Occupations over the business cycle

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Abstract

The business cycle does not have a homogenous effect on workers in different occupations. This paper documents and analyzes unemployment patterns between 1983 and 2012 in broad and detailed occupation categories using the CPS. I find that the skill level of occupations has a monotone negative effect on the level and volatility of unemployment. This result is robust to different measures of general skills and it occurred in all recessions in last 30 years, including the 2007 one. The result also holds within and across major occupation categories. In order to understand the causes of it, I decompose unemployment fluctuations into changes in the job-loss and the job-finding probabilities in each occupation. I find that even though separations are less important for aggregate fluctuations in unemployment, they are more important for understanding the differences between occupational unemployment, as the job-finding probability follows a highly similar pattern across occupations. These results are in line with a model in which employers are more likely to hoard skilled workers due to higher recruitment/training and other adjustment costs in skilled jobs. I consider alternative models and argue that none can explain why job-finding probabilities are so similar while unemployment rates are so different across occupations. Particularly, it seems unlikely that productivity differences are the main driving fource behind occupational unemployment patterns. Future research will compare the evolution of occupational job-loss and job-finding probabilities in the US to those in Germany, and I plan to propose a new labor protection system which maximizes the welfare of citizens by concentrating protection in risky occupations and uncertain times and therefore minimizing the incidence of unemployment and decreasing the burden on the unemployment insurance systems.

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1 Introduction

Numerous studies have shown that the effect of recessions on different demographic groups is heterogeneous (Clark and Summers, 1981; Kydland, 1984; Keane and Prasad, 1993; Hoynes, 1999; Jaimovich and Siu, 2009 and Hoynes et al., 2012). Unskilled workers (the young, the less educated, some minority groups, the recently employed) are found to exhibit greater fluctuations in unemployment and smaller fluctuations in their income. These findings are usually interpreted as mainly due to some sort of "skill" differences among these groups. However, little is known about what skills are actually rewarded in recessions and why. This paper documents in detail the relationship of occupational skills and unemployment transition probabilities across the business cycle and examines empirically the predictions arising from a comprehensive set of candidate explanations.

First, I examine which jobs are risky and which jobs are safe in recessions. I create a consistent and detailed labor force categorization into 191 occupations and track how within-occupation rates of unemployment evolved in the last 30 years. I find very big differences between the level and the volatility of unemployment rates across occupations. For example, while the unemployment rate among highly skilled professional workers went up from 1.7 percent in 2006-2007 to 3.5 percent in 2009-2012, it went up from 8 percent to 15 percent among low skilled operators and laborers. By looking at detailed occupation categories, I find that the skill level of occupations has a strong negative effect on unemployment prospects in and after recessions. This finding is robust to the definition of skills in occupations (for example, average years of education or wage in different census years; non-routine cognitive skills using the O*NET data), and to different recessions, including the 2007 one. When occupational skills are defined as average years of completed education, the results are stronger and monotone, with the lowest skilled occupations being the most risky. For example, while the unemployment rate in the lowest educated decile went up from 9.5 percent in 2006-2007 to 15.4 percent in 2009-2012, it went up from 1.3 percent to 2.8 percent in the highest educated decile. When occupational skills are defined as average log wages, or various direct skill measures (cognitive, psychomotor or physical) the results are somewhat weaker.

Secondly, I investigate the source of the differential unemployment patterns in occupations. I suggest simple tests of six potential explanations. I compute job-loss and job-finding probabilities across occupations over time. This approach is motivated by two observations. Fluctuations in the aggregate unemployment rate is strongly influenced by changes in the job-finding probability while the job-loss probability has a smaller and less persistent effect (Shimer, 2012; Davis et al., 2006; Elsby et al., 2009; Fujita and Ramey, 2009). In contrast, Elsby et al. (2010) find that fluctuations in the job-finding probability are remarkably similar across different demographic groups while the job-loss probability varies greatly. I repeat this exercise with my detailed occupation classification and find similar results: even though the job-finding probability is highly pro-cyclical, it follows broadly the same pattern in all occupational groups. This is not the case for the job-loss probability: even though it is only weakly counter-cyclical, there is a big variation across occupations, with the unskilled ones being more volatile and higher in levels. These findings question the conventional premise that some skills are particularly productive in recessions. Instead, they are consistent with a model in which employers are more likely to hoard skilled workers. Alternative models predict that the job-finding probability is more stable in skilled occupations. However, this is not observed in the data. Out of the six hypotheses I consider, I find labor hoarding to be the most important.

The literature provides two main rationales for hoarding labor: the existence of adjustment costs and firm specific skills. Thus, skilled workers might be hoarded more either because hiring, training and other adjustment costs are higher or because skilled workers possess more firm specific skills.[2] Unfortunately, empirically we know very little about the importance of these factors; how they vary by occupations and perhaps over time. As Oyer and Schaefer (2011) noted in their chapter in the last Handbook of Labor Economics "*We are certainly not the first to make the point that the demand side of the labor market—and hiring, in particular—is understudied.*" Nevertheless, the available evidence confirms that hiring costs, particularly training costs, are substantial and that they are proportionally higher for skilled workers. (See Manning (2011) section 2.1.2 for a review of this scarce literature.)

Understanding recruitment costs, thus, is very important to understand labor market dynamics in different occupations. The structure of these costs, however, is quite complex. In an interesting paper Blatter et al. (2012) estimated that roughly 70 percent of total hiring costs are related to what they call *adaptation* costs, mostly reduced productivity of new hires, which was missing from previous estimates. The literature on employer training (Lillard and Tan, 1986; Brown, 1990; Lerman et al., 2004; Leuven, 2005 provide thorough reviews) also find that training is widespread and it correlates positively with

[2] There is also a somewhat related literature on implicit contracts (e.g. Baily, 1974, Azariadis, 1975, 1976). The theory assumes that firms are risk-neutral, workers are risk-averse and they can write long-term contracts about wage and employment fluctuations contingent on future product demand conditions. The main result of this theory is that optimal contracts specify rigid wages as a form of insurance provided by the firm to the worker. Employment, however, is more likely to be stochastic, but under some conditions full employment is also part of the insurance.

workers' skills. Moreover, they also emphasize the difficulty in measuring informal training which is perhaps more important than formal training.

Understanding the source of variation in occupational unemployment is important for several reasons. First, many studies have shown that unemployment has a major negative effect on the welfare of affected families (Jacobson et al., 1993; von Wachter et al., 2009; Hijzen et al., 2010). It is important to know how this risk is concentrated in certain job types. A related second point is that labor economists should care about occupational unemployment, because workers seem to care, too. If one writes "recession" in Google then one of the first pop-up search offers is "recession proof jobs". By choosing it one gets almost 3 million hits with numerous popular websites, like Wikipedia or Time Business, offering a list of best recession proof jobs. It seems to be a common knowledge that there are more and less risky jobs and one should aim for choosing the latter ones. Thus, it is surprising how little labor economists know about the extent and determinants of this risk. Third, my paper is important for its policy implications. I lay out a simple rigid wage model with hiring and firing costs and show that in occupations where adjustment costs are low, the market outcome features inefficiently high lay-off rates in recessions. Therefore, a policy that increases firing costs, through for example taxing lay-offs, in these occupations during weak economic conditions can be welfare improving, because it minimizes the incidence of inefficient unemployment. Another policy implication is that supporting job-creation in recessions is ineffective and wasteful, because firms already hold excess labor in recessions. The last reason why my results are useful is that by analyzing the heterogeneity in job-loss, job-finding, and unemployment in occupations we learn about the hiring strategies of firms which has been an understudied area in labor economics.

My paper is related to several different literatures. The skill content of occupations became an important factor in explaining recent trends in wage inequality and job polarization (Autor et al., 2003; Autor et al., 2006; Goos and Manning, 2007; Firpo et al., 2011; Acemoglu and Autor, 2011); job mobility and task specific human capital (Ingram and Neumann, 2006; Poletaev and Robinson, 2008; Abraham and Spletzer, 2009; Kambourov and Manovskii, 2009; Geel and Backes-Gellner, 2009; Gathmann and Schönberg, 2010; Robinson, 2011); and learning and career decisions (James, 2011; Yamaguchi, 2012). The business cycle properties of occupations, however, are rarely analyzed. Moscarini and Vella (2008) find that occupation choice appears to be more "random" in recessions. Devereux (2000, 2004) finds that people get lower quality jobs in recessions and this explains half of the wage procyclicality of new hires. Campbell III (1997) found that wages are more rigid in skilled 1 digit occupations. These results are in line with and complementary to the ones of this paper. Jaimovich and Siu (2012) show that the permanent disappearance of some middle skilled occupations took place mostly in downturns. Acemoglu and Autor (2011) discuss that middle skilled occupations continued to disappear in the 2007 recession. Even though low skilled occupations have not been disappearing in the last 30 years, I will show that they were more strongly affected by the business cycle in the short run compared to middle skilled occupations.

My paper is also related to the macro-labor literature of the business cycle with heterogeneous labor. A couple of papers derived search and matching models with skilled and unskilled labor and jobs (Acemoglu, 1999; Albrecht and Vroman, 2002; Dolado et al., 2009; Khalifa, 2009; Chassamboulli, 2011). One implication of these models is that skilled workers might crowd out the unskilled in recessions and move back into skilled jobs in booms. They also find some empirical evidence for this mechanism. I will show, however, that it explains little of the overall differential between the unemployment patterns of occupations. Some papers find evidence for rising hiring standards and quality adjustment of labor over the cycle (Reder, 1955; Teulings, 1993; van Ours and Ridder, 1995; Solon et al., 1997; Evans, 1999; Devereux, 2004; Büttner et al., 2010), although it does not appear to be very strong.

My paper is also related to the literature on labor hoarding. Since the seminal work of Oi (1962), many papers found strong evidence for labor hoarding (for example Fay and Medoff, 1985; Fair, 1985; Burnside and Eichenbaum, 1996; Basu and Kimball, 1997; Marchetti and Nucci, 2001 and Liu and Spector, 2005) and analyzed the causes of it (for example Miller, 1971; Topel, 1982; Hamermesh, 1995; Galeotti et al., 2005; Wen, 2005 and Platt and Platt, 2011). These papers rarely analyze the occupational differences in labor hoarding. The original Oi (1962) paper is one exception, who showed that recruitment costs are lower and labor turnover is higher among "Common laborers".

The paper is organized as follows. Section 2 shows patterns in unemployment, job-loss and job-finding probabilities in detailed occupations and shows the relationship between these patterns and various measures of occupational skills. Section 3 discusses and tests a set of potential economic explanations, and it concludes that large differences in the extent of labor hoarding is the only explanation that is consistent with all the available the data. Section 4 describes my simple labor hoarding model and discusses its policy implications and Section 5 concludes.

2 Descriptive analysis of the business cycle properties of occupations

In this section I show properties of occupational unemployment over the business cycle. In the first half, I analyze how volatile unemployment is within occupations, and how it varies with skills. In the second half of the section, I compute job-loss and job-finding probabilities within occupations and show how they vary by skills and over time.

There is no unique way of defining skill levels of occupations in the literature. There are two main decisions to make: 1. how detailed occupation classification and; 2. what proxy of skills we should use. My decision for the first one was to use 3 different levels of aggregation. The most aggregate one follows the definition of Acemoglu and Autor (2011) and uses ten occupation categories.[3,4] Some contain mostly high-paid high skilled white-collar occupations; some are middle skilled white-collar ones; and some are mixes of middle and low skilled blue-collar or service jobs. I will show, that there is an enormous variation in the unemployment prospects within these occupation categories and it is worth defining occupations at a finer level. The most detailed occupation categorization I use is the 383 three digit 1990 census codes and the crosswalk created by IPUMS.[5] This classification turns out to be too detailed, as some cells have too few people in them, and some occupations even disappear over time. As a remedy I created a new classification and cross walk for 191 occupations.[6] Results based on the 383 and the 191 occupations turn out to be almost identical.

Second, I had to choose a proxy for occupational skills. There are three approaches in the literature. One is to directly use the major occupational groups; the second is to use average wage or average years of education as proxies; and the third is to use an outside data-source (like the Dictionary of Occupational Titles or the O*NET) to merge task content of occupations. The O*NET[7] has a very detailed evaluation of more than 1000 occupations in dimensions like abilities and skills of workers, work styles, worker requirements, tasks, etc. My preferred definition is the average years of education

[3]These are 1. management and related; 2. professionals; 3. technicians; 4. sales; 5. office and administrative support; 6. production, craft and repair; 7. operators, fabricators and laborers; 8. protective services; 9. food preparation and cleaning and 10. personal care and personal services.

[4]Acemoglu and Autor (2011) convincingly show that there has been a trend of disappearance of the middle skilled occupations in the last twenty years. They also show that these middle skilled occupation suffered employment losses in the last 2007 recession. Employment losses and unemployment rates, however, are different objects. As the focus of my paper is not about long run trends, but short run fluctuations, I focus here on unemployment rates.

[5]http://usa.ipums.org/usa/volii/census_occtooccsoc.shtml

[6]See the Appendix for details on the definitions and the crosswalk between different databases.

[7]See http://www.onetcenter.org/content.html for further details.

in my 191 occupations measured in the 2000 census, but the Appendix discusses results with alternative definitions. The education based skill definition is very similar to a measure of non-routine cognitive abilities in the occupations created from the O*NET data.[8]

2.1 Unemployment fluctuations in occupations

There are two conceptual problems in measuring unemployment rates in occupations. The first is how to assign occupations to the unemployed. From a theoretical point of view at least two approaches are interesting. A backward looking concept assigns the occupation in the last job, and a forward looking concept assigns the occupation in which the unemployed are searching for jobs. Ideally we would like to know both. However, the forward looking concept is not feasible using available datasets, and thus, I use the backward looking concept and assign occupation in the last job to the unemployed.[9] If workers never changed occupations, the interpretation of this variable is straightforward. In other cases the interpretation is the unemployment rate among those whose most recent affiliation is with a given occupation.[10,11] The second conceptual problem is that for the new entrant unemployed we cannot assign the occupation at their last job. This paper, thus, only uses unemployment in the experienced labor force, and the new entrant unemployed are excluded.[12]

The two panels of Figure 1 show the unemployment rate in different occupational groups in different time periods. In each occupational group there are 6 bars. The four black ones correspond to years when the aggregate unemployment rate was higher than 5.5 percent, and the gray bars correspond to years when it was lower than 4.5 percent. Panel A classifies the workforce into 10 major groups following the definition of Acemoglu and Autor (2011). There are several interesting patterns in this graph. First, even though the 2007 recession had the largest impact on the labor market, there was nothing unusual in terms of how different occupational groups were affected. Moreover, the last recession was also

[8]By using different census years, one gets an almost identical occupational skill variable. As I will show, however, it matters more whether one uses average education or average wage as a proxy of skills in occupations, especially at the lower end of the skill distribution.

[9]In the CPS it is only available for people who worked in the last 5 years.

[10]Using long panel datasets such as the PSID, SIPP or HRS, one could create alternative measures. For example, we can fix a reference period; look at the occupational composition of the workforce in this reference period and track the fraction of unemployed over time within these groups. The choice of reference periods, however, would not be straightforward. Another problem is that long panel datasets are usually too small to analyze occupations in detail.

[11]Another alternative in the CPS is to use the occupation in the longest job last year instead of the last job. By using last year's occupation, however, we seriously underestimate real unemployment in long recessions, since we have to condition on having a job last year. I will show that my main qualitative results do not change if I use this alternative measure, but the level of unemployment shrinks in all occupations.

[12]Given that my results are not sensitive to age restrictions, this decision is not restrictive.

comparable in size to the aftermath of the double-dip recession of the 80s. Second, the unemployment rate varies a lot both across occupational groups and over time. While the unemployment rate among managers, professionals and technicians never exceeds five percent, it is rarely below ten percent among operators and laborers. The third interesting finding is that unemployment tends to fluctuate more in occupations where its level is high to begin with, but in a proportional sense the changes are similar. For example, while the unemployment rate among professionals went up from 1.7 percent in 2006-2007 to 3.5 percent in 2009-2012, it went up from 8 percent to 15 percent among operators and laborers. In a proportional sense, we see the doubling of the unemployment rates in almost all occupation groups, but in a level sense the differences are enormous. It is important to note, however, that from a welfare point of view we care about level changes in employment probabilities and not percent changes. A Von Neumann-Morgenstern utility function is linear in probabilities and, thus, agents care about level, and not percent, changes in their unemployment probabilities.[13]

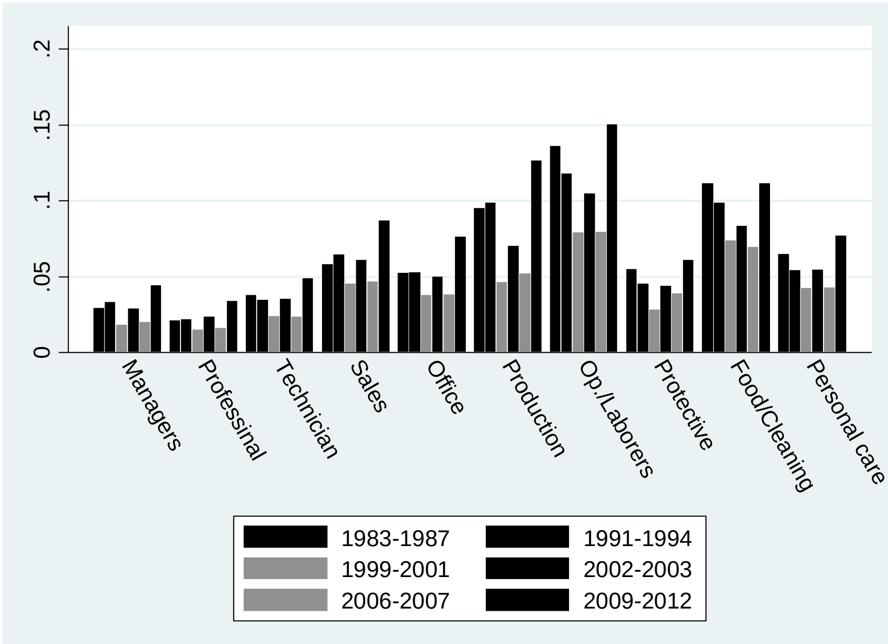
In terms of the effect of skills, panel A of Figure 1 is rather inconclusive. The level and change of unemployment seem to be the highest among operators, laborers, production workers, food preparation-, cleaning-, personal care and personal services workers. Unfortunately, these categories contain many low- and some middle skilled occupations, and it is hard to draw a conclusion about the effect of skills. The situation is clearer on panel B, where occupations are grouped based on the average years of education in my 191 occupations in the 2000 census. Occupations are grouped so that there are roughly equal number of people in them in the 2000 census, and higher deciles in panel B correspond to better educated workers in the occupation. As opposed to panel A, it is immediately apparent that skills are negatively related to unemployment and to changes in unemployment over time. The effect seems remarkably monotone, with maybe an exception at the lowest skill decile.

The four panels of Figure 6 and 7 in the Appendix show the same results with alternative definitions of occupations and skills. Figure 6 shows that when the occupation last year is used instead of the occupation in the last job, we get a very similar pattern to Figure 1. The only difference is that the level of unemployment is uniformly smaller in the Appendix, because I had to condition on people who had a job last year. As panel B of Figure 7 shows, the results are almost identical if I use the 393 three digit occupations of the 1990 census or if I create occupational skills from the 1990 instead of the 2000 census. As panel A of Figure 7 shows, however, the results are considerably weaker and less

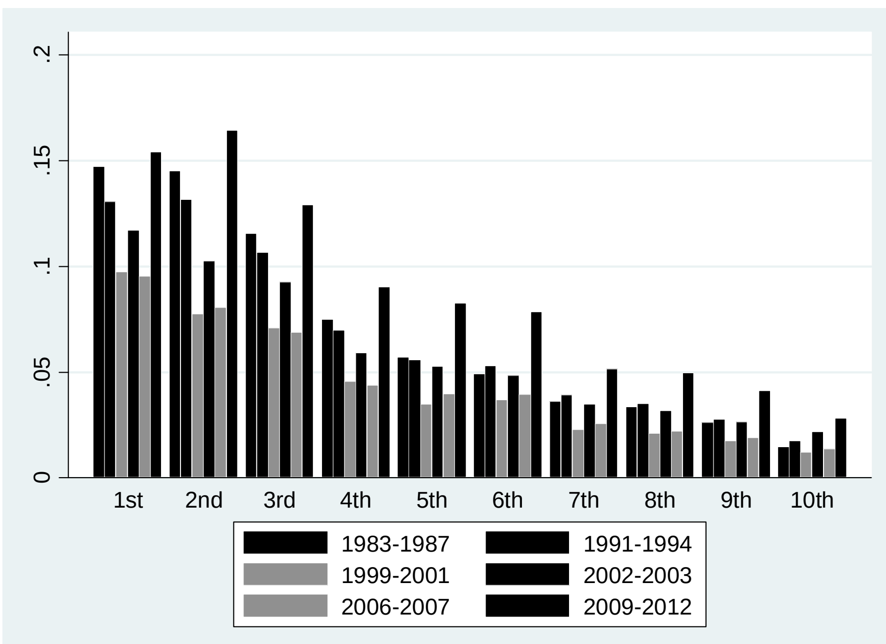
[13]Ambiguity averse agents would disprefer employment probability fluctuations even more, because larger fluctuations would make it harder to predict these probabilities.

Figure 1: Unemployment rate by occupational group in different time periods, March CPS 1983-2012

Panel A: In major occupational groups



Panel B: In occupational skill deciles*



*Occupational skill is defined as the average years of education in the 2000 census in each of my 191 occupations. Deciles are taken in the 2000 census, and higher number means higher skilled occupation. In each occupational group there are 6 bars representing 6 time periods with the ones on the right being the more recent.

monotone when occupational skills are defined in terms of average wage as opposed to average years of education.[14] A usual finding in the job polarization literature is that the middle skilled occupations have been disappearing in the last 20 years. This result appears to be robust to the definition of skills, including average wage, average years of education or task content. Panel A of Figure 7 shows that the business cycle properties of occupations, however, are considerably weaker when wage as opposed to education is used as a proxy of skills. To further elaborate on this issue, Table 6 in the Appendix shows the distribution of major occupational groups within skill deciles based on education (Panel A) and wages (Panel B). We can also see that the skill definition using education follows the major occupation groups better as there are more zero cells (53 as opposed to 41) in panel A compared to panel B. The two skill measures operate similarly at high and middle skilled occupations, but they are quite different at the low skilled ones. The lowest educated occupations are operators, laborers, food and cleaning workers, then production and personal service workers. Recall that in panel A of Figure 1 these were exactly the occupations with the highest unemployment rate and unemployment volatility. However, even though operators, laborers and production workers are uneducated, they are paid comparatively well. From a technical point of view this is the main reason why the skill definition based on education worked better than the one based on wages.

In the next section I will argue that the strong relationship between occupational skills and occupational unemployment patterns should not be though of as the marginal effect of various skills. Instead, it illustrates that occupational skills are positively related to hiring, training and other adjustment costs that induce employers to hoard workers in recessions. Nevertheless, it might be interesting to directly look at various occupational skills from the O*NET project. I use the Abilities section of the O*NET because the dimensions used there are the most similar to the task measures in the Dictionary of Occupational Titles that many researchers used in the job polarization literature.[15] I aggregate abilities into the following 4 categories:[16] 1. Non-routine cognitive abilities (such as reasoning); 2. Routine cognitive abilities (such as attentiveness); 3. Psychomotor abilities (such as finger dexterity)

[14] Average wage is computed in the same way as in Acemoglu and Autor (2011): it is the average weakly log wage of the 16-64 year old full-time, full-year workers in the 2000 census. Full-time, full-year workers are those who worked at least 40 weeks last year, and their usual hours of work per week was at least 35. Similarly to Acemoglu and Autor (2011), I excluded observations with weekly earnings less than $136 in 2008 dollars. The only difference between my definition and that of Acemoglu and Autor (2011) is that I used the 2000 census instead of the 1980 one.

[15] The O*NET has many other sections as well, including one on Tasks. From a theoretical point of view, the distinction between tasks and abilities is important. Occupations can be though of as a bundle of tasks, and abilities can be though of as attributes of workers that are important for carrying out these tasks. Task information is useful to test if certain tasks are more important in recession than others. Ability information is useful to test if employers hoard certain types of workers in recessions. In this project I only use abilities, because the 17th edition of O*NET still has incomplete information on occupational tasks.

[16] The appendix describes the aggregation, and provides further details about the definitions of my ability measures.

and 4. Physical abilities (such as strength). Table 5 shows correlations between various occupational skill measures in my 191 occupations. The highest correlation is between psychomotor and physical abilities; and between education and non-routine cognitive skills. Figure 8 and 9 show occupational unemployment by occupational skills defined based on the O*NET ability measures. The non-routine cognitive skill content of an occupation gives a very similar picture than my preferred average education based skill measure. Physical skill measures show the reverse picture: the more important physical strength and endurance are in an occupation, the higher is the level and volatility of unemployment. Both of these measures, however, show a weaker association than my simple education based measure, and the other two measures show even weaker associations.

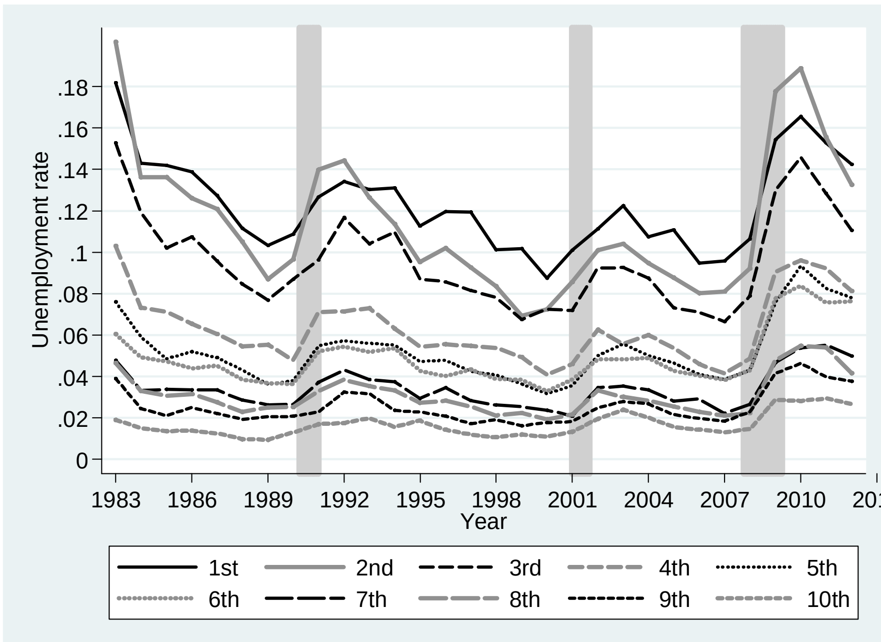
Figure 2 shows the level and log unemployment rates in the ten skill deciles in each March from 1983 to 2012. Qualitatively the evolution of the unemployment rates are similar in each occupation. It starts increasing in recessions, it continues increasing after the recession is over and it starts decreasing only with some lag. Quantitatively, however, these changes are very different. The pattern is, of course, very similar to panel B of Figure 1: both the unemployment rate and the volatility of the unemployment rate are higher in less skilled occupations, but in the log scale (Panel B) we can see that the percentage changes in the unemployment rates over time are similar. What is also fascinating in this figure, is the difference between the rate of recovery of the labor market in the different skill groups. Even though low skilled occupations suffered more during the 2007 recession, the unemployment rate shrank significantly since 2010. At the same time, even though the unemployment rate in middle skilled occupations never reached that of the low skilled occupations, it stuck at its highest level since 2010. This is in line with the findings of Acemoglu and Autor (2011) and Jaimovich and Siu (2012) who showed that middle skilled occupations continued to disappear in the last recession.

Figure 10 in the appendix shows the graphs broken down by gender. The patterns are very similar for both males and females, but the female unemployment rate is somewhat smaller in level and volatility especially prior to the 2007 recession. In the 2007 recession the male and female unemployment rate followed a very similar pattern.

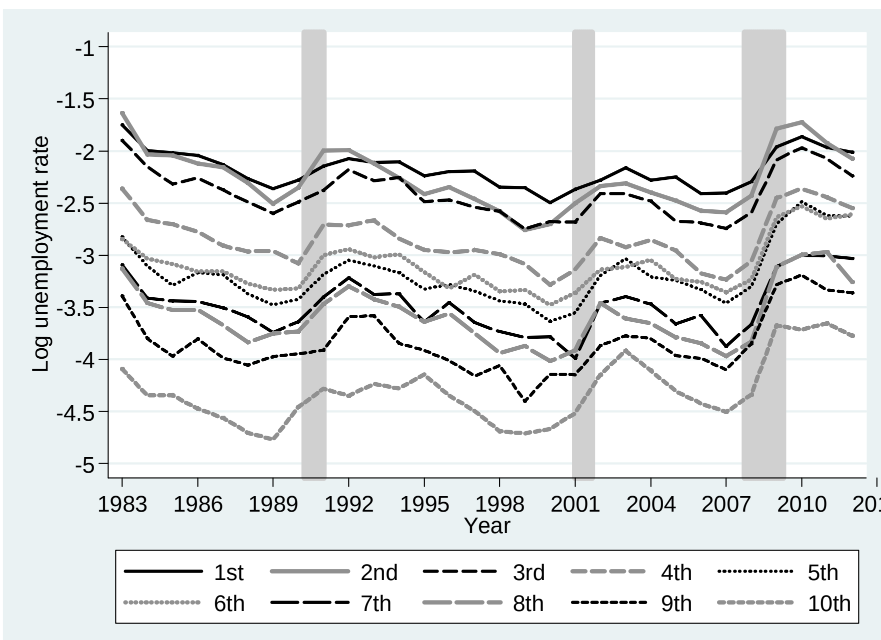
To further illustrate the power of my education based occupational skill variable, I run OLS regressions of unemployment probabilities on skills, different demographic variables and their interaction with GDP growth. GDP growth is defined as the log difference between GDP in the previous calendar year and

Figure 2: Level and log unemployment rates by the skill decile of the last occupation*, March CPS 1983-2012

Panel A: Unemployment rates



Panel B: Log unemployment rates



*Occupational skill is defined as the average years of education in the 2000 census in each of my 191 occupations. Deciles are taken in the 2000 census, and higher number means higher skilled occupation. The gray areas indicate NBER recession dates.

the year before that.[17] Table 1 shows the output of the regressions together with an estimate of the marginal effect of a 10% higher GDP growth on unemployment at various percentiles of the skill or education distribution. By comparing columns 1 and 2 we can see that occupational skill is a better predictor of unemployment than education, which is remarkable since my occupational skill variable is defined as an occupation specific average years of education. A 10% higher GDP growth induces 7.3 percentage point decrease in unemployment in occupations at the 5th percentile of the skill distribution, and a 7.4 percentage point decrease at the 5th percentile of the education distribution. At the 95th percentiles, however, these numbers are 1.5 and 3 percentage points, respectively, which means that by going from the 95th to the 5th percentiles, the fluctuation in unemployment increases 4.9 times when occupational skills, but only 2.4 times when education is considered. By comparing columns 3 and 4 we can see further evidence that occupational skills are better predictors of unemployment: more than half of the educational difference in unemployment can be explained by my occupational skill variable, but at the same time, occupational skill does not decrease much after controlling for the actual level of education of workers. We can also see, however, that education and other demographic variables all remain significant, which means that within occupational skill groups there is still systematic differences in the unemployment prospects of workers. This might indicate that I used too broad occupational groups, or that these variables actually predict unemployment.

Table 7 in the appendix shows the same results when a log-specification is used. The model fits the following regression with non-linear least squares:

$$U_{it} = exp\left(X_{it}\beta\right) + u_{it}$$

and the marginal effects of GDP growth at various percentiles of the skill and education distribution are evaluated at the mean GDP growth.[18] The estimated models are non-linear and thus it is not easy to read the output of these models. Nevertheless, the implied effects of GDP growth on various percentiles of the skill and education distribution are very close to the ones based on the level model in Table 1. Therefore I will use the level model from now on.[19]

Table 8 in the appendix repeats this exercise in different age, gender and race groups. The occupational

[17]Other lags of GDP has further explanatory power, but I only use this single variable to make the table easier to read and because this GDP variable has the strongest load on unemployment.

[18]See the appendix for further details.

[19]The R-squared values in the non-linear models are significantly higher than in the level models, which might indicate that the log specification gives a better fit. Nevertheless, because the level model implies similar estimates and it is much easier to work with, I use the level model, instead.

distribution is kept the same in all regressions. As we can see, the gender difference in the level and volatility of unemployment remains large even when occupational skills are controlled. At the 5th percentile of the skill distribution, a 10% increase in GDP causes a 9.2 percentage point increase in the male unemployment rate, while it leads to only 4.5 percentage point increase among females. The corresponding numbers at the 95th percentile are 1.1 percentage point (males) and 2.4 percentage point (females). Thus, male unemployment rate is more volatile at the bottom of the skill distribution and less volatile at the top of it. Race differentials in the level and volatility of unemployment are less stark, when occupational skills are controlled. Even more interesting is the differences among age groups. The level of unemployment is lower for older people, but this difference is very similar at all occupational skill levels.

Table 9 in the appendix shows the same regressions by using alternative occupational skill measures from either the census (average education or wage), or the O*NET. As we can see my education based skill measure is the strongest predictor of occupational unemployment. Non-routine cognitive skills behave similarly to the education based measure, and psychomotor and physical abilities work in the opposite way.[20]

Finally I show scatter plots of unemployment rates in each of the 191 occupation I defined above. The two panels of Figure 11 show the unemployment rates in a period of favorable labor market conditions (2006-2007) and in a period of weak labor market (2009-2012). Figure 3 shows the change in the unemployment rates between these two periods. In all figures I colored the occupations based on the major occupation groups they belong to. The general pattern is very clear: lower skilled occupations have higher unemployment in all periods, and they are more strongly hit by the business cycle. It seems to be true both within and across major occupation groups. Moreover, we can also see that there is an enormous heterogeneity at the low end of the skill distribution that is not explained by my skill proxy.

2.2 Job-loss and job-finding probabilities in occupations

There is a debate in the macro labor literature about the relative importance of job-separation and job-finding probabilities in explaining fluctuations in the aggregate unemployment rate. The usual finding

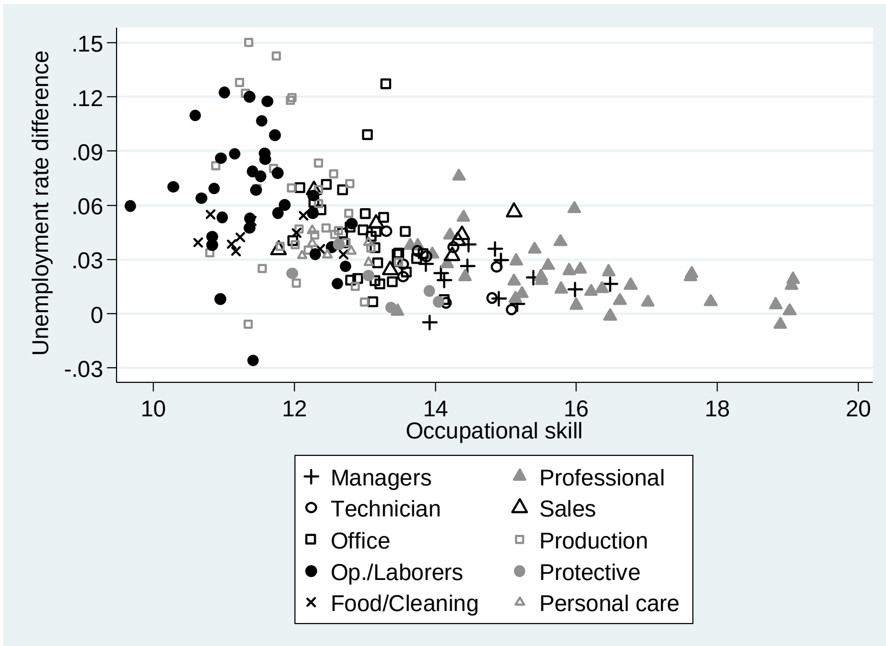
[20]When one runs a horse race between the alternative measures, the education based one comes down to be the strongest, but all the others remain significant with the expected sign, too.

Table 1: OLS regressions of unemployment, March CPS, 1983-2012

	[1]	[2]	[3]	[4]
dln(GDP), DG	-0.5	-1.236	-1.459	-0.964
	[0.007]**	[0.037]**	[0.046]**	[0.056]**
Occupational skill, SE	-0.036			-0.025
	[0.000]**			[0.000]**
SE X DG	0.176			0.135
	[0.007]**			[0.009]**
Years of education, E		-0.011	-0.01	-0.004
		[0.000]**	[0.000]**	[0.000]**
E X DG		0.055	0.05	0.016
		[0.003]**	[0.003]**	[0.004]**
Age, A			-0.001	-0.001
			[0.000]**	[0.000]**
A X DG			0.002	0.002
			[0.001]**	[0.001]**
Female, F			-0.018	-0.014
			[0.000]**	[0.000]**
F X DG			0.25	0.224
			[0.015]**	[0.015]**
White, W			-0.037	-0.034
			[0.001]**	[0.001]**
W X DG			0.082	0.074
			[0.020]**	[0.020]**
Constant	0.074	0.222	0.305	0.216
	[0.000]**	[0.001]**	[0.001]**	[0.002]**
N	2462447	2462447	2462447	2462447
R squared	0.02	0.014	0.022	0.027
Marginal effect of 10% higher GDP growth on unemployment at various percentiles of the skill distribution (model 1) and the education distribution (model 2)				
5th percentile	-0.073	-0.074		
	[0.001]**	[0.001]**		
25th percentile	-0.063	-0.058		
	[0.001]**	[0.001]**		
Median	-0.05	-0.052		
	[0.001]**	[0.001]**		
75th percentile	-0.037	-0.036		
	[0.001]**	[0.001]**		
95th percentile	-0.015	-0.03		
	[0.002]**	[0.001]**		
Ratio: 5th / 95th percentile	4.941	2.442		
	[0.579]**	[0.128]**		

*dln(GDP) is defined as the log difference between GDP in the previous calendar year and the year before that; Occupational skill is defined as the average years of education in the 2000 census in each of my 191 occupations standardized to have zero mean and standard deviation 1 in the 2000 census.

Figure 3: Average increase in unemployment rate by occupations between 2006-2007 and 2009-2012, March CPS, 2006-2012, colored by 10 major groups



is that the job-finding probability is relatively more important, but the job-loss probability also has explanatory power, especially at the early phases of recessions. (Shimer, 2012; Davis et al., 2006; Elsby et al., 2009; Fujita and Ramey, 2009). In this section I derive job-loss and job-finding probabilities by occupations. Elsby et al. (2010) found that the job-finding probability fluctuates remarkably similarly in different demographic groups, while the job-loss probability varies greatly. I will show that this holds for occupations as well. Even though the job-finding probabilities are very volatile, they fluctuate just as much in skilled occupations as in unskilled ones. The job-loss probabilities, however, are smaller and more smooth in skilled occupations compared to unskilled ones.

For this exercise I merge the monthly CPS from September 1995 to January 2013[21]. The job-loss probability is defined as the ratio of people in an occupation who become unemployed by the next month. The job-finding probability is defined as the ratio of people who find a job by the next month among those whose last job was in a given occupation. Occupation switches are not modeled here. I

[21] Going back further in time is possible, but tricky. CPS changed the individual identifiers a couple of times in the past and at these dates we cannot merge consecutive CPS waves. The last change was in the entire summer of 1995, when for three months the identifiers were changing every month. Before 1994, the occupation data is less reliable than after 1994. In January 1994 CPS introduced CAPI, they preloaded the previous occupations of workers and only asked about changes (or potential miscoding) in occupations. Thus, the pre-1994 occupation data contains considerably more measurement error. For occupational unemployment, it might not be a big problem, but in later sections I will also analyze occupation switches for which the pre-1994 values are much less reliable.

only estimate whether someone in a given occupation is employed or not employed by the next month.

Figure 4 and 12 show how the job-loss ($E \rightarrow U$) and job-finding ($U \rightarrow E$) probabilities evolved between 1996 and 2013 in different occupations. As we can see the job-finding probabilities are considerably more volatile over the business cycle than the job-loss probabilities, which is in line with the macro labor literature cited above. For example, the average monthly job-finding probability was over 30 percent in 1998, while it was below 20 percent in 2009. However, even if the job-finding probabilities are more volatile, we see little difference between occupational groups. It seems that it is not significantly easier for the skilled to find a job neither in booms nor in busts. The sample average of the job-finding probability in the total 1996-2013 period was the lowest for managers (24 percent) and the highest for professional workers (29 percent). This difference is not huge, and it does not seem to systematically vary by skills.

The job-loss probabilities, however, are smoother and they basically track the pattern of occupational unemployment shown in Figure 1 and 2. The job-loss probabilities are very small and they do not vary much in the most skilled occupations (like managers, professional workers, and technicians) but they are high and volatile for less skilled occupations. It seems, thus, that even though separations are less important to understand aggregate fluctuations in unemployment, they are very important to understand the differences between occupational unemployment.

Table 2 shows the regression versions of Figure 4. In the regressions I use various lags of quarterly GDP growth data in the following way:

$$P_{ot} = \beta_0 + \beta_1 S_o + (1 + \beta_2 S_o)\left(\sum_{l=1}^{L} \gamma_l \left(\ln GDP_{t-l} - \ln GDP_{t-l-1}\right)\right) + u_{ot} \tag{1}$$

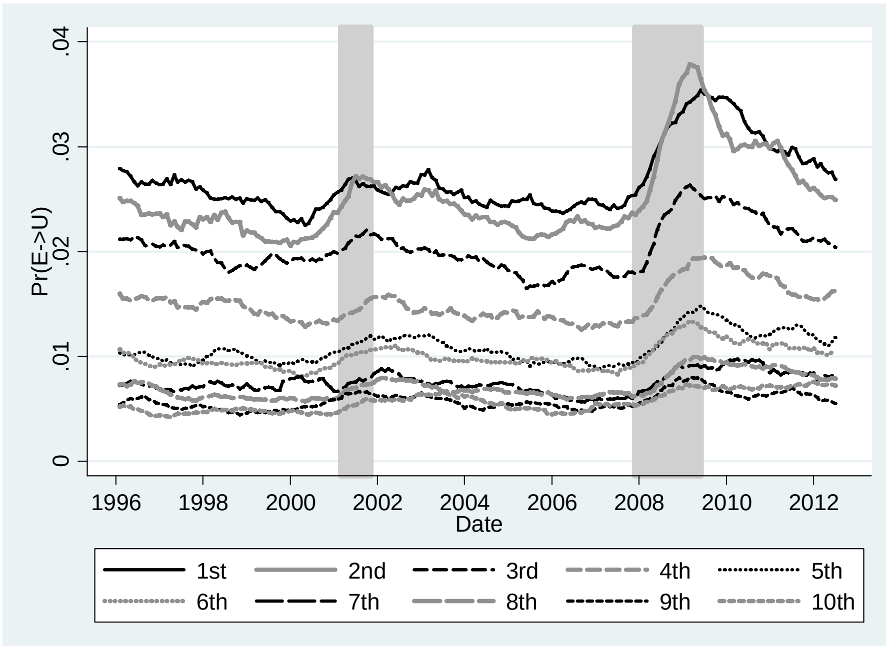
where o indexes occupations. The specification in (1) restricts the shape of the impulse response function to be the same in every occupations, and β_2 determines the scale. A negative β_2 implies a smoother impulse response in skilled occupations. The transition probabilities are seasonally adjusted in each occupation separately[22] and the regressions are weighted by the size of the occupation-month cells.[23] As we can see in Table 2, GDP growth has a sharp, but short-lasting negative effect on job-loss

[22]In each occupation, I regressed the transition probabilities on month dummies and I added up the residuals and the occupational means.

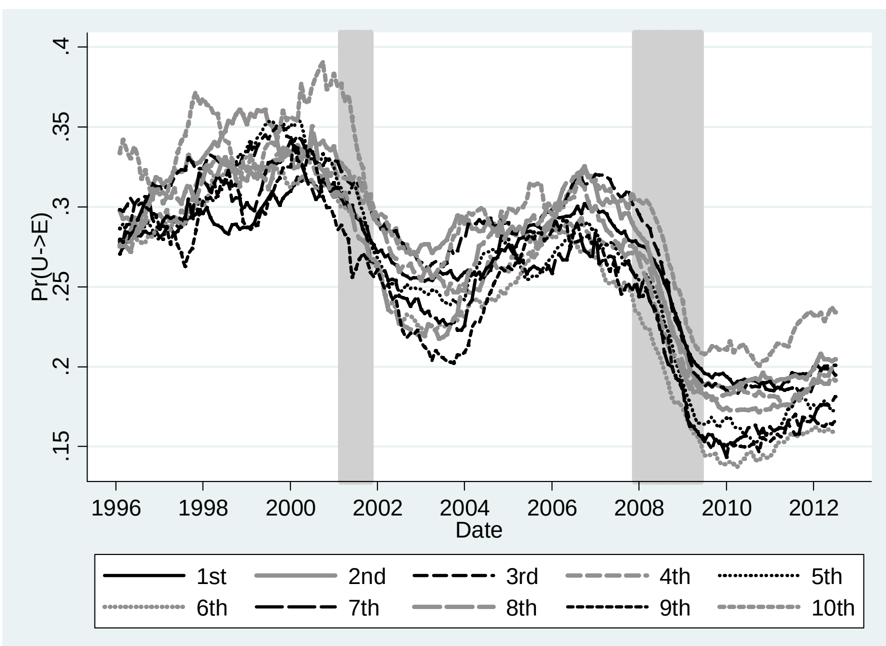
[23]The weight is is the sum of the employed and unemployed persons in each occupation in every months.

Figure 4: Evolution of job-loss and job-finding probabilities by the skill level of the last occupation*, 1996-2013

Panel A: job-loss probabilities



Panel B: job-finding probabilities



*The figure shows yearly moving averages of monthly job-loss and job-finding probabilities using the monthly CPS. For the unemployed, the occupation at the last job is used. Occupational skill is defined as the average years of education in the 2000 census in each of my 191 occupations. Deciles are taken in the 2000 census, and higher number means higher skilled occupation. The gray areas indicate NBER recession dates.

probabilities, but the response of the job-finding probabilities is more persistent. This is in line with the macro labor literature of aggregate job-loss and job-finding probabilities cited in the introduction. Even more important is that while there are large occupational differences in the level and volatility of job-loss probabilities, there are no significant differences in the level and volatility of job-finding probabilities. Differences in occupational unemployment, thus, are only driven by differences in the incidence of job-loss.

3 Possible economic explanations

In this section I collect six alternative hypotheses that might explain the large heterogeneity in occupational unemployment and provide simple tests of them. In the end I find that differential labor hoarding by occupational skills is the only explanation that is consistent with all tests. First, let me briefly outline the six hypotheses.

1. Industrial composition: Low-skilled occupations might be clustered in industries that are disproportionally more strongly hit by recessions, such as durable good manufacturing.
2. Quality adjustment (à la Reder): The skilled might crowd out the unskilled from the labor market in recessions as employers prefer hiring skilled workers even into low skilled jobs.
3. Productivity differences: Some skills might be useful in recessions and they might be positively correlated with the general skill proxies that I use in this project.
4. Employment flexibility: Skilled workers might have more flexible work arrangements with their employers that make work adjustments more likely on the intensive as opposed to the extensive margin.
5. Labor hoarding due to adjustment costs: Hiring, training and other adjustment costs might be higher in skilled occupations. Due to these costs firms might decide to hoard their skilled workers to save on their future rehiring costs.
6. Labor hoarding due to firm specific skills: Workers in skilled occupations might acquire more firm specific skills which are valued by the employer.

Table 2: Non-linear least squares models of job-loss and job-finding probabilities, Monthly CPS, from September 1995 to January 2013

	Job-loss		Job-finding	
	[1]	[2]	[3]	[4]
Occupational skill	-0.007	-0.007	0.003	0.003
	[0.000]**	[0.000]**	[0.001]*	[0.001]
Interaction	-0.401	-0.402	-0.010	0.007
	[0.038]**	[0.035]**	[0.025]	[0.020]
dln(GDP), lag 1	-0.084	-0.075	1.394	1.075
	[0.009]**	[0.009]**	[0.156]**	[0.155]**
dln(GDP), lag 2	-0.061	-0.070	1.076	1.450
	[0.009]**	[0.010]**	[0.167]**	[0.167]**
dln(GDP), lag 3	-0.056	-0.043	1.596	1.064
	[0.010]**	[0.010]**	[0.167]**	[0.170]**
dln(GDP), lag 4	-0.077	-0.050	2.742	1.361
	[0.009]**	[0.010]**	[0.154]**	[0.169]**
dln(GDP), lag 5		-0.022		0.823
		[0.010]*		[0.168]**
dln(GDP), lag 6		-0.021		1.504
		[0.009]*		[0.164]**
dln(GDP), lag 7		-0.065		2.751
		[0.009]**		[0.152]**
Constant	0.015	0.016	0.223	0.204
	[0.000]**	[0.000]**	[0.001]**	[0.001]**
N	39919	39919	36900	36900
R squared	0.286	0.288	0.040	0.063
Marginal effect of 1% higher GDP growth in each quarter on unemployment at various percentiles of the skill distribution				
5th percentile	-0.004	-0.005	0.069	0.099
	[0.000]**	[0.000]**	[0.003]**	[0.003]**
25th percentile	-0.004	-0.004	0.069	0.100
	[0.000]**	[0.000]**	[0.002]**	[0.003]**
Median	-0.003	-0.004	0.068	0.100
	[0.000]**	[0.000]**	[0.002]**	[0.002]**
75th percentile	-0.002	-0.003	0.068	0.101
	[0.000]**	[0.000]**	[0.002]**	[0.002]**
95th percentile	-0.000	-0.001	0.067	0.102
	[0.000]*	[0.000]*	[0.004]**	[0.004]**
Ratio: 5th / 95th percentile	9.465	9.540	1.036	0.977
	[4.938]	[4.641]*	[0.089]**	[0.065]**

*The left hand side contains occupation specific job-loss and job-finding probabilities by months. The probabilities are seasonally adjusted separately for each occupation, by collecting the residuals from a regression of occupation specific probabilities on month dummies. The regressions are weighted by the number of employed and unemployed workers in a given month in a given occupation. The GDP growth is computed from aggregate quarterly data. For the unemployed, the occupation at the last job is used. Occupational skill is defined as the average years of education in the 2000 census in each of my 191 occupations. Deciles are taken in the 2000 census, and higher number means higher skilled occupation. The interaction term means β_2 in specification (1).

3.1 Industrial composition

Different industries use different occupations, and thus, it is possible that the differential effect of the business cycle on occupations is only a consequence of industry-specific shocks. For example, a common belief is that manufacturing uses more unskilled production workers, and this industry suffers relatively more during contractions.

Even though the industry composition hypothesis could explain large differences in occupational unemployment, it cannot explain why the job-finding probabilities are so similar in different occupations. In fact the hypothesis predicts that occupations with relatively stable unemployment profiles should have relatively stable job-finding probabilities, too. However, this is not what we see in the data.

In order to test this hypothesis more formally, I created industry specific GDP series using the BEA reports. I had to make some aggregation of the industries to get a comparable specification with the CPS.[24] I ended up with 38 industries. Figure 13 in the appendix shows that industry specific GDP growth is only weakly related to occupational skills in these industries. We can see that in the most skilled industries (professional services and public administration) the volatility of GDP growth is small, and the GDP in 2007-2009 was not strongly hit, either. However, at lower skilled industries the relationship is quite weak. Thus, it is unlikely that the industry composition hypothesis is responsible for the occupational unemployment patterns.

A more formal test of the hypothesis can be carried out by comparing the β_2 coefficients in the following regressions:

$$U_i = \beta_0 + \beta_1 S_i + (1 + \beta_2 S_i)\left[\beta_3 d\ln(GDP_t)\right] + \varepsilon_i \quad (2)$$

$$U_i = \beta_0 + \beta_1 S_i + (1 + \beta_2 S_i)\left[\beta_3 d\ln(GDP_t) + \beta_4 d\ln(GDP_{jt})\right] + \varepsilon_i, \quad (3)$$

where $d\ln(GDP_{jt})$ denotes industry GDP growth. The industry composition hypothesis predicts a large negative β_2 in equation (2) and a close to zero β_2 in equation (3). Table 3 shows, however, that the interaction term β_2 actually decreases more after industry specific shocks are taken into account.

[24] In fact the crosswalk was even more complicated because the CPS definitions also changed over time. A major change occurred in 2003 where the previously used Standard Industrial Classification (SIC) got replaced by the North American Industry Classification System (NAICS). The BEA information is also based on NAICS and thus the crosswalk is simpler for the post 2003 years. There has also been two minor changes in the industry classification in CPS in 1992 and 2009.

Table 3: Testing the industry composition hypothesis with industry GDP data, March CPS 1983-2012

	[1]	[2]
Occupational skill	-0.036	-0.036
	[0.000]**	[0.000]**
Interaction	-0.352	-0.410
	[0.015]**	[0.016]**
dln(GDP)	-0.500	-0.391
	[0.007]**	[0.008]**
dln(Industry GDP)		-0.080
		[0.003]**
Constant	0.074	0.074
	[0.000]**	[0.000]**
N	2462447	2462447
R squared	0.020	0.020
Marginal effect of 10% higher GDP growth on unemployment at various percentiles of the skill distribution		
5th percentile	-0.073	-0.072
	[0.001]**	[0.001]**
25th percentile	-0.063	-0.061
	[0.001]**	[0.001]**
Median	-0.050	-0.047
	[0.001]**	[0.001]**
75th percentile	-0.037	-0.032
	[0.001]**	[0.001]**
95th percentile	-0.015	-0.008
	[0.002]**	[0.002]**
Ratio: 5th / 95th percentile	4.941	8.563
	[0.578]**	[1.666]**

*dln(GDP) and dln(Industry GDP) are defined as the log difference between aggregate and industry GDP in the previous calendar year and the year before that; Occupational skill is defined as the average years of education in the 2000 census in each of my 191 occupations standardized to have zero mean and standard deviation 1 in the 2000 census. For the unemployed, the occupation and industry at the last job is used. The interaction term means β_2 in specification (2) and (3). The percentiles at model 2 show the marginal effect of a 10% higher GDP growth both in the aggregate and in the industry of the worker.

By comparing the effects at various percentiles of the skill distribution we can see that this difference is driven by the highest skilled occupations.

Overall, the industry composition hypothesis cannot explain the large differences in occupational unemployment patterns.

3.2 Quality adjustment

It is possible that people in skilled occupations can get jobs in both skilled and unskilled ones and in recessions they crowd out the unskilled from the labor market. This could happen if skilled workers increase their search effort for unskilled jobs (Albrecht and Vroman, 2002; Dolado et al., 2009; Khalifa, 2009; Chassamboulli, 2011) or if firms raise hiring standards in recessions (Reder, 1955; Teulings, 1993; van Ours and Ridder, 1995; Evans, 1999; Devereux, 2004; Büttner et al., 2010). This mechanism can explain why the unemployment rate is more volatile in unskilled occupations.

The mechanism also predicts that the job-finding probability fluctuates more for the unskilled. As we saw in the previous chapter, however, the job-finding probability follows a broadly similar pattern in all occupations. Thus, the quality adjustment hypothesis is very unlikely to explain why different occupations are affected by the business cycle so differently.

Nevertheless I also tested this hypothesis directly. The hypothesis predicts that in recessions we see an increase in flows from high to low skilled jobs, while in booms the trend reverses. Panel A of Figure 5 shows the average education level of job-switchers in different occupational skill deciles in the last 30 years in the March CPS.[25] The hypothesis predicts then in recessions the average education levels converge to each other, and in booms they diverge. We do not see that in the data. Panel B shows the average occupational skill in the next job among those who changed occupations between two months. Again, there is not evidence for any convergence in busts and divergence in booms. Overall the quality adjustment hypothesis cannot explain the large differences in the occupational unemployment patterns.

3.3 Productivity differences

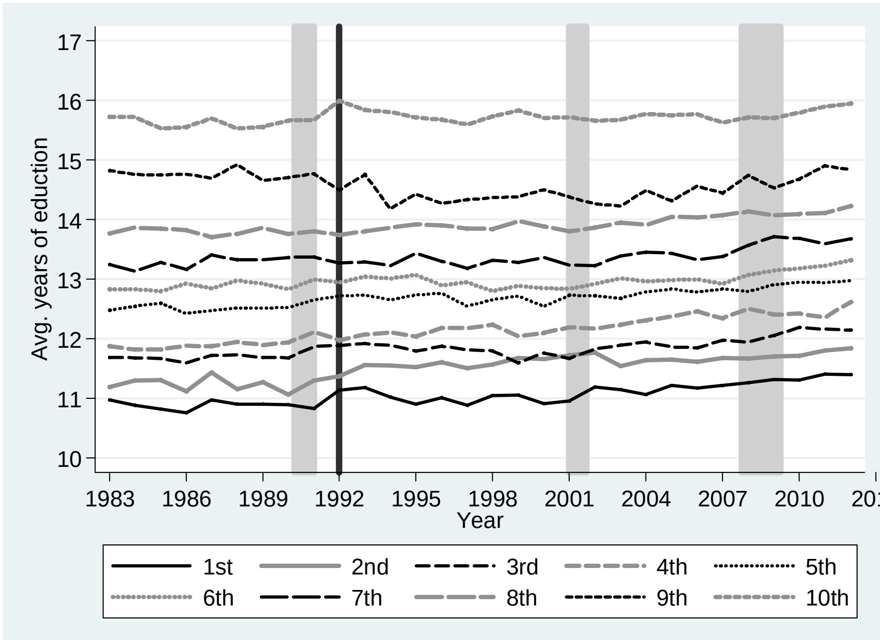
Some skills might be useful in recessions and they might be positively correlated with the general skill proxies that I use in this paper. For example, even if a manufacturing firm wants to lay off some production workers, it might still need as many (or even more) market analysts. Recessions, thus, might affect occupations differently just because some tasks carried out in some occupations are relatively more useful in recessions than tasks carried out in other occupations.

The productivity hypothesis, similarly to the previous quality adjustment one, also predicts that the job-finding probability fluctuates less for skilled workers. As long as skilled workers are more useful

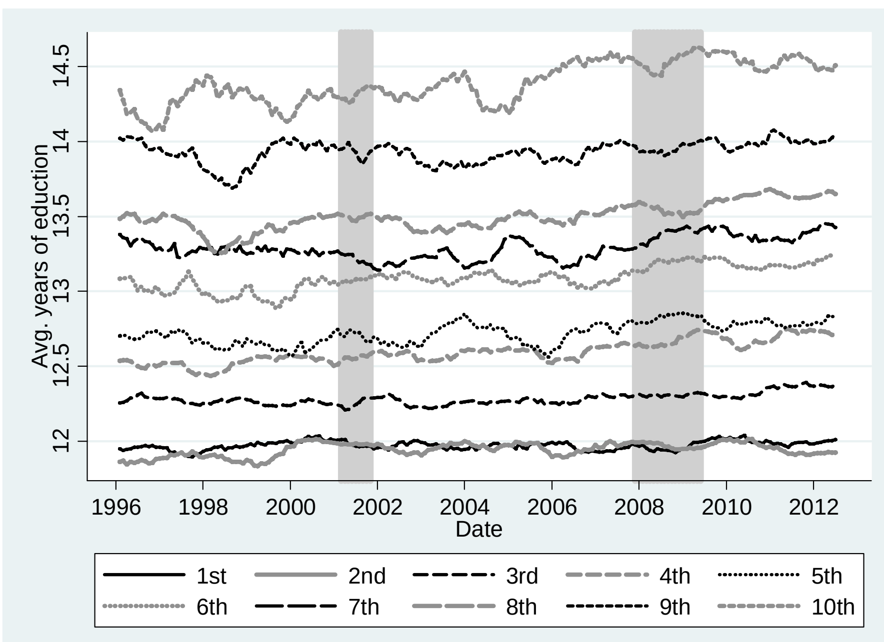
[25] Job-switchers are those whose occupation last year was different from the occupation in the March CPS.

Figure 5: Quality of job-switches among job-switchers, March CPS 1983-2012 and Monthly CPS 1996-2013

Panel A: March CPS



Panel B: Monthly CPS, 1 year moving average



*Panel A shows the average years of education measured in the CPS in 10 occupational skill categories among those whose occupation last year was not the same as their occupation in the March CPS. Panel B shows 1 year moving averages of the average occupational skill in the next job among those who switched occupations between two months. Occupational skill is defined as the average years of education in the 2000 census in each of my 191 occupations. The light gray areas indicate NBER recession dates. The dark gray column on Panel A at 1992 indicates a change in the education measurement in the CPS.

in recessions, the job-finding probabilities of the skilled should be less volatile than the ones of the unskilled. As we do not see any evidence for this in the data it seems very unlikely that this mechanism plays an important role in understanding differences in the unemployment patterns of occupations.

3.4 Employment flexibility

In principle employers can adjust labor both on the extensive and the intensive margins. If, for some reason, it is easier to adjust skilled labor on the intensive margin, we would expect smaller fluctuation in unemployment among skilled workers. To test this hypothesis, I computed average hours of work per week by occupations over time among those who worked positive hours. Table 4 shows, however, that people actually work longer hours in skilled occupations, and their work hours are affected less by the business cycle. Figure 14 in the appendix shows the same results in various occupation groups. We can see that average hours worked per week is procyclical, and lower skilled occupations are somewhat more affected on the intensive margin. Altogether, work flexibility is not responsible for seeing less unemployment fluctuations in skilled occupations.

3.5 Labor hoarding due to adjustment costs

The available empirical evidence suggest that hiring, training and other adjustment costs are higher in skilled occupations even proportionally to the wage rate (Manning, 2011). These costs might induce firms to hoard skilled workers in order to save on their rehiring costs in the future. At the same time, unskilled workers are less likely to be hoarded because it is comparatively cheaper to lay them off in recessions and rehire them in booms. Oi (1962) found that recruitment costs are lower and labor turnover is higher among “Common laborers”. Since Oi’s work many papers provided evidence for labor hoarding, but I am not aware of any papers that analyzed occupational differences in the extent of labor hoarding.

This mechanism can explain the empirical finding in the previous section that the job-finding probabilities are so similar while unemployment rates are so different across occupations. In recessions employers have excess labor in each occupation on average. Consequently, the rate of hiring is cut back, and the job-finding rate decreases. The fact that the job-finding probabilities empirically move

Table 4: OLS on average hours of work last week by occupational groups*, March CPS 1983-2012

	[1]	[2]
dln(GDP), DG	14.947	21.54
	[0.448]**	[3.321]**
Occupational skill, SE	2.015	1.432
	[0.014]**	[0.018]**
SE X DG	-1.85	-2.67
	[0.437]**	[0.545]**
Years of education, E		0.359
		[0.007]**
E X DG		0.743
		[0.206]**
Age, A		0.163
		[0.001]**
A X DG		-0.113
		[0.035]**
Female, F		-6.222
		[0.028]**
F X DG		-13.951
		[0.861]**
White, W		0.043
		[0.038]
W X DG		-1.681
		[1.196]
Constant	38.561	30.363
	[0.015]**	[0.108]**
N	2231454	2231454
R squared	0.022	0.106
Marginal effect of 10% higher GDP growth on hours worked per week at various percentiles of the skill distribution		
5th percentile	1.728	2.49
	[0.073]**	[0.297]**
25th percentile	1.62	2.335
	[0.055]**	[0.312]**
Median	1.493	2.152
	[0.045]**	[0.332]**
75th percentile	1.355	1.952
	[0.054]**	[0.358]**
95th percentile	1.125	1.62
	[0.095]**	[0.405]**
Ratio: 5th / 95th percentile	1.536	1.537
	[0.168]**	[0.228]**

*dln(GDP) is defined as the log difference between GDP in the previous calendar year and the year before that; Occupational skill is defined as the average years of education in the 2000 census in each of my 191 occupations standardized to have zero mean and standard deviation 1 in the 2000 census.

together indicates that skilled occupations are just as useful (or useless) in recessions as unskilled occupations. However, given that adjustment costs are higher in skilled occupations, employers are more likely to hoard their skilled employees and lay off their unskilled ones. If adjustment costs are monotonically increasing with skill, we expect unemployment volatility to monotonically decrease with the skill level of the occupation. It would be very useful to have a direct measure of adjustment costs by occupations so that this hypothesis can be tested directly.

3.6 Labor hoarding due to firm specific skills

Workers in skilled occupations might acquire more firm specific skills than workers in unskilled occupations. The firm specific skill is valued by both the worker and the employee and thus they might decide to keep the match even in recessionary times when the match does not produce much value. This hypothesis is closely related to the previous one as the presence of firm specific skills might be a reason for hoarding labor.

Labor hoarding models, however, usually emphasize adjustment costs such as recruitment, training or lay-off costs. These costs appear at the beginning and at the end of the employment spells. Firm specific skills, however, perhaps increase with tenure more gradually. It is interesting, thus, to test whether occupational differences in layoff probabilities change with tenure, or not. Imagine, for example, that we find that among newly hired workers the difference in the lay-off probabilities among occupations is small, but this differential is increasing with tenure. This would be indirect evidence that firm specific skills, as opposed to adjustment costs are responsible for hoarding skilled workers.

Unfortunately, there is no information about tenure in the CPS. A second best approach is to use age. Younger workers, on average, have shorter employment spells and less firm specific human capital for at least two reasons. First, they have spent less time on the labor market, and thus, they had less chance to acquire skills. Second, younger workers tend to switch employers more often than older workers.

In Table 8 we have already seen that older workers are less likely to be laid-off in recessions, which indicates that employers do value labor market experience when they decide about layoffs. However, we also saw that the occupational differences in unemployment are just as large among the young as they are among the old. If employers hoard their skilled workers because skilled workers acquire more firm specific human capital, we should see smaller occupational unemployment differences among the young. Based on Table 8 we can conclude that if firm specific skills are responsible for the large occupational unemployment differences, then these firm specific skills are acquired early on, and thus, they are more similar to adjustment costs.

4 A simple model of occupation specific labor hoarding

The model I lay out here intends to illustrate that under rigid wages and adjustment costs there is a possibility for a market failure in certain low-skilled occupations. When wages are rigid and adjustment costs are positive, lay-offs are never socially optimal. Instead, workers are hoarded in recessions and wages are equal to the average of the worker's productivity minus the adjustment costs over the business cycle. When adjustment costs are high enough, the market outcome is the same as the social optimum. However, when adjustment costs are low, the market outcome features inefficient lay-offs, because firms cannot commit to future employment in exchange for some reduction in wages. Even though workers would prefer lower wages for assured future employment, such contracts are not credible.

I am not aware of a model that analyzed the social efficiency of labor hoarding.[26] Labor hoarding models in macroeconomics are usually interested in firms' optimal adjustment of labor and the resulting volatility and persistence of aggregate unemployment. The implicit contract literature tries to explain why wages are rigid and layoffs are frequent if firms and workers can write contracts that are contingent on future economic conditions and workers are risk-averse. Search and matching models usually assume that the Hosios condition holds, which implies efficiency, although there has been some work analyzing more general models.

4.1 The setup of the model

1. In each period there is a recession (R) with probability p^R and a boom (B) with probability $p^B \equiv 1 - p^R$. These states are uncorrelated over time.

[26] I am in the process of finding relevant labor hoarding or related models that can be used to analyze occupational differences in unemployment patterns; and to analyze policy implications for influencing adjustment costs. Any suggestions would be greatly appreciated.

2. There are O occupations indexed by $o \in \{1, ..., O\}$. Firms either use zero or one workers and their problem is to optimally hire and lay-off over the business cycle. Firms can offer two types of contract, but they cannot commit to them:

   (a) A stable contract S: the firm offers to keep its worker in recessions and if it does not have a worker, it hires one in booms.

   (b) An unstable contract U: the firm fires its worker in recessions and if it does not have a worker, it hires one in booms.

3. Employers can hire someone in occupation o after paying a fixed hiring cost, $h_o \geq 0$, they can fire workers after paying a fix firing cost $f_o \geq 0$, and they discount the future with discount rate β.

4. Wages (w_o) are rigid in each occupation and are determined in equilibrium. Free entry among firms assures that the value of a new hire is zero.

5. Workers are homogenous within occupations and they cannot change their occupations. Their productivity depends on the occupation and the state of the economy

$$p_o = a_t s_o$$

   with $a_t \in \left\{a^R; a^B\right\}$ $a^B > a^R > 0$.

6. Employees quit a job with exogenous probability γ_o, and they maximize their expected wages, which is the product of the rigid wage and employment probability, $W_o = w_o \Pr(E_o)$. The outside option of workers is 0.

The model asks two questions: Which contract is socially optimal and under what conditions does the market achieve it? In the appendix I show that the equilibrium wage in the stable and the unstable contracts are:

$$\begin{aligned} w_o^S &= a^B s_o - \beta p^R (1-\gamma_o)\left(a^B - a^R\right) s_o - h_o \left(1 - \beta (1-\gamma_o)\right) \\ w_o^U &= a^B s_o - \beta p^R (1-\gamma_o) f_o - h_o \left(1 - \beta p^B (1-\gamma_o)\right) \end{aligned}$$

In both contracts, wages are positively related to the productivity terms (a^B, a^R and s^o), to the probability of a boom (p^B) and negatively related to the adjustment costs (h_o and f_o). The appendix also shows that the expected wages of workers are

$$\begin{aligned} W_o^S &= \frac{p^B}{p^B + p^R \gamma_o} \left[a^B s_o - \beta p^R (1 - \gamma_o) \left(a^B - a^R \right) s_o - h_o (1 - \beta (1 - \gamma_o)) \right] \\ W_o^U &= p^B \left(a^B s_o - \beta p^R (1 - \gamma_o) f_o - h_o \left(1 - \beta p^B (1 - \gamma_o) \right) \right) \end{aligned}$$

4.2 The social optimum

In this model firms make zero profit, and thus, the socially optimal contract maximizes the expected wage of workers. In the appendix I show that the unstable contract is never socially optimal: If the expected wage of the unstable contract is positive, then the stable contract always offers a higher expected wage:

$$\begin{aligned} W_o^U &> 0 \\ &\Downarrow \\ W_o^S &> W_o^U \end{aligned}$$

Hoarding labor socially dominates lay-offs, because it minimizes the number of instances when adjustment costs are paid. If firms can commit to future employment, that is, they can credibly offer the stable contract, then the market always achieves the social optimum. However, if firms cannot commit to future employment, the market outcome might be sub-optimal.

4.3 The market outcome

If firms cannot commit to future employment, then workers always pick a contract that maximizes per-period wages. This is the case, because firms cannot credibly assure future employment in exchange for a reduction in per-period wages. In the appendix I show that the the socially optimal stable contract is achieved in occupations where

$$w_o^S \geq w_o^U$$

$$\Updownarrow$$

$$h_o + f_o \quad \geq \quad \left(a^B - a^R\right) s_o \tag{4}$$

This is quite intuitive. The left hand side of (4) is the marginal benefit of keeping workers in recessions (saving adjustment costs) and the right hand side is the marginal cost (the reduction in productivity). Thus, in occupations where the hiring and firing costs are large enough, firms can credibly offer the socially optimal stable contract. Based on the empirical hiring cost literature these occupations are typically the skilled ones, because recruitment and training costs are proportionally higher in these jobs. In unskilled occupations, however, firms cannot credibly offer the socially optimal stable contract, and we expect inefficiently large fluctuations in unemployment.

4.4 Discussion of the model

Even though this simple model cannot be used to calibrate a realistic labor market and analyze welfare implications of alternative policies, it does have some interesting qualitative policy suggestions. The first is that supporting job-creation in recessions might not be a good idea, since labor hoarding is pervasive in the economy and firms have excess labor in recessions anyways. The second implication is that the large unemployment fluctuations in many unskilled jobs might indicate a market failure that might be mitigated with appropriate policies. The market failure is the consequence of the relatively rigid wages and the relatively low adjustment costs in low-skilled jobs. A good policy, thus, should either aim at making wages less rigid or increasing the adjustment costs. Out of the alternatives, influencing firing costs seems to be the easiest to implement,[27] and by appropriately targeting the policy we might be able to maximize the social benefit and minimize the cost. One idea is to increase firing costs only in recessions and only in occupations where adjustment costs are too low. This way the labor market can clear in normal economic circumstances, and the policy targets the population that is most affected by the market failure.

[27] Wage rigidity might be influenced by generating inflation, but that, of course, creates many additional problems.

5 Conclusion

This paper documented large differences in unemployment rates and unemployment fluctuations across occupations. By looking at detailed occupations I found that the skill level of an occupations had a strong negative effect on unemployment prospects in all recessions of the last 30 years. This was robust to different measures of general skills, but education-based measures led to the strongest and most monotone results. I decomposed unemployment fluctuations into changes in the job-loss and the job-finding probabilities in each occupation. I found that even though separations are less important for aggregate fluctuations in unemployment, they are more important for understanding the differences between occupational unemployment, as the job-finding probability followed a highly similar pattern across occupations. I argued that this result is in line with a model in which employers are more likely to hoard skilled workers due to higher recruitment/training and other adjustment costs in skilled jobs. I also considered five other hypotheses that can explain why unemployment fluctuations are lower in skilled occupations. These were the industrial composition; the quality adjustment; the productivity differences; the employment flexibility and the firm specific skills hypotheses. I provided simple tests of these alternative hypotheses and I found that they were considerably less important to understand occupational differences in unemployment patterns than the labor hoarding hypothesis.

Future research will compare the evolution of job-loss and job-finding probabilities in the US to those in Germany. Even though the more flexible labor laws of the US could be better than the more protective German ones in normal economic circumstances, it is possible that at least in unskilled occupations, unemployment can grow faster in the US in recessions. I plan to propose a new labor protection system which maximizes the welfare of citizens by concentrating protection in risky occupations and uncertain times and therefore minimizing the incidence of unemployment and decreasing the burden on the unemployment insurance systems.

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6 Appendix

6.1 Definition of occupational skills using the O*NET

I define four occupational skill measures using the Abilities section of the 17th edition of the O*NET. In the abilities section[28] each occupation was evaluated by 8 analysts on 52 ability measures that may have influenced work performance in the occupation in 2006. The analysts evaluated on a scale of 1 to 5 how important the ability is in given occupations, and on a scale of 0 to 7 what level is needed to perform well. The level scales were anchored. For example at evaluating the level of oral comprehension, the anchor ran from "understand a television commercial" up to "understand a lecture on advanced physics", and at evaluating mathematical reasoning the anchor ran from "Determine how much 10 oranges will cost when they are priced at 2 for 20 cents" to "Determine the mathematics required to simulate a space craft landing on the moon".

The 52 ability measures were classified into 15 minor and 4 major categories:

1. Cognitive abilities
   (a) Verbal abilities
   (b) Idea generation and reasoning abilities
   (c) Quantitative abilities
   (d) Memory
   (e) Perceptual abilities
   (f) Spatial abilities
   (g) Attentiveness
2. Psychomotor abilities

[28]See, for example, at http://www.onetcenter.org/content.html.

    (a) Fine manipulative abilities
    (b) Control movement abilities
    (c) Reaction time and speed abilities

3. Physical abilities
    (a) Physical strength abilities
    (b) Endurance
    (c) Flexibility, balance and coordination

4. Sensory abilities
    (a) Visual abilities
    (b) Auditory and speech abilities

In this project I did not use the sensory abilities, and I aggregated the rest of the information into 4 categories:

1. Non-routine cognitive abilities (From 1a to 1e)
2. Routine cognitive abilities (1f and 1g)
3. Psychomotor abilities
4. Physical abilities

Then the procedure I followed was the following:

1. I rescaled both the importance and the level scores to be between 0 and 1.
2. Then I aggregated the occupations to be the same as the most detailed occupations in the 2000 census, the 3-digit SOC codes.
3. Then I took the occupational means of the importance and level scores in the four aggregate ability measures.

4. Then I took the weighted average of these ability measures in my 191 occupation categories, where the weights were the number of workers in the occupations in the 2000 census.

5. Finally I standardized the occupational abilities in the 2000 census, and I created 10 deciles as well.

6.2 Deriving the marginal effect of GDP growth at various percentiles of the skill and education distribution

The estimated non-linear least squares model is

$$U_{it} = exp\left(\beta_0 + \beta_1 d\ln GDP_t + \beta_2 S_i + \beta_3 d\ln GDP_t \times S_i\right) + u_{it}$$

The marginal effect of a 10% higher GDP growth is

$$\frac{1}{10}\frac{\partial E\left(U_{it}|S_i, d\ln GDP_t\right)}{\partial d\ln GDP_t} = \frac{1}{10}\left(\beta_1 + \beta_3 S_i\right) exp\left(\beta_0 + \beta_1 d\ln GDP_t + \beta_2 S_i + \beta_3 d\ln GDP_t \times S_i\right)$$

The marginal effect at various percentiles of the skill (or education) distribution and at mean GDP growth m_{gdp} is

$$\frac{1}{10}\frac{\partial E\left(U_{it}|S_i = S_\tau, d\ln GDP_t = m_{gdp}\right)}{\partial d\ln GDP_t} = \frac{1}{10}\left(\beta_1 + \beta_3 S_\tau\right) exp\left(\beta_0 + \beta_1 m_{gdp} + \beta_2 S_i + \beta_3 m_{gdp} \times S_\tau\right)$$

6.3 Derivations in the simple labor hoarding model

6.3.1 Equilibrium wages in a stable contract

There are two state variables: aggregate productivity $a_t \in \left\{a^B, a^R\right\}$ and whether the firm has a worker or not, $l \in \{0, 1\}$. The values in these states are:

$$\begin{aligned} V_o^S\left(a^B, 1\right) &= \left(a^B s_o - w_o\right) + \beta p^B\left(1-\gamma_o\right) V_o^S\left(a^B, 1\right) + \beta p^B \gamma_o V_o^S\left(a^B, 0\right) \\ &\quad + \beta p^R\left(1-\gamma_o\right) V_o^S\left(a^R, 1\right) + \beta p^R \gamma_o V_o^S\left(a^R, 0\right) \\ V_o^S\left(a^R, 1\right) &= \left(a^R s_o - w_o\right) + \beta p^B\left(1-\gamma_o\right) V_o^S\left(a^B, 1\right) + \beta p^B \gamma_o V_o^S\left(a^B, 0\right) \end{aligned}$$

$$
\begin{aligned}
& +\beta p^R \left(1-\gamma_o\right) V_o^S \left(a^R,1\right) + \beta p^R \gamma_o V_o^S \left(a^R,0\right) \\
V_o^S \left(a^B,0\right) &= \left(a^B s_o - w_o - h_o\right) + \beta p^B \left(1-\gamma_o\right) V_o^S \left(a^B,1\right) + \beta p^B \gamma_o V_o^S \left(a^B,0\right) \\
& +\beta p^R \left(1-\gamma_o\right) V_o^S \left(a^R,1\right) + \beta p^R \gamma_o V_o^S \left(a^R,0\right) \\
V_o^S \left(a^R,0\right) &= 0 + \beta p^B V_o^S \left(a^B,0\right) + \beta p^R V_o^S \left(a^R,0\right)
\end{aligned}
$$

Thus

$$
V_o^S \left(a^B,1\right) - V_o^S \left(a^B,0\right) = h_o \tag{5}
$$

Free entry among firms assures that the value of hiring a worker is zero, which implies that

$$
\begin{aligned}
V_o^S \left(a^B,0\right) &= 0 \\
V_o^S \left(a^R,0\right) &= 0 \\
V_o^S \left(a^B,1\right) &= \left(a^B s_o - w_o^S\right) + \beta p^B \left(1-\gamma_o\right) V_o^S \left(a^B,1\right) + \beta p^R \left(1-\gamma_o\right) \left(V_o^S \left(a^B,1\right) - \left(a^B - a^R\right) s_o\right) \\
&= \frac{\left(a^B s_o - w_o^S\right) - \beta p^R \left(1-\gamma_o\right) \left(a^B - a^R\right)}{1-\beta\left(1-\gamma_o\right)} \\
V_o^S \left(a^R,1\right) &= \frac{\left(a^R s_o - w_o^S\right) - \beta p^B \left(1-\gamma_o\right) \left(a^B - a^R\right) s_o}{1-\beta\left(1-\gamma_o\right)}
\end{aligned}
$$

Using (5) the equilibrium wage is

$$
\begin{aligned}
h_o &= \frac{\left(a^B s_o - w_o^S\right) - \beta p^R \left(1-\gamma_o\right) \left(a^B - a^R\right)}{1-\beta\left(1-\gamma_o\right)} \\
w_o^S &= a^B s_o - \beta p^R \left(1-\gamma_o\right) \left(a^B - a^R\right) s_o - h_o \left(1-\beta\left(1-\gamma_o\right)\right)
\end{aligned}
$$

In order to compute the expected wage of a worker we need the probability that he is employed. In booms everyone is employed. In recessions people are only employed if they were employed at the last time and they did not quit exogenously:

$$
\begin{aligned}
P_o^S (E) &= p^B + p^R \left(1-\gamma_o\right) P_o^S (E) \\
&= \frac{p^B}{1-p^R\left(1-\gamma_o\right)}
\end{aligned}
$$

The expected wage of a worker

$$W_o^S = \frac{p^B}{1-p^R\left(1-\gamma_o\right)}\left[a^B s_o - \beta p^R\left(1-\gamma_o\right)\left(a^B-a^R\right)s_o - h_o\left(1-\beta\left(1-\gamma_o\right)\right)\right]$$

6.3.2 Equilibrium wages in an unstable contract

The values in different states are

$$\begin{aligned}
V_o^U\left(a^B,1\right) &= \left(a^B s_o - w_o\right) + \beta p^B\left(1-\gamma_o\right)V_o^U\left(a^B,1\right) + \beta p^B\gamma_o V_o^U\left(a^B,0\right)\\
&\quad +\beta p^R\left(1-\gamma_o\right)V_o^U\left(a^R,1\right) + \beta p^R\gamma_o V_o^U\left(a^R,0\right)\\
V_o^U\left(a^R,1\right) &= -f_o + \beta p^R V_o^U\left(a^R,0\right) + \beta p^B V_o^U\left(a^B,0\right)\\
V_o^U\left(a^B,0\right) &= \left(a^B s_o - w_o - h_o\right) + \beta p^B\left(1-\gamma_o\right)V_o^U\left(a^B,1\right) + \beta p^B\gamma_o V_o^U\left(a^B,0\right)\\
&\quad +\beta p^R\left(1-\gamma_o\right)V_o^U\left(a^R,1\right) + \beta p^R\gamma_o V_o^U\left(a^R,0\right)\\
V_o^U\left(a^R,0\right) &= \beta p^R V_o^F\left(a^R,0\right) + \beta p^B V_o^F\left(a^B,0\right)
\end{aligned}$$

Thus

$$V_o^S\left(a^B,1\right) - V_o^S\left(a^B,0\right) = h_o \tag{6}$$

Free entry among firms assures that the value of hiring a worker is zero, which implies that

$$\begin{aligned}
V_o^U\left(a^B,0\right) &= 0\\
V_o^U\left(a^R,0\right) &= 0\\
V_o^U\left(a^R,1\right) &= -f_o\\
V_o^U\left(a^B,1\right) &= \left(a^B s_o - w_o^U\right) + \beta p^B\left(1-\gamma_o\right)V_o^F\left(a^B,1\right) - \beta p^R\left(1-\gamma_o\right)f_o\\
&= \frac{\left(a^B s_o - w_o^U\right) - \beta p^R\left(1-\gamma_o\right)f_o}{1-\beta p^B\left(1-\gamma_o\right)}
\end{aligned}$$

Using (6) the equilibrium wage is

$$\begin{aligned}
h_o &= \frac{\left(a^B s_o - w_o^U\right) - \beta p^R\left(1-\gamma_o\right)f_o}{1-\beta p^B\left(1-\gamma_o\right)}\\
w_o^U &= a^B s_o - \beta p^R\left(1-\gamma_o\right)f_o - h_o\left(1-\beta p^B\left(1-\gamma_o\right)\right)
\end{aligned}$$

Workers are only employed in booms:

$$P_o^U(E) = p^B$$

And thus, the expected wage is

$$W_o^U = p^B \left(a^B s_o - \beta p^R (1-\gamma_o) f_o - h_o \left(1 - \beta p^B (1-\gamma_o)\right)\right)$$

6.4 Proof that the unstable contract is never socially optimal

I prove by contradiction that if $W_o^U > 0$ then $W_o^S > W_o^U$. Let's assume that $W_o^U > 0$ and $W_o^S \leq W_o^U$. The first condition sequentially imply that

$$\begin{aligned}
W_o^U &> 0 \\
a^B s_o &> \beta p^R (1-\gamma_o) f_o + h_o \left(1 - \beta p^B (1-\gamma_o)\right) > h_o \left(1 - \beta p^B (1-\gamma_o)\right) \\
(1-\beta) a^B s_o &> (1-\beta) h_o \left(1 - \beta p^B (1-\gamma_o)\right) = h_o \left(1 - \beta p^B (1-\gamma_o) - \beta + \beta p^B (1-\gamma_o)\right) \\
&> h_o \left(1 - \beta p^B (1-\gamma_o) - \beta\right) = h_o \left(1 - \beta \left(1 + \beta p^B (1-\gamma_o)\right)\right)
\end{aligned}$$

and thus

$$(1-\beta) a^B s_o > h_o \left(1 - \beta \left(1 + \beta p^B (1-\gamma_o)\right)\right) \tag{7}$$

The second condition sequentially imply that

$$\begin{aligned}
0 &\leq W_o^U - W_o^S \\
&\leq p^B \left(a^B s_o - \beta p^R (1-\gamma_o) f_o - h_o \left(1 - \beta p^B (1-\gamma_o)\right)\right) \\
&\quad - \frac{p^B}{1 - p^R (1-\gamma_o)} \left[a^B s_o - \beta p^R (1-\gamma_o) \left(a^B - a^R\right) s_o - h_o \left(1 - \beta (1-\gamma_o)\right)\right] \qquad (8) \\
0 &\leq \left(1 - p^R (1-\gamma_o)\right) \left(a^B s_o - \beta p^R (1-\gamma_o) f_o - h_o \left(1 - \beta p^B (1-\gamma_o)\right)\right) \\
&\quad - a^B s_o - \beta p^R (1-\gamma_o) \left(a^B - a^R\right) s_o - h^o \left(1 - \beta (1-\gamma_o)\right) \qquad (9) \\
0 &\leq h_o \left[\left(1 - \beta (1-\gamma_o)\right) - \left(1 - \beta p^B (1-\gamma_o)\right) + p^R (1-\gamma_o) \left(1 - \beta p^B (1-\gamma_o)\right)\right] \\
&\quad - \left(1 - p^R (1-\gamma_o)\right) \beta p^R (1-\gamma_o) f_o - p^R (1-\gamma_o) \left(a^B (1-\beta) + a^R \beta\right) s_o \qquad (10) \\
0 &\leq h_o \left(1 - \beta \left(1 + p^B (1-\gamma_o)\right)\right) - \left(1 - p^R (1-\gamma_o)\right) \beta f_o - \left(a^B (1-\beta) + a^R \beta\right) s_o
\end{aligned}$$

$$(1-\beta)\, a^B s_o \quad < \quad h_o \left(1-\beta \left(1+p^B \left(1-\gamma_o\right)\right)\right) \tag{11}$$

(7) and (11) contradict each other and thus the original claim is proved.

6.5 Derivation of the market outcome

A stable contract is the market outcome if the per-period wage is higher in the stable contract

$$\begin{aligned}
w_o^S &\geq w_o^U \\
a^B s_o - \beta p^R \left(1-\gamma_o\right) \left(a^B - a^R\right) s_o - h_o \left(1-\beta\left(1-\gamma_o\right)\right) &\geq a^B s_o - \beta p^R \left(1-\gamma_o\right) f_o - h_o \left(1-\beta p^B \left(1-\gamma_o\right)\right) \\
\beta p^R \left(1-\gamma_o\right) h_o + \beta p^R \left(1-\gamma_o\right) f_o &\geq \beta p^R \left(1-\gamma_o\right) \left(a^B - a^R\right) s_o \\
h_o + f_o &\geq \left(a^B - a^R\right) s_o
\end{aligned}$$

6.6 Tables and figures

Table 5: Correlations between 7 alternative occupational skill variables

	E	W	NC	RC	PM	PS
Avg. education, E	1.00					
Avg. wage, W	0.78	1.00				
Non-routine cognitive abilities, NC	0.80	0.71	1.00			
Routine cognitive abilities, RC	-0.03	0.29	0.21	1.00		
Psychomotor abilities, PM	-0.58	-0.25	-0.47	0.62	1.00	
Physical abilities, PS	-0.61	-0.39	-0.57	0.43	0.82	1.00

*Occupational skills are all based on averages in the 2000 census in each of my 191 occupations.; N=191

Table 6: Distribution of major occupational groups within occupational skill deciles, weighted 2000 census values

	Panel A										
	Occupational skill deciles (avg. yrs. of educ. in 191 occupations)										
Major occupation groups	1	2	3	4	5	6	7	8	9	10	Total
Management and related	0.0	0.0	0.0	0.0	0.0	0.0	0.0	50.7	49.2	8.5	11.4
Professional	0.0	0.0	0.0	0.0	0.0	0.0	3.0	17.2	38.8	91.5	15.1
Technicians	0.0	0.0	0.0	0.0	0.0	0.0	16.8	8.7	9.3	0.0	3.2
Sales	0.0	0.0	24.1	1.7	0.0	39.4	33.5	8.6	2.7	0.0	11.5
Office and admin. support	0.0	0.0	10.1	6.9	40.1	56.2	41.8	7.5	0.0	0.0	16.7
Production and repair	3.7	21.3	23.1	34.6	27.7	0.8	2.6	0.0	0.0	0.0	11.0
Operators and laborers	47.2	71.3	25.6	13.8	8.0	0.0	0.0	0.0	0.0	0.0	16.2
Protective service	0.0	0.0	1.5	0.0	5.4	2.2	2.4	7.3	0.0	0.0	2.0
Food prep. and cleaning	49.1	7.4	15.6	8.8	2.5	0.0	0.0	0.0	0.0	0.0	8.2
Personal services	0.0	0.0	0.0	34.2	16.2	1.4	0.0	0.0	0.0	0.0	4.8
Total	100	100	100	100	100	100	100	100	100	100	100

	Panel B										
	Occupational skill deciles (avg. ln weakly wage in 191 occupations)										
Major occupation groups	1	2	3	4	5	6	7	8	9	10	Total
Management and related	0.0	0.0	0.0	0.0	0.0	0.0	1.7	15.4	20.6	64.9	11.4
Professional	0.0	3.7	0.0	2.2	4.7	19.1	6.4	31.7	53.2	26.3	15.1
Technicians	0.0	0.0	0.0	0.0	11.0	4.5	5.3	6.3	0.0	6.1	3.2
Sales	24.9	0.0	1.5	0.0	0.0	0.0	74.6	3.3	6.0	2.7	11.5
Office and admin. support	6.9	15.6	42.4	62.3	5.8	23.4	0.0	8.6	0.0	0.0	16.7
Production and repair	0.0	2.1	3.6	6.2	40.9	16.3	10.3	31.4	2.6	0.0	11.0
Operators and laborers	3.8	29.7	35.7	22.9	37.5	34.1	1.8	0.6	0.8	0.0	16.2
Protective service	0.0	0.0	7.1	0.0	0.0	2.7	0.0	2.8	6.8	0.0	2.0
Food prep. and cleaning	53.5	19.5	6.0	1.7	0.0	0.0	0.0	0.0	0.0	0.0	8.2
Personal services	11.0	29.6	3.7	4.7	0.0	0.0	0.0	0.0	0.0	0.0	4.8
Total	100	100	100	100	100	100	100	100	100	100	100

Table 7: Non-linear least squares estimates of unemployment, March CPS, 1983-2012

	[1]	[2]	[3]	[4]
dln(GDP), DG	-8.757	-6.644	-1.419	-3.418
	[0.139]**	[0.320]**	[0.434]**	[0.560]**
Occupational skill, SE	-0.631			-0.499
	[0.004]**			[0.004]**
SE X DG	-1.666			-1.44
	[0.135]**			[0.146]**
Years of education, E		-0.102	-0.1	-0.04
		[0.001]**	[0.001]**	[0.001]**
E X DG		-0.109	-0.118	-0.084
		[0.027]**	[0.027]**	[0.034]*
Age, A			-0.024	-0.019
			[0.000]**	[0.000]**
A X DG			-0.137	-0.123
			[0.008]**	[0.007]**
Female, F			-0.231	-0.152
			[0.006]**	[0.005]**
F X DG			2.763	3.227
			[0.188]**	[0.179]**
White, W			-0.472	-0.425
			[0.006]**	[0.006]**
W X DG			-2.305	-1.967
			[0.191]**	[0.181]**
Constant	-2.762	-1.291	0.033	-1.134
	[0.004]**	[0.010]**	[0.013]*	[0.017]**
N	2462447	2462447	2462447	2462447
R squared	0.082	0.071	0.082	0.091
Marginal effect of 10% higher GDP growth on unemployment at various percentiles of the skill distribution (model 1) and the education distribution (model 2)				
5th percentile	-0.08	-0.069		
	[0.001]**	[0.001]**		
25th percentile	-0.063	-0.053		
	[0.001]**	[0.001]**		
Median	-0.044	-0.048		
	[0.001]**	[0.001]**		
75th percentile	-0.03	-0.036		
	[0.001]**	[0.001]**		
95th percentile	-0.016	-0.033		
	[0.000]**	[0.001]**		
Ratio: 5th / 95th percentile	5.03	2.077		
	[0.202]**	[0.052]**		

*The right hand side of the models is the exponent of an index created by the linear combination of the variables in the model; dln(GDP) is defined as the log difference between GDP in the previous calendar year and the year before that; Occupational skill is defined as the average years of education in the 2000 census in each of my 191 occupations standardized to have zero mean and standard deviation 1 in the 2000 census; The marginal effects are computed at the mean GDP growth in the sample which is 2.5 percent.

Table 8: OLS regressions of unemployment, March CPS, 1983-2012

	Males	Females	Whites	Non-whites
dln(GDP), DG	-0.6	-0.365	-0.472	-0.546
	[0.011]**	[0.010]**	[0.008]**	[0.022]**
Occupational skill, SE	-0.04	-0.029	-0.033	-0.045
	[0.000]**	[0.000]**	[0.000]**	[0.001]**
SE X DG	0.243	0.065	0.179	0.133
	[0.010]**	[0.011]**	[0.008]**	[0.022]**
Constant	0.08	0.067	0.069	0.101
	[0.000]**	[0.000]**	[0.000]**	[0.001]**
N	1302531	1159916	2077104	385343
R squared	0.023	0.015	0.018	0.023
Marginal effect of 10% higher GDP growth on unemployment at various percentiles of the skill distribution				
5th percentile	-0.092	-0.045	-0.071	-0.072
	[0.002]**	[0.002]**	[0.001]**	[0.004]**
25th percentile	-0.078	-0.041	-0.06	-0.064
	[0.001]**	[0.001]**	[0.001]**	[0.003]**
Median	-0.06	-0.036	-0.047	-0.055
	[0.001]**	[0.001]**	[0.001]**	[0.002]**
75th percentile	-0.042	-0.032	-0.034	-0.045
	[0.001]**	[0.001]**	[0.001]**	[0.003]**
95th percentile	-0.011	-0.024	-0.011	-0.028
	[0.002]**	[0.002]**	[0.002]**	[0.005]**
Ratio: 5th / 95th percentile	8.054	1.907	6.15	2.571
	[1.706]**	[0.228]**	[0.944]**	[0.537]**

	Age 16-29	Age 30-39	Age 40-49	Age 50-64
dln(GDP), DG	-0.579	-0.506	-0.483	-0.486
	[0.017]**	[0.014]**	[0.013]**	[0.014]**
Occupational skill, SE	-0.051	-0.034	-0.028	-0.023
	[0.001]**	[0.000]**	[0.000]**	[0.000]**
SE X DG	0.213	0.187	0.184	0.152
	[0.019]**	[0.013]**	[0.013]**	[0.013]**
Constant	0.096	0.072	0.062	0.059
	[0.001]**	[0.000]**	[0.000]**	[0.000]**
N	674346	654536	618760	514805
R squared	0.022	0.02	0.016	0.012
Marginal effect of 10% higher GDP growth on unemployment at various percentiles of the skill distribution				
5th percentile	-0.086	-0.075	-0.072	-0.068
	[0.003]**	[0.002]**	[0.002]**	[0.002]**
25th percentile	-0.074	-0.064	-0.062	-0.06
	[0.002]**	[0.002]**	[0.002]**	[0.002]**
Median	-0.058	-0.051	-0.048	-0.049
	[0.002]**	[0.001]**	[0.001]**	[0.001]**
75th percentile	-0.042	-0.036	-0.034	-0.037
	[0.003]**	[0.002]**	[0.002]**	[0.002]**
95th percentile	-0.015	-0.013	-0.011	-0.018
	[0.005]**	[0.003]**	[0.003]**	[0.003]**
Ratio: 5th / 95th percentile	5.63	5.657	6.318	3.74
	[1.750]**	[1.300]**	[1.601]**	[0.640]**

*dln(GDP) is defined as the log difference between GDP in the previous calendar year and the year before that; Occupational skill is defined as the average years of education in the 2000 census in each of my 191 occupations standardized to have zero mean and standard deviation 1 in the 2000 census

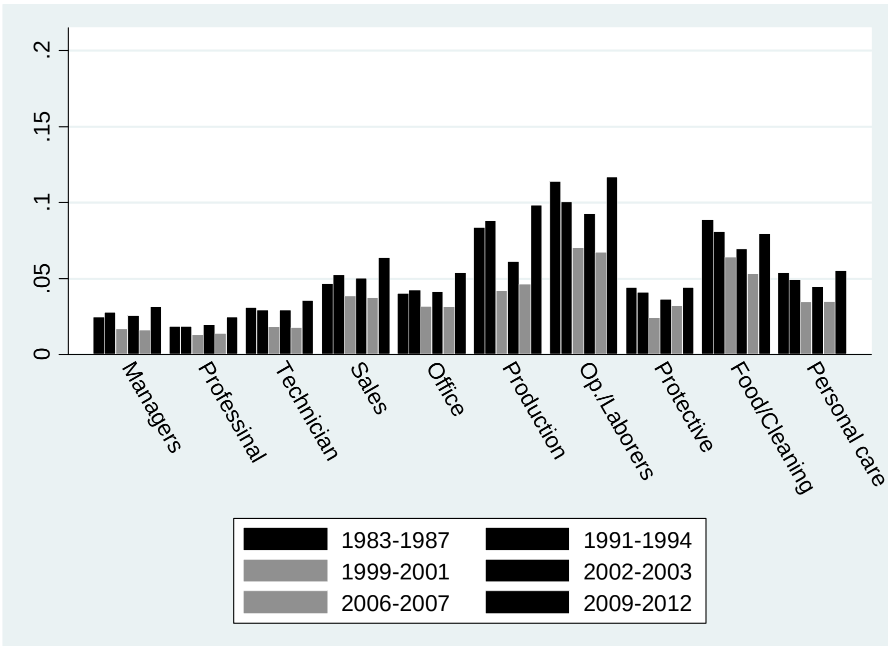
Table 9: OLS regressions of unemployment by alternative skill measures, March CPS, 1983-2012

	E	W	NC	RC	PM	PS
dln(GDP), DG	-0.5	-0.48	-0.49	-0.471	-0.489	-0.473
	[0.007]**	[0.007]**	[0.007]**	[0.007]**	[0.007]**	[0.007]**
Occupational skill, SE	-0.036	-0.025	-0.034	0.006	0.029	0.03
	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**
SE X DG	0.176	0.067	0.147	-0.108	-0.191	-0.153
	[0.007]**	[0.007]**	[0.007]**	[0.007]**	[0.007]**	[0.007]**
Constant	0.074	0.074	0.074	0.072	0.073	0.073
	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**
N	2462447	2462447	2462447	2462447	2462447	2462447
R squared	0.02	0.012	0.018	0.002	0.012	0.014
Marginal effect of 10% higher GDP growth on unemployment at various percentiles of the skill distribution						
5th percentile	-0.073	-0.059	-0.077	-0.029	-0.021	-0.025
	[0.001]**	[0.001]**	[0.002]**	[0.001]**	[0.001]**	[0.001]**
25th percentile	-0.063	-0.052	-0.058	-0.039	-0.033	-0.035
	[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]**
Median	-0.05	-0.048	-0.05	-0.047	-0.047	-0.047
	[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]**
75th percentile	-0.037	-0.043	-0.036	-0.053	-0.064	-0.06
	[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]**
95th percentile	-0.015	-0.037	-0.028	-0.067	-0.079	-0.069
	[0.002]**	[0.001]**	[0.001]**	[0.002]**	[0.001]**	[0.001]**
Ratio: 5th / 95th percentile	4.941	1.635	3.499	0.482	0.275	0.351
	[0.579]**	[0.096]**	[0.320]**	[0.025]**	[0.017]**	[0.020]**

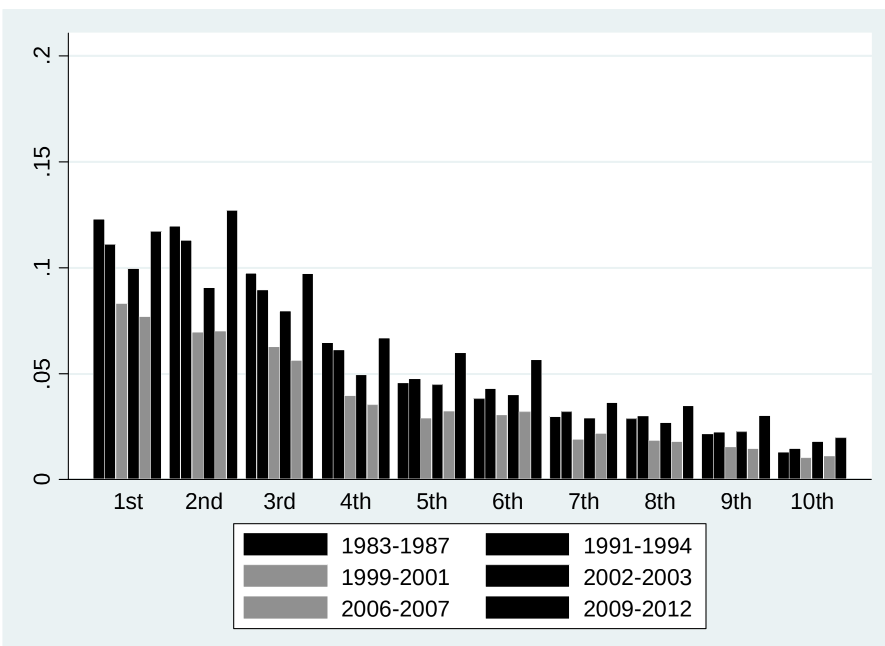
*dln(GDP) is defined as the log difference between GDP in the previous calendar year and the year before that; Different columns are based on difference occupational skill measures. E: average years of education in the 2000 census; W: average wage of full time full year workers in the 2000 census; NC: Non-routine cognitive abilities in the O*NET; RC: routine cognitive abilities in the O*NET; PM: psychomotor abilities in the O*NET; PS: Physical abilities in the O*NET

Figure 6: Unemployment rate by the skill level of last year's occupation in different periods, March CPS 1983-2012

Panel A: In major occupation groups



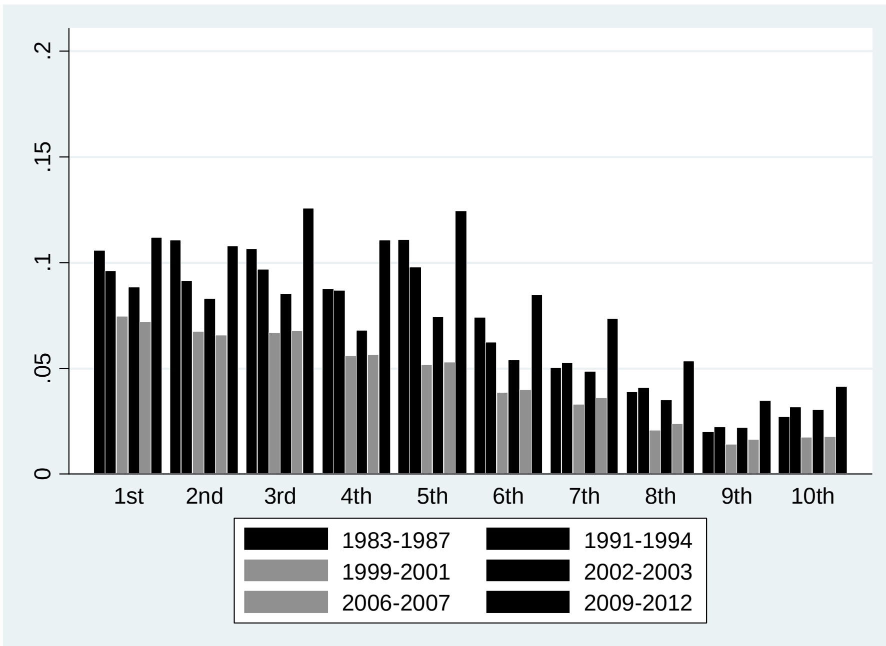
Panel B: By occupational skill deciles*



*Occupational skill is defined as the average years of education in the 2000 census in each of my 191 occupations. Deciles are taken in the 2000 census by dividing the population into 10 roughly equal groups based on their occupations. Higher number means higher skilled occupation. In each occupational group there are 6 bars representing 6 time periods with the ones on the right being the more recent.

Figure 7: Unemployment rate by the skill level of last occupation in different periods, March CPS 1983-2012

Panel A: Skill is average wage in 2000 census in 191 occupations



Panel B: Skill is average years of education in 1990 census in 383 occupations

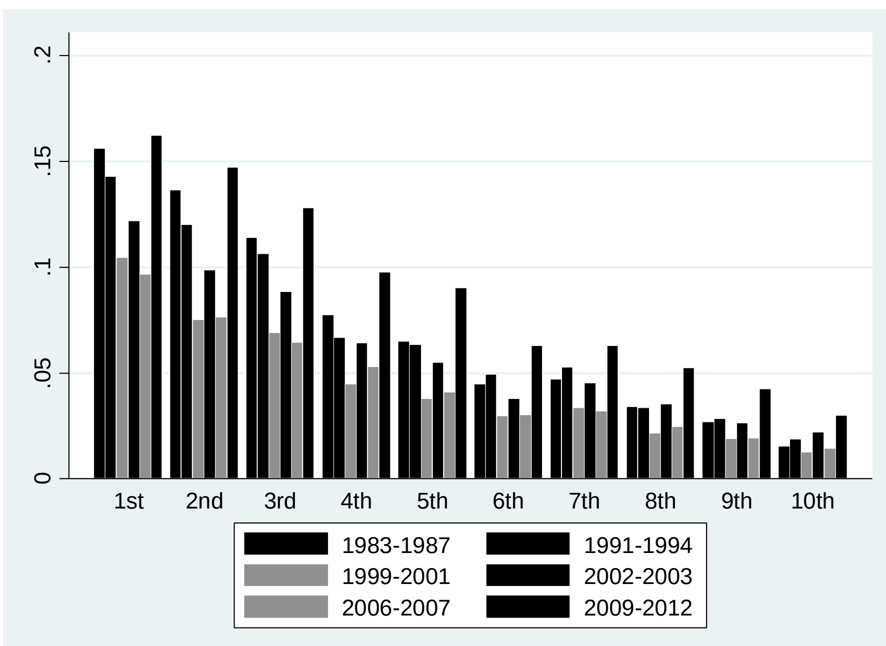
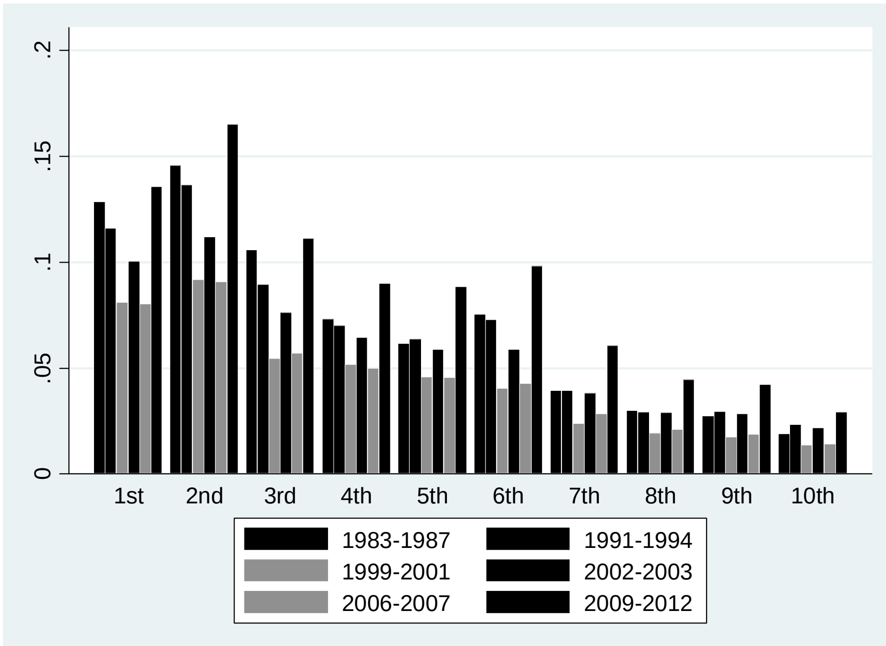


Figure 8: Unemployment rate by occupational skills in different periods, March CPS 1983-2012

Panel A: Non-routine cognitive skills in 191 occupations



Panel B: Routine cognitive skills in 191 occupations

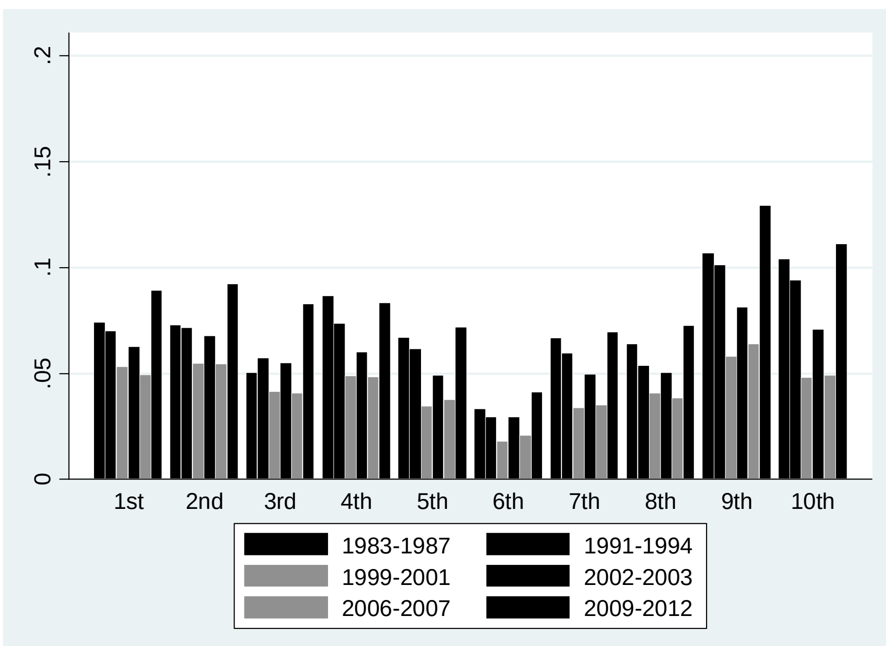
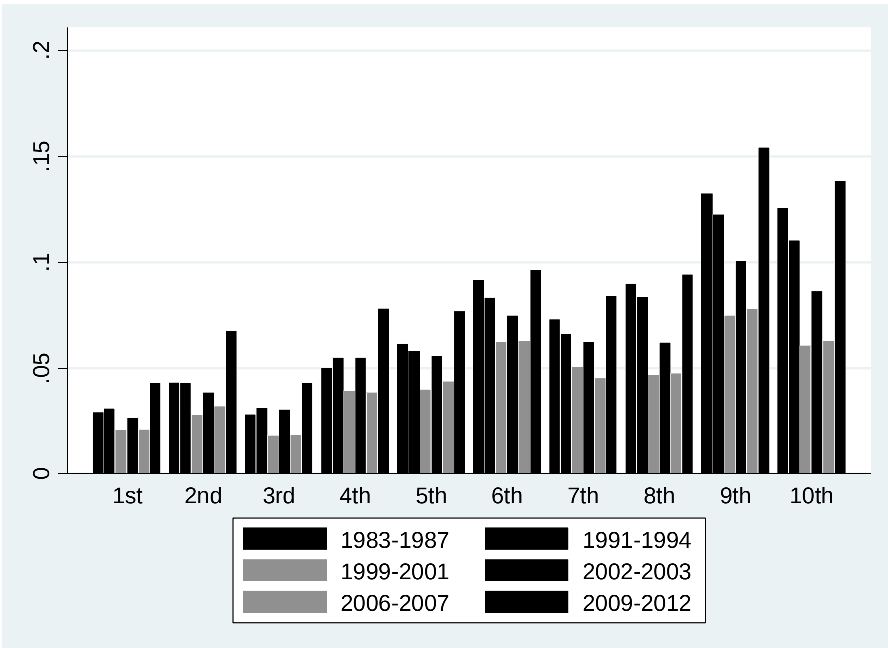


Figure 9: Unemployment rate by occupational skills in different periods, March CPS 1983-2012
Panel A: Psychomotor skills in 191 occupations



Panel B: Physical skills in 191 occupations

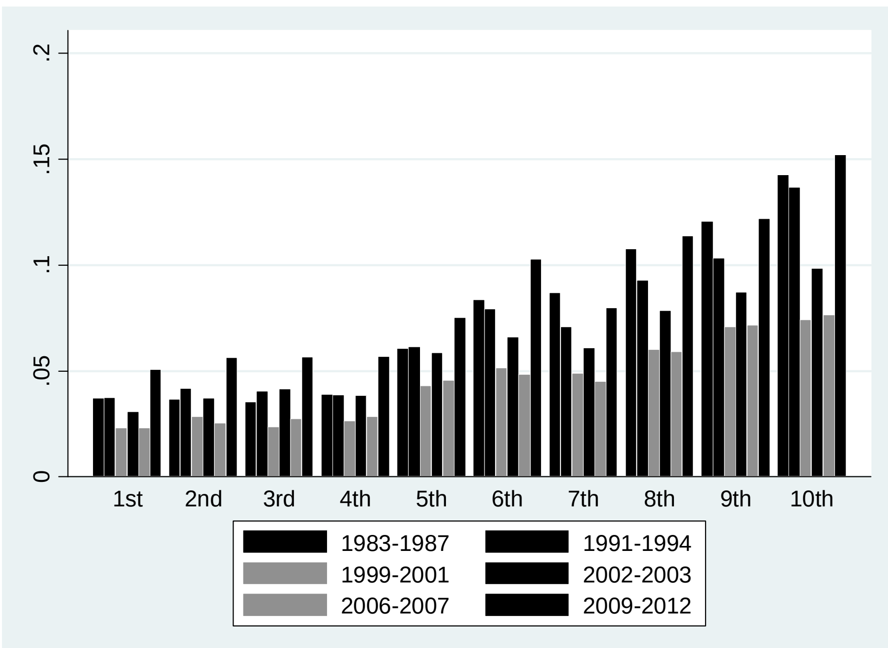
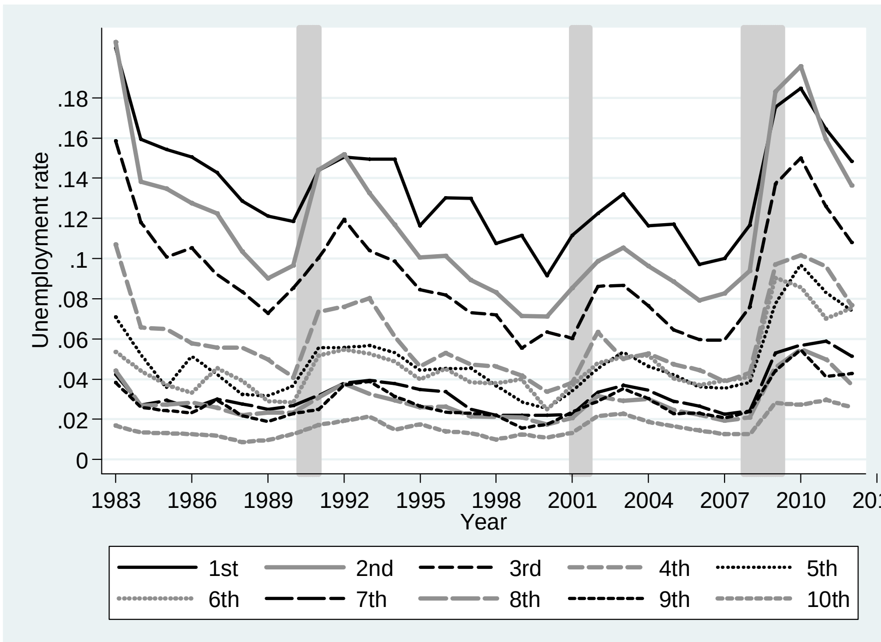
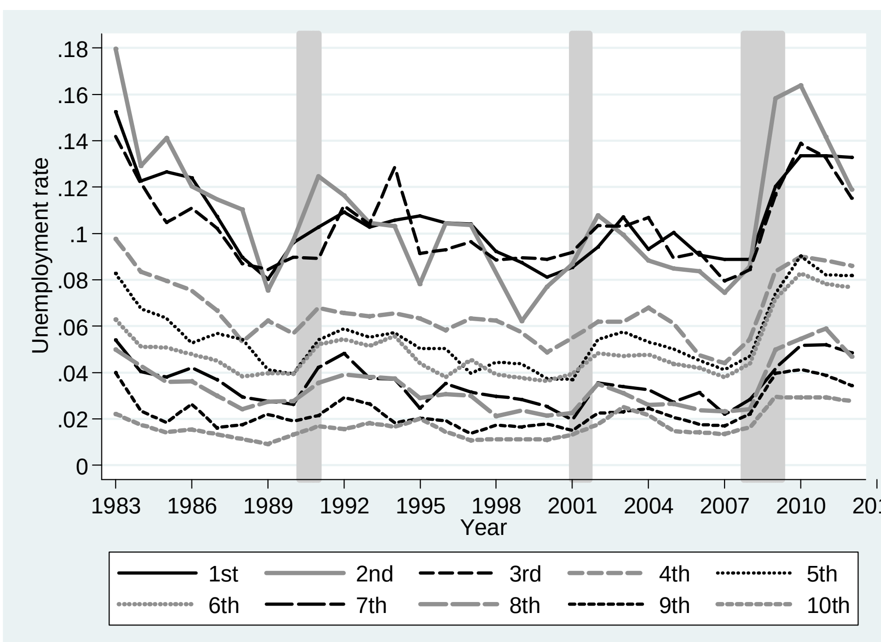


Figure 10: Unemployment rates by gender and the skill decile of the last occupation*, March CPS 1983-2012

Panel A: Males



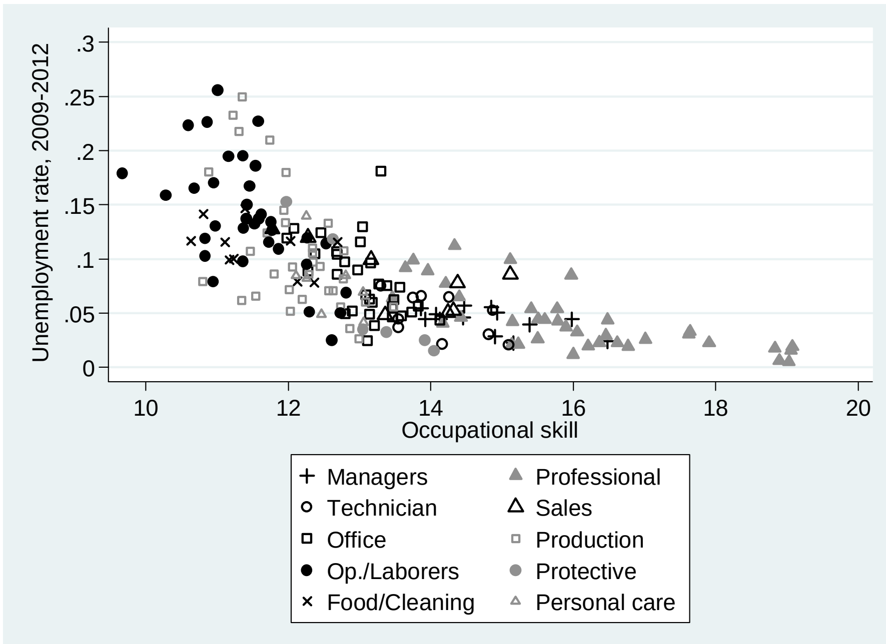
Panel B: Females



*Occupational skill is defined as the average years of education in the 2000 census in each of my 191 occupations. Deciles are taken in the 2000 census, and higher number means higher skilled occupation. The gray areas indicate NBER recession dates.

Figure 11: Average unemployment rate by occupation, March CPS, 2006-2012, colored by 10 major groups.

Panel A: 2009-2012



Panel B: 2006-2007

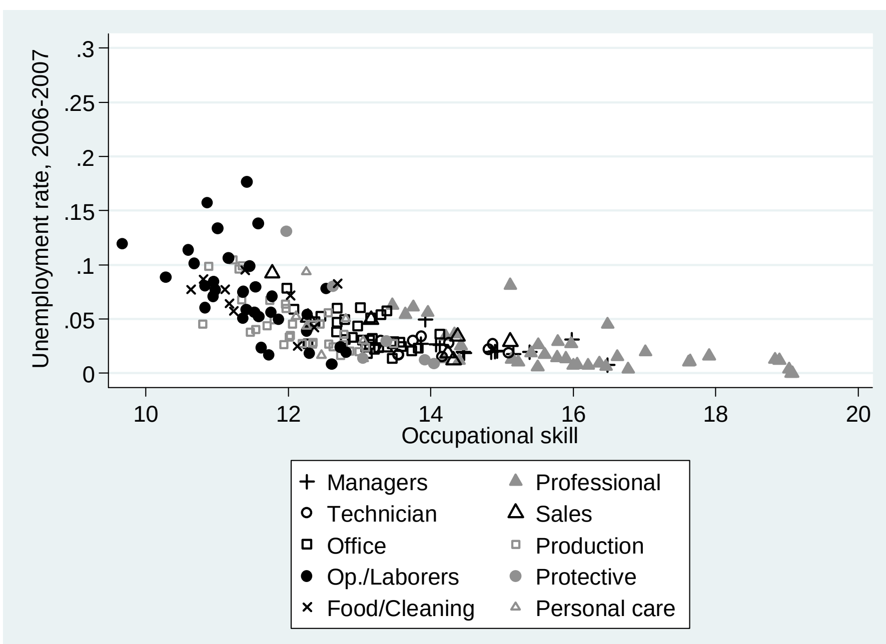
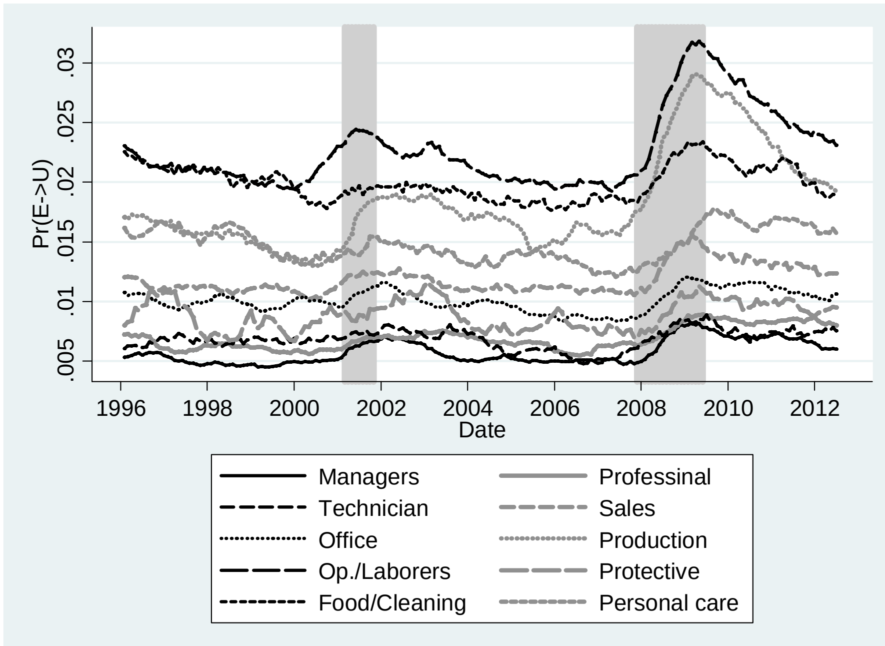
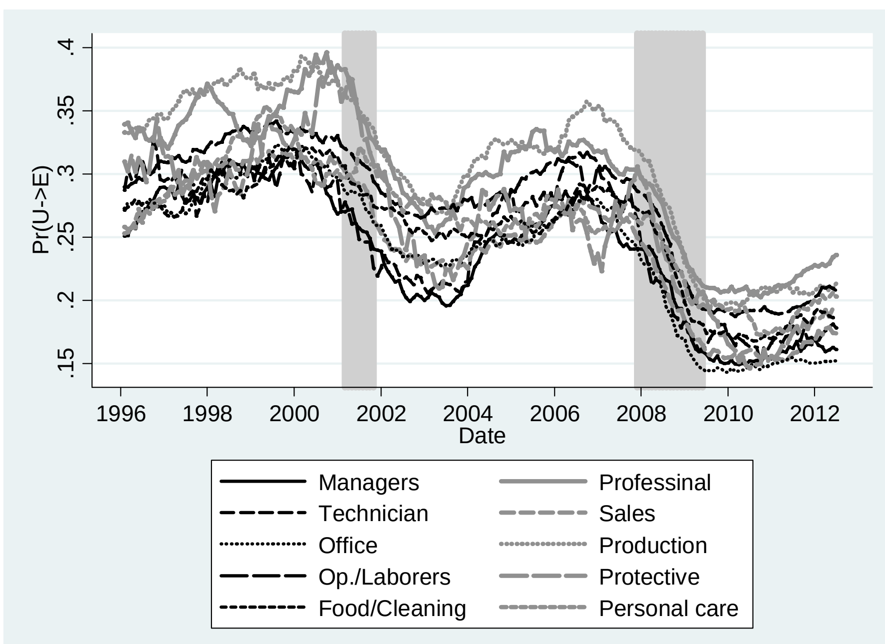


Figure 12: Evolution of job-loss and job-finding probabilities by major occupational groups, 1996-2013

Panel A: job-loss probabilities

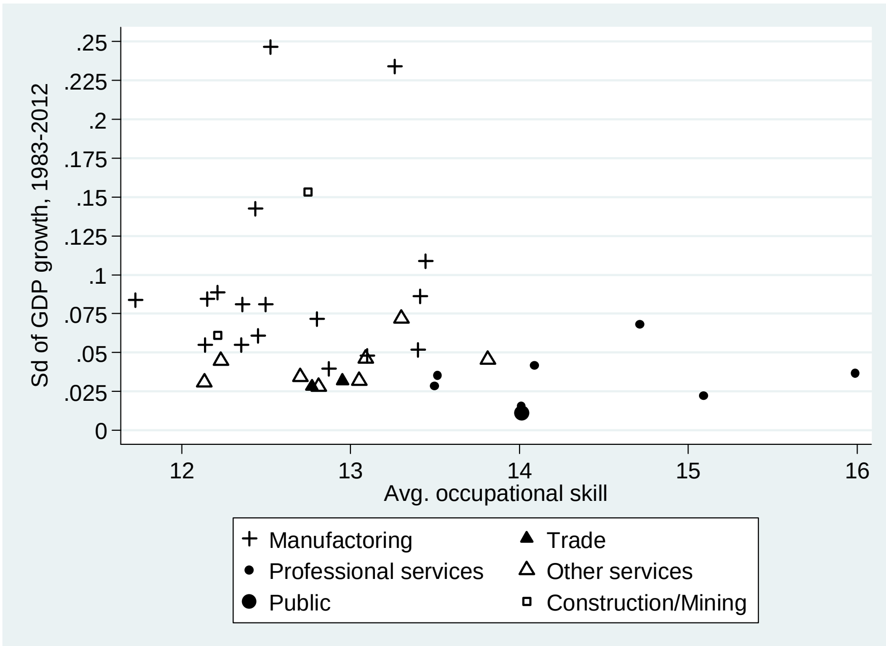


Panel B: job-finding probabilities

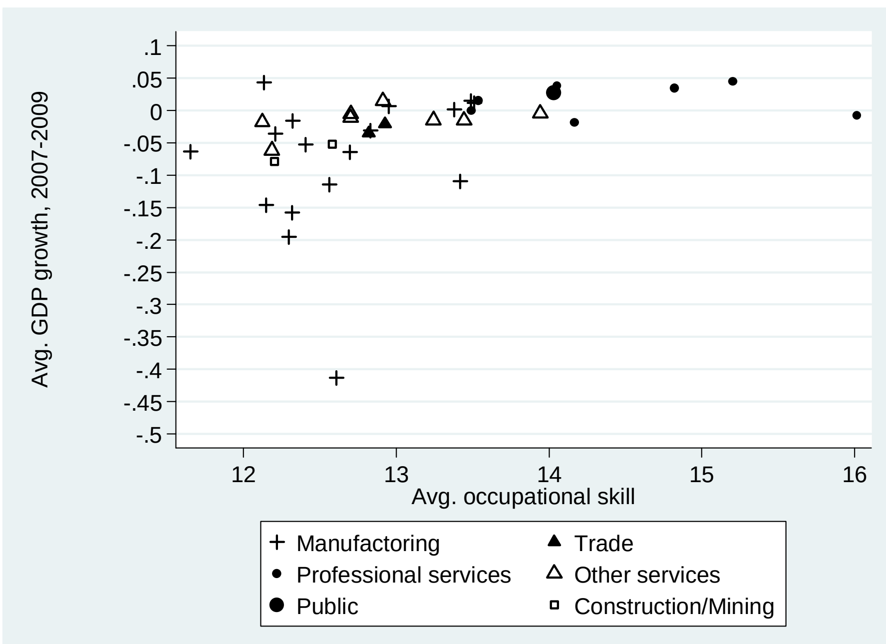


*The figure shows yearly moving averages of monthly job-loss and job-finding probabilities using the monthly CPS. For the unemployed, the occupation at the last job is used. The gray areas indicate NBER recession dates.

Figure 13: Industry GDP growth and skills
Panel A: Standard deviation of industry GDP growth, 1983-2012

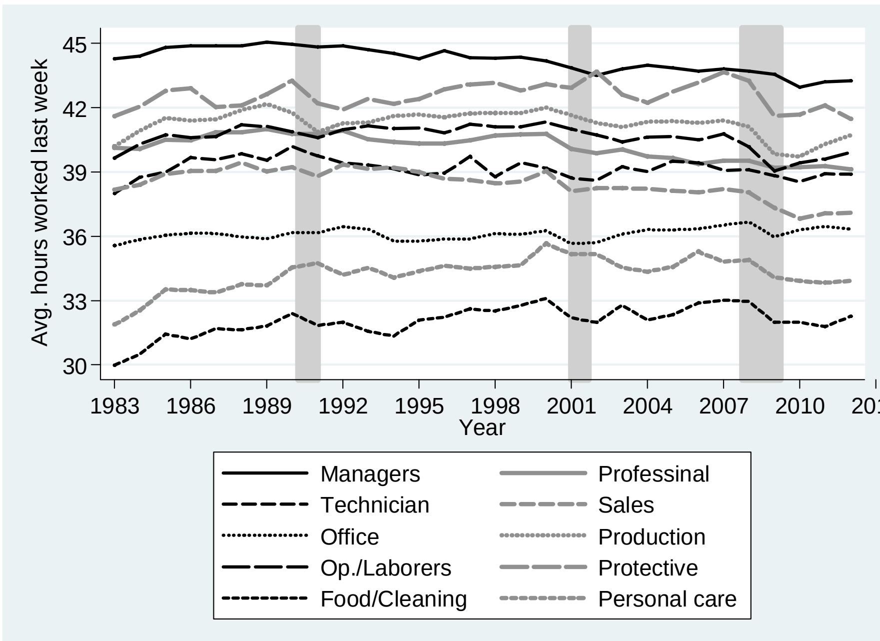


Panel B: Average industry GDP growth, 2007-2009

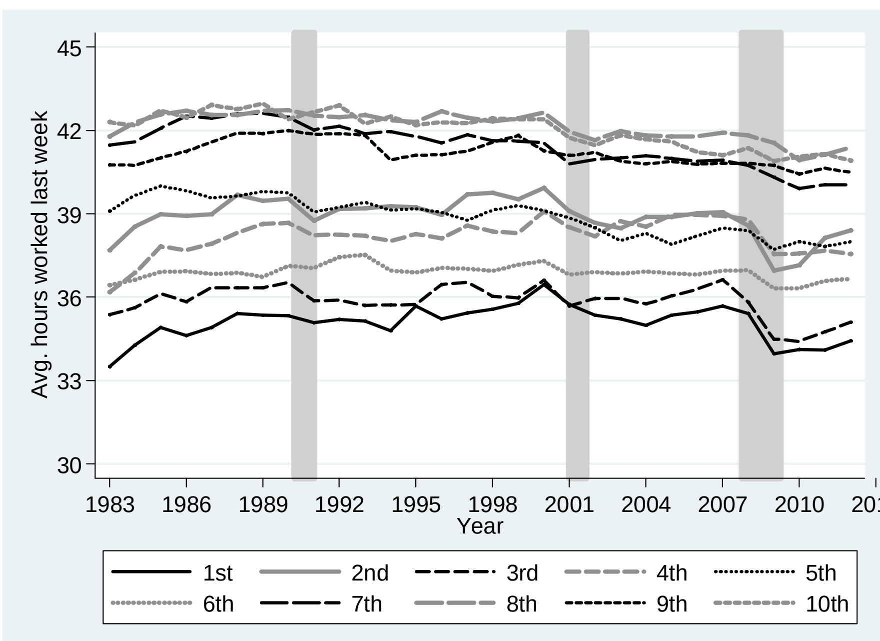


*Occupational skill is defined as the average years of education in the 2000 census in each of my 191 occupations. Deciles are taken in the 2000 census, and higher number means higher skilled occupation.

Figure 14: Average hours of work last week by occupational groups*, March CPS 1983-2012
Panel A: In major occupational groups



Panel B: In occupational skill deciles



*Conditional on working positive hours last week. Occupational skill is defined as the average years of education in the 2000 census in each of my 191 occupations. Deciles are taken in the 2000 census by dividing the population into 10 roughly equal groups based on their occupations. Higher number means higher skilled occupation.