping press operatives	656	29
Riveters and fasteners	660	29
Solderers	665	29
Carding, lapping, and combing operatives	670	29
Knitters, loopers, and toppers	671	29
Textile operatives, n.e.c.	674	29
Winding operatives, n.e.c.	681	29
Fork lift and tow motor operatives	706	29
Transport equipment operatives–allocated	726	29
Animal caretakers, except farm	740	29
Demonstrators	262	28
Asbestos and insulation workers	601	28
Meat cutters and butchers, manufacturing	633	28
Sawyers	662	28

Conductors and motormen, urban rail transit	704	28
Deliverymen and routemen	705	28
Assemblers	602	27
Drillers, earth	614	27
Dry wall installers and lathers	615	27
Motormen; mine, factory, logging camp, etc.	710	27
Farm service laborers, self-employed	824	27
Collectors, bill and account	313	26
Glaziers	445	26
Cutting operatives, n.e.c.	612	26
Mine operatives, n.e.c.	640	26
Lumbermen, raftsmen, and woodchoppers	761	26
Cooks, except private household	912	26
Millers; grain, flour, and feed	501	25
Dyers	620	25
Sewers and stitchers	663	25
Spinners, twisters, and winders	672	25
Weavers	673	25
Child care workers, except private households	942	25
household–allocated	976	25
Housekeepers, private household	982	25
Paperhangers	512	24
Oilers and greasers, except auto	642	24
Longshoremen and stevedores	760	24
Crossing guards and bridge tenders	960	24
Stock clerks and storekeepers	381	23
Bottling and canning operatives	604	23
Carpenters' helpers	750	23
Gardeners and groundkeepers, except farm	755	23
Midwives	924	23
Child care workers, private household	980	23
Garage workers and gas station attendants	623	22
Parking attendants	711	22
Taxicab drivers and chauffeurs	714	22
Busboys	911	22
Dishwashers	913	22
Food service workers, except private household	916	22
Boarding and lodging housekeepers	940	22
School monitors	952	22
Guards and watchmen	962	22
Elevator operators	943	21

Warehousemen, n.e.c.	770	20
Bartenders	910	20
Waiters	915	20
Messengers and office boys	333	19
Filers, polishers, sanders, and buffers	621	19
Produce graders and packers, except factory and farm	625	19
Meat wrappers, retail trade	634	19
Packers and wrappers, n.e.c	643	19
Farm laborers, farm foremen, and kindred workers	846	19
Hucksters and peddlers	264	18
Clothing ironers and pressers	611	18
Laundry and dry cleaning operatives, n.e.c.	630	18
Farm laborers, wage workers	822	18
Farm laborers, unpaid family workers	823	18
Cooks, private household	981	18
Laundresses, private household	983	18
Maids and servants, private household	984	18
Private household workers–allocated	986	18
Construction laborers	751	17
Freight and material handlers	753	17
Garbage collectors	754	17
Stockhandlers	762	17
Vehicle washers and equipment cleaners	764	17
Miscellaneous laborers	780	17
Not specified laborers	785	17
Laborers, except farm–allocated	796	17
Janitors and sextons	903	16
Newsboys	266	15
Food counters and fountain workers	914	15
Attendants, recreation and amusement	932	15
Ushers, recreation and amusement	953	15
Chambermaids and maids, except private household	901	14
Attendants, personal service, n.e.c.	933	14
Baggage porters and bell hops	934	14
Personal service apprentices	945	14
Welfare service aides	954	14
Teamsters	763	12
Cleaners and charwomen	902	12
Bootblacks	941	9
Engineering and science technicians	162	7

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