Fall 9-1-2012

Unemployment, Skills, and the Business Cycle Since 2000

Chad Sparber
Colgate University, csparber@colgate.edu

Jasmine Sijie Fan
Colgate University, sfan@colgate.edu

Unemployment, Skills, and the Business Cycle Since 2000

Jasmine Sijie Fan*and Chad Sparber†

September 2012

Abstract

This paper employs reduced-form microeconometric analysis to examine how fluctuations in aggregate personal income and gross domestic product affect the unemployment probability of individuals with varied skills in the United States. The paper goes beyond traditional education-based measures and assesses how manual, communication, and quantitative skills affect the relationship between macroeconomic shocks and unemployment. Workers specialized in communication skills exhibit lower unemployment rates, reduced unemployment volatility, and less sensitivity to macroeconomic fluctuations.

Key Words: Unemployment, Skills, Business Cycle, Macroeconomic Shocks, GDP

JEL Classification Codes: E24, E32, J21, J24, J64

*Fan is an undergradate student at Colgate University (sfan@colgate.edu; 13 Oak Drive, Hamilton, NY 13346)

†Sparber (corresponding author) is an Associate Professor of Economics at Colgate University (csparber@colgate.edu; 13 Oak Drive, Hamilton, NY 13346; 315-228-7967); and External Research Fellow, Centre for Research and Analysis of Migration (CReAM), University College London.

1 Introduction

The first decade of the 2000s saw great volatility in macroeconomic activity. The National Bureau of Economic Research (NBER) recognizes US GDP peaks in March 2001 and December 2007, with troughs at November 2001 and June 2009. Bureau of Economic Analysis (BEA) data records real GDP growth of 17.4% during the expansion between the fourth quarter 2001 and the fourth quarter 2007, but a drop of more than 4% during the subsequent recession.

Rising unemployment is one of the biggest concerns of macroeconomic contraction. Differences in unemployment rates by education level are well-documented. Table 1 illustrates that between January 2000 and December 2011, the average US unemployment rate among individuals with a high school degree or less education was 7.84%, whereas unemployment averaged just 3.96% for those with some college or more education. Volatility is much higher for less-educated individuals as well. The standard deviation of monthly unemployment rates was 2.64 percentage-points for less-educated workers, nearly twice the figure for college-educated labor (1.41 percentage-points). Such regularities are important to document as they are informative about the variation in business-cycle welfare effects across groups of workers with heterogeneous skills.

Sole reliance upon education to define skills might lead to a myopic understanding of the economic effects of business cycles, however. The occupational skills, knowledge, and type of work performed by individuals can vary tremendously within education groups. A more complete characterization of skills would improve understanding about the heterogeneous effects of business cycles. Economists could more-specifically identify groups of workers vulnerable to economic fluctuations. Risk-averse agents could avoid particular types of work. Unemployed workers might find it easier to invest in skill-development than in returning to school to acquire more formal degrees. Moreover, government agencies could target worker retraining efforts toward specific skills.

This paper uses *O*NET* data on occupation-specific characteristics to better characterize the skills of workers. The dataset – and its predecessor the *Dictionary of Occupational Titles* (*DOT*) – has been widely used in the labor literature.[1] The limitation is that unlike with education, *O*NET* skills are associated with an occupation, not an individual: When an individual changes occupations, his/her measurable skills will change (possibly even decline) even if he/she made no explicit attempt to alter his/her skill set. Nonetheless, the data is useful in providing a greater understanding of skill than education alone can provide.

Our dataset merges occupation-level *O*NET* skill information, individual-level Current Population Survey (CPS) data, and BEA aggregate macroeconomic indicators. We then perform microeconometric estimation by regressing individual unemployment outcomes on macroeconomic variables including state personal income and national GDP. Most importantly, we interact the macro variables with education and skill information to examine potential variation in effects across different education and skill levels. The paper finds that laborers engaged in communication-intensive work experience low unemployment and unemployment volatility. Moreover, communication workers are least vulnerable to macroeconomic shocks, facing disproportionately low unemployment when aggregate income falls. This result tends to hold even when controlling for industry characteristics over time. Additional evidence suggests that usual hours worked and weekly earnings may be less-sensitive to macro fluctuations for communication-intensive workers as well.

2 Motivation

Macroeconomists often employ theoretical models or calibration exercises to estimate the costs of business cycles. Lucas (1987) is the most seminal work in this field, with Krussell and Smith (1999) and Krussell et al. (2009) importantly noting that such costs vary across types of individuals due to incomplete markets. It is well-known that labor market volatility varies across demographic groups. Section 3 of Gomme et. al. (2005) provides a recent

[1] See for example, Peri and Sparber (2009, 2011), Freeman and Hirsch (2008), or Maxwell (2008).

summary of volatility for groups defined by gender, education, and age. Women, workers with higher levels of educational attainment, and prime-age workers exhibit less variation (in hours worked) compared with other demographic groups.[2] Mukoyama and Sahin (2006) show how business cycles affect this relative volatility. In particular, they differentiate the skills of workers according to educational attainment and conclude (p. 2192), "Unskilled agents face more cyclical unemployment risk and have less opportunity to self-insure. As a result, the cost of business cycles is much larger for a typical unskilled agent than for a typical skilled agent."

Labor economists, in contrast, usually employ reduced-form empirical estimation of the labor market effects of business cycles. Hoynes (2000) adopts a semi-parametric approach to examine effects on people in different demographic groups. Using 1975-1997 variation across metropolitan statistical areas (MSAs), gender, race, and education, she uncovers results that "consistently show that the labor market outcomes of less-skilled [i.e., less-educated] workers exhibit more variability than those of higher-skill groups over business cycles." Economic shocks generate an employment-rate response among white men with no college experience that is roughly 30% greater than the response among men with some college or more education.

Other labor economists have used similar reduced-form approaches to identifying differential effects between native and foreign-born workers. Using UK and German data, Dustmann, Glitz, and Vogel (2010) find that economic shocks induce a greater response among immigrants than natives within the same education group. Orrenius and Zavodny (2010) find similar results using US data. Geis (2010) attributes some of the difference in outcomes to language skills (measured by language spoken in the home), while Paggiaro (2011) notes that job characteristics explain much of the immigrant/native gap.

Trends and volatility by education group since 2000 can be seen in Figure 1.[3] The

[2] See Jaimovich and Siu (2009) and Menu (2011) for more extensive discussion on age and labor market volatility.

[3] The data comes from monthly CPS outgoing rotation groups (ORG), and is available from the NBER.

left panel displays the unemployment rates of American workers by education level. Not surprisingly, unemployment rates are higher among less-educated workers, while all workers saw rising and high unemployment during the financial crisis and Great Recession. The right panel of Figure 1 illustrates the cyclical component of unemployment after detrending the data with the Hodrick-Prescott Filter and the recommended smoothing parameter for monthly data of 14,400. This graph clearly demonstrates the greater volatility of unemployment among less-educated workers. Table 1 similarly notes that the standard deviation of the cyclical component of unemployment is twice as high for less-educated labor (0.96) than for college-educated workers (0.46).

This paper adopts the reduced-form approach to analyzing how aggregate income shocks affect the unemployment outcomes of workers, but it provides a more complete assessment of the role of skills in amplifying or mitigating business cycle effects. Our empirical strategy uses an individual-level approach that borrows elements from Hoynes (2000), Dustmann, Glitz, and Vogel (2010), and Orrenius and Zavodny (2010). We use repeated cross sectional data to analyze labor market outcomes (Y) of individual i living in state s at date t as described by Equation (1).

$$Y_{i,s,t} = \alpha + \beta_1 \cdot Cycle_{s,t} + \beta_2 \cdot X_{i,s,t} + \beta_3 \cdot Time_t + \beta_4 \cdot State_s + \varepsilon_{i,s,t} \quad (1)$$

Our principle labor market outcome of interest (Y) is a dichotomous unemployment variable equalling one for individuals who are unemployed, and equalling zero for the employed (those not in the labor force are excluded). Further extensions also explore usual hours worked per week and the log of weekly earnings for individuals who are employed. Individual data is provided by the Current Population Survey Outgoing Rotation Group (CPS-ORG) dataset.

Our main explanatory variable, *Cycle*, represents various measures of cyclical macroeconomic performance. We explore two main indicators of aggregate activity: state personal income and national gross domestic product. We use the log of real quarterly data (the highest frequency available) and employ an HP filter (and a smoothing parameter for quarterly data of 1600) to detrend the macroeconomic data, deriving the cyclical component of macroeconomic performance as the difference between the actual value and the trend. Importantly, we interact macroeconomic variables with education and skills to explore the heterogenous effects of business cycle activity across groups of workers.[4]

The remaining variables in the model represent various control variables. The vector X accounts for demographic variables such as education-level, gender, race, nativity, and age. The model also accounts for variation in dependent variables caused by time differences. For regressions using national GDP as the macroeconomic variable, the $Time$ vector includes a quadratic time trend with four quarter dummies (Winter, Spring, Summer, Autumn) to control for any seasonal effects. For regressions using state personal income as an explanatory variable, $Time$ represents year-by-quarter (date) fixed effects. The variable $State$ accounts for state fixed effects, and ε represents an idiosyncratic error term. All regressions cluster standard errors by state.

3 Data

The model in Equation (1) requires individual-level data on labor market outcomes and aggregate-level information on macroeconomic conditions. We measure macroeconomic performance with BEA quarterly real US gross domestic product (GDP) and state-level personal income data (both measured in constant 2005 dollars). Individual-level data comes from the NBER's monthly CPS-ORG survey on employment and assorted demographic characteristics including educational attainment. The CPS interviews households once a month for four months. After an eight month break, the CPS returns to the household for four more interviews. The fourth and eighth interviews occur one year apart and constitute the outgoing rotation groups. It is possible to construct a repeated cross-sectional dataset

[4] Note that although the CPS-ORG is a monthly dataset, the frequency of availability for macro data requires us to define dates (t) by the year and quarter in which individuals responded to the survey.

by merging individual surveys taken at different dates.

The chief contribution of this paper is to assess how macroeconomic fluctuations might have heterogeneous effects on people of different skill levels beyond simple educational attainment. For an alternative measure of skill, we use occupation-specific data from the National Center for *O*NET* Development's *O*NET* database. *O*NET* and its predecessor the *DOT* have previously been used by labor economists to assess the skill characteristics of the labor force. For example, Autor, Levy, and Murnane (2003) used *DOT* data to evaluate how technological change has affected the nature of work in the economy, whereas Peri and Sparber (2009, 2011) used *O*NET* data to estimate how immigration affects the skills used by native-born workers. Using Peri and Sparber (2009, 2011) as a guide, we use the *O*NET* abilities survey and measure three types of skills: Manual Labor, Communication, and Quantitative skills.[5] *O*NET* provides skill measures for each occupation defined by Standard Occupational Classification (SOC) codes. Each value is a percentile representing the fraction of workers using less of a particular skill in 2000. Economists, for example, have respective manual, communication, and quantitative skill values of 0, 0.65, and 0.93, indicating that they use more manual skills than 0% of the labor force, more communication skills than 65% of the labor force, and more quantitative skills than 93% of the labor force. Some occupations possess little of any skill (telemarketers have manual, communication, and quantitative skills of 0.02, 0.49, and 0.09), while managers of blue-collar industries tend to be high in all three (0.73, 0.88, and 0.92 for food service mangers, for example).

The CPS asks individuals to state their current occupation, or in the case of the unemployed, their most recent occupation. CPS occupation codes are closely-related to *O*NET* codes since 2000, thus enabling us to merge datasets and create skill values for all individuals in the labor force. The resulting dataset covers January 2000 through December 2011. We use data only on residents of the contiguous 48 states and excluding the District

[5] The procedure for calculating skill values is outlined in Peri and Sparber (2009, 2011). Manual skills average responses to *O*NET* abilities survey questions 22-40. Communication averages questions 1-4, 51, and 52, Quantitative skills are the average of questions 12 and 13.

of Columbia.

Not surprisingly, *O*NET* skills correlate with education. Table 2 reports the average, median, and quartile values of skills used by workers within education groups (overall medians equal 0.5 by construction). The average worker with a high school degree or less education uses more manual skills than 64% of the labor force. The figure is just 42% for the average individual with some college or more educational experience. Conversely, college-educated workers tend to use more communication and quantitative skills.

Figures 2-4 display unemployment rates for the top and bottom skill quartiles within education groups. Left panels exhibit rates for less-educated workers, right panels are for workers with at least some college experience. Graphs in the top row represent unemployment rates; the bottom row displays deviations from trend unemployment.

Figure 2 illustrates unemployment rates by manual skill quartile. Not only do less-educated workers who intensively use manual skills exhibit high unemployment rates, but those unemployment rates are incredibly volatile. Workers specializing in communication skills, in contrast, exhibit the opposite behavior. Figure 3 shows that workers who intensively use communication skills experience lower unemployment and diminished volatility. This is similarly true for quantitative skills in Figure 4. Interestingly, differences in unemployment volatility across skill levels are much less apparent among workers with college experience. This is true for each skill considered.

Table 1 provides summary statistics on unemployment and unemployment volatility. The statistics echo the regularities in Figures 2-4, but perhaps better demonstrate the greater volatility of bottom quartile communication workers and top quartile manual and quantitative-intensive workers. Moreover, it demonstrates that volatility disparities across skills occur among both less-educated and college-educated workers, but with a smaller gap among the latter group. The heterogenous behavior across skill levels within education groups encourages us to further analyze the role of macroeconomic income fluctuations in determining labor market outcomes of individuals.

4 Empirical Analysis

4.1 Main Unemployment Results

We explore the unemployment effects of macroeconomic fluctuations in several steps, first examining parsimonious estimates that do not account for skill variation, then adding various skill measures and interaction terms to the model in Equation (1), and finally performing a number of robustness checks. Table 3 displays results from the most basic regressions. The dependent variable measures whether the individual is unemployed, while the explanatory macroeconomic variable of interest measures deviations of log income from trend. The model controls for gender, a quadratic for age, race, educational attainment, and nativity, but it assumes that macroeconomic fluctuations affect all individuals equally. Standard errors are clustered by state. Since the macro variables are measured in log differences from trend, coefficients can be interpreted as effects from percentage-point changes in cyclical deviations from trend economic conditions.

Columns 1 and 2 exploit regional variation by adopting the log of quarterly state personal income as the main macro variable. Since labor markets may be national in scope, we also include a weighted average of neighboring states' macroeconomic activity in which the weights represent the reciprocal of the distance between two states. Column 1 omits state and date fixed effects, whereas Column 2 includes fixed effects for both. Evidence for own-state income effects occur in both regressions – a 1 percentage-point increase in own-state personal income relative to trend is associated with 0.19 to 0.23 percentage-point decrease in the probability of a person becoming unemployed. Neighboring state income declines are associated with unemployment in Column 3, but this effect disappears when controlling for state and date fixed effects in Column 2.

Columns 3 and 4 are analogous to Columns 1 and 2 but use national real GDP to substitute for state and neighboring state personal income as the measure of macroeconomic performance. Also, since national GDP does not vary across states at date t, we replace date fixed effects in Column 4 with a quadratic time trend and seasonal dummy variables. The results are qualitatively comparable but quantitatively larger than in the state income regressions. A 1 percentage-point increase in national GDP relative to trend is associated with a 0.7 percentage-point decrease in the probability of being unemployed when accounting for state and date fixed effects. For context, the Great Recession of December 2007 through June 2009 saw an output loss of 4%. Our estimates suggest that a level of output 4% below potential is therefore associated with an estimated 2.8 percentage-point rise in unemployment.

Empirical work in Hoynes (2000), Orrenius and Zavodny (2010), and others notes that economic shocks have a heterogeneous effect on individuals of different levels of educational attainment. Our results in Table 4 replicate this effect by interacting our main macroeconomic shock variables with education. Columns 1 to 4 demonstrate a nearly monotonic relationship such that workers with more educational attainment are less affected by business cycle fluctuations relative to their less-educated counterparts. Column 2 suggests that a 1 percentage-point decline in state personal income relative to trend is associated with a 0.45 percentage-point rise in the probability of being unemployed for high school dropouts, but an insignificant effect among those with a Bachelor's degree. Magnitudes are larger when using national-level real GDP as the macro variable (Columns 3 and 4), but the qualitative results are identical.

Table 5 begins to explore our larger question of interest by controlling for manual, communication, and quantitative skills and interacting those skills with the macroeconomic variables to measure the effects of short-term business cycle fluctuations. As always, the regressions account for gender, age, age-squared, race, educational attainment, and nativity (though the table suppresses coefficients), and standard errors are clustered by state. Column 2 demonstrates that a worker with no measurable communication, manual, or quantitative skills in a state experiencing a 1 percentage-point decrease in aggregate personal income relative to trend is 0.3 percentage-points more likely to be unemployed. Not surprisingly, negative macro shocks increase the probability of unemployment. However, the positive and highly significant coefficient on the communication term reveals that communication workers are much less sensitive to state income shocks than other workers are. The median communication worker, for example, experiences only a 0.05 percentage-point rise in unemployment probability for the same income shock ($-0.0514 = -0.2997 + 0.5 * 0.4966$). The negative and significant coefficients on the manual and quantitative skill interaction terms provide evidence that workers engaged in manually-intensive and quantitative work see heightened sensitivity to business cycle fluctuations.

These results are echoed when using national real GDP as the explanatory variable (Columns 3 and 4). After controlling for state fixed effects and time trends (Column 4), we see that negative GDP shocks increase unemployment in general, but the effect would completely disappear for a worker with maximum communication skills. Workers in manually-intensive occupations are more susceptible to GDP fluctuations, whereas additional effects for quantitative workers are insignificant.

Our discussion of the data noted that occupational skills are likely correlated with educational attainment. Though the regressions in Table 5 controlled for education, the failure to interact education with the macro variables could generate false conclusions for skill interaction terms. Table 6 enriches the evidence by including both skill and educational attainment interactions with macro shocks. Focusing first on the unemployment results of Column 1 and 2, we again see evidence broadly consistent with the literature – Income shocks affect unemployment outcomes for less-educated labor more than for the college-educated. More interestingly, we also see that the coefficient on the communication interaction term in Column 2 (0.378) remains positive, significant, and similar to the results of Table 5. Unemployment among workers who use communication skills is less sensitive to business cycle fluctuations. Every decile increase in communication skill intensity is associated with a 0.0378 percentage-point decrease in the negative correlation between state income and a worker's probability of becoming unemployed. Column 3 and

4 results using national GDP find similar effects. Results for manual skills are less robust. While each specification in Table 5 argued for heightened sensitivity to business cycles for manual workers, Table 6 argues for this result only when using national GDP as the macro variable. Both Tables 5 and 6 find significant (and negative) coefficients on quantitative skills in only the state personal income regressions. Thus, we are more confident that communication skills help protect individuals from unemployment spells caused by macroeconomic fluctuations than in concluding that manual and quantitative skills lead to heightened sensitivity to cyclical conditions.

Table 7 provides an alternative view of the results in Table 6 by displaying the estimated change in unemployment probability for individuals of varied educational attainment and skill level that are caused by aggregate income being 1% above potential. Values are presented for shocks in both state income (top panel) and national GDP (bottom panel). Figures in the first column represent estimates for workers with median manual, communication, and quantitative skills (0.5 for each skill). The next three columns increase each skill value, in turn, to 0.75 to represent workers within the top quartile of each skill. Thus, for example, values in the third column represent the percentage-point change in unemployment probability due to a one percentage-point increase in cyclical income for a worker who is manual skill intensive, but has average communication and quantitative skills.

The top panel lists estimates due to changes in state incomes. The bottom panel displays similar estimates using national macro shocks. Both panels illustrate that the more educated an individual is, the less likely that person will become unemployed as cyclical GDP declines. Moreover, they give a sense that skills (particularly communication skills) are relevant in determining the unemployment effects of aggregate income shocks. For example, a 1 percentage-point deviation in state income relative to potential will increase the probability of a median-skilled worker with a bachelors degree becoming unemployed by approximately 0.099 percentage-points. For a worker who differs from the median only by being in the top quartile of manual skills, the same shock increases the unemployment probability by 0.12 percentage-points. Conversely, a top quartile communication worker would see his or her unemployment probability rise by only 0.004 percentage points.

4.2 Robustness of Unemployment Results

4.2.1 Asymmetric Effects

One concern might be whether the unemployment effects of GDP shocks are similar during expansions (or when GDP is above potential) and recessions (or when GDP is below trend). It is therefore worth exploring whether the response to business cycle fluctuations demonstrates asymmetric behaviors.

We start by identifying expansionary periods as dates with positive cyclical activity (that is, when income exceeds potential as identified by HP filter detrended data). Recessionary periods are identified analogously. Then we run two separate sets of regressions for expansionary and recessionary periods, respectively. The regression methodology is similar to the unemployment specifications in Table 6 in which both state personal income and national GDP serve as macroeconomic variables. Table 8 displays the results of specifications exploring these asymmetric effects. Columns 1 and 3 reveal the changes of employment during recessions and Columns 2 and 4 represent employment behaviors during expansions. The first two columns use state personal income as the macro variable while the last two columns employ national GDP. All regressions include state fixed effects and time controls.

Most specifications uncover the expected result that individuals with higher education levels are less sensitive to income deviations from potential. More interestingly, however, the interaction term between business cycles and communication skills remains significant in all regressions. It appears that communication-intensive workers are less sensitive to cyclical activity during both recessions and expansions. Moreover, the interaction of business cycles and manual skills is usually negative and significant, indicating greater business cycle sensitivity for manual workers.

Also note that the general effects of business cycles (the education interaction terms) tend to be larger during business expansions than in contractions. For example, every one percent-point decrease in GDP relative to potential is associated with a 1.13 percent-point increase in the probability a high school dropout without skills is currently unemployed, but the same shock would be associated with 1.46 percent-point decrease in unemployment probability during business expansions. Conversely, the magnitude of the interaction terms is larger in recessions than in expansions for both communication and manual skills, suggesting that skills distinct from educational differences can help protect or exacerbate the employment effects of GDP fluctuations during recessionary periods.

4.2.2 Longitudinal Data

Although the main regressions in this paper employ repeated cross-sectional methods, we are also able to perform limited analysis using longitudinal panel data. Since the CPS-ORG interviews households in both year t and $t+1$, we will have two observations for all individuals who do not move. The regressions in Table 9 use a quasi-panel structure that includes only individuals observed in the labor force in both year t and $t+1$. This allows us to use individual fixed effects to absorb idiosyncratic characteristics that might be correlated with employment outcomes. The limitation is that we lose individuals who move, die, or are absent from the labor force in one of the two potential periods of observation.

Table 9 provides the results. Columns 1 and 3 replicate the specifications of Columns 2 and 4 in Table 6, differing only in that the sample in Table 9 is smaller due to the modified selection criteria. Results in the two tables are quite similar, suggesting that our individual fixed effects regressions are likely to suffer from substantial bias from its restrictive sample selection criteria. Columns 2 and 4 of Table 9 introduce individual fixed effects. When using state personal income as the macroeconomic indicator, individual-level fixed effects (Column 2) absorb much data variation, and most of the coefficients on terms interacting business cycles lose significance. Results are more robust when using national GDP, as the fixed effects specification (Column 4) continues to find the expected significance on the education interaction terms. Moreover, the coefficient on the communication skill interaction term remains positive and significant. Thus, even when controlling for individual fixed effects, we find that communication skills help a person maintain employment in the face of economic downturns.

4.2.3 Industry Controls

Labor market outcomes can vary significantly across industries.[6] Gomme et. al. (2005, p. 425) notes that, "In particular, goods-producing sectors display more volatility than do service sectors." Their concern is about whether industry of employment drives the quadratic relationship between age and labor market volatility (it does not). Our concern is that occupational skills are not evenly distributed across industries. Manual skills, for example, are more widely used in manufacturing (average of 0.58) and construction (0.74) than in educational services (0.39). Conversely, communication skills are more prominent in health care (0.66) and education (0.65) than in manufacturing (0.37) and construction (0.31). Baseline regressions could have falsely attributed the heterogenous effects of business cycles to skill differences if it is rather that macroeconomic shocks affect some industries more strongly than others. It is not clear whether workers adverse to business cycle fluctuations should embrace communication-intensive occupations, or instead try to find employment in industries employing many communication workers.

Table 10 addresses industry concerns. The dependent dichotomous variable indicates whether a person is employed or not. Top panel results use state personal income as the income variable; bottom panel results use US GDP. Each regression includes the same explanatory variables as in Table 6 (including interactions between income and education levels), but we report only the interactions between income and occupational skills. Column 1 introduces industry-specific time controls. For state income results, this is accomplished through industry-by-date fixed effects. GDP regressions instead use industry-

[6] The US Bureau of Labor Statistics (BLS) publishes job statistics by individual industry. See Chart 1 for each industry at www.bls.gov/bdm/bdmind.htm, for example.

specific quadratic time trends. These specifications have the advantage of controlling for all time shocks specific to industries, but come at the cost of absorbing much data variation and reducing model efficiency. Nonetheless, state income regressions continue to find that unemployment among communication-intensive workers is less sensitive to business cycle shocks. Declines in state income increase the probability of unemployment, but each decile increase in communication skill mitigates this probability by 0.038 percentage points. The magnitude of this effect is similar for US GDP regressions, and is also significant at 5% level.

Columns 2-6 explore industry-specific effects for the five US industries that together comprise roughly 50% of US employment during the period. Regressions continue to include date dummies or quadratic time terms, as well as the usual explanatory variables, though the table only displays coefficients for terms interacting macro variables and occupational skills. Even within industries, we find that macroeconomic shocks have differential unemployment effects across workers of different skill levels. Communication-intensive workers in manufacturing and health care industries are less-sensitive to business cycle shocks than their coworkers are. Manual labor in manufacturing and construction is more sensitive to income fluctuations (Column 3 and 6). Results for quantitative skills are less robust across methodologies, but do find that quantitative workers in the education industry are more susceptible to business cycle fluctuations. Altogether, the results of Table 10 suggest that macroeconomic fluctuations do have heterogenous effects across individuals who possess differing occupational skills, and that this heterogeneity remains even after accounting for industry-specific shocks that might confound baseline analysis.

4.3 Usual Hours and Earnings per Week

Though our analysis has focused on the unemployment effects of macroeconomic fluctuations, economists are often interested in alternative measures of labor market outcomes including earnings and hours of employment.[7] Fortunately, our dataset also provides information on an individual's usual number of hours worked and earnings per week (converted into real 2010 dollars). We use the model in Equation (1) to estimate how skills affect the relationship between macroeconomic performance and these labor market outcomes.

The regressions in Table 11 are analogous to the unemployment specifications in Table 6 except that they include only people who are employed. Regressions control for gender, age, age-squared, nativity, education, and skill, and they include state fixed effects and time controls. Macroeconomic variables are interacted with skill and educational attainment. Columns 1 and 3 adopt the usual hours worked per week as the dependent variable, while Columns 2 and 4 analyze the change in inflation-adjusted weekly earnings. The first two columns use state personal income as the macro variable; the last two columns use national real GDP.

Coefficients on neighboring-state income in real weekly earnings regressions are insignificant but point estimates are positive in sign. Positive macroeconomic shocks increase earnings for workers of all education levels, though no pattern emerges for differences across education levels. Importantly, the negative and significant coefficients on the communication interaction terms, when coupled with the significantly positive coefficients of the other macro interaction terms, indicate that communication-intensive workers are again less-sensitive to macro conditions. For example, every one percentage-point decrease in own-state personal income relative to potential is associated with a 0.12 percentage-point decrease in earnings for a high school dropout in the top quartile of intensive communication skills, but is associated with 0.24 percentage-point decrease for a person with median skills.

The results for usual hours worked are broadly consistent with those in earnings regressions. In Column 2, we see that increases in own-state personal income are associated with increases in usual hours worked – a one percentage-point increase in own-state per-

[7] See Menu (2011), Baler and van Rens (2009), Dustmann, Glitz, and Vogel (2010), Gomme et al. (2005), and Hoynes (1999) for examples related to our exploration of skills and the business cycle.

sonal income relative to trend is associated with a 0.068 hour increase in weekly hours worked for high school dropouts. This relationship is weakened, however, for workers with high communication skills. The same macroeconomic shock is only associated with a 0.043 hours increase for high school dropouts who specialize in communication skills, but a 0.017 hours increase for high school dropouts in the top communication skill quartile. Estimates from national GDP shocks are similar. A one percentage-point increase in national GDP is associated with a 0.2 rise in hours worked of a high school dropout without skills, but this effect decreases significantly for workers in the most communication-intensive occupations.

Macroeconomic interactions with manual skills are positive and significant in usual hours regressions, again suggesting heightened business cycle sensitivity for manual workers. Earnings, however, exhibit no significant differential effect of cyclical performance for manual workers. In addition, the coefficient on the interaction with quantitative skills is always insignificant.

5 Conclusion

Many economists are concerned about how macroeconomic shocks affect individuals of varied skill levels. Most studies employ educational attainment as the sole measure of skill. This paper, however, notes that skills and the nature of work can vary across individuals within education groups. By using *O*NET* data on occupational skill, this paper developed improved insight into groups of workers particularly vulnerable to business cycle fluctuations.

A one percentage-point decline in aggregate income relative to potential is associated with roughly a 0.2 percentage-point increase in the probability of an employed person becoming unemployed. Workers in communication-intense occupations are less vulnerable to such shocks – for every decile increase in communication skill, the probability of a macro shock causing an employee to become unemployed decreases by 0.03 percentage-points. Estimates are robust to controls for education and to education-specific effects of business cycle fluctuations. Magnitudes of these effects decrease yet still remain in regressions controlling for industry-specific shocks. These results should be interesting to workers and policy-makers alike. Risk-averse agents might want to embrace communication-intense occupations so as to avoid unemployment spells, while government agencies might want to advocate worker retraining programs geared toward developing communication skills to reduce new entrants into cyclical unemployment.

References

Autor, David H., Frank Levy, and Richard Murnane (2003) "The Skill Content of Recent Technological Change: an Empirical Exploration." *Quarterly Journal of Economics*, Vol. 118(4), pp. 1279-1333.

Baler, Almut and Thijs van Rens (2009) "Cyclical Skill-Biased Technological Change." IZA Discussion Paper No. 4258.

Dustmann, Christian, Albrecht Glitz, and Thorsten Vogel (2010) "Employment, Wages, and the Economic Cycle: Differences between Immigrants and Natives," *European Economic Review*, Vol. 54(1), pp. 1-17.

Freeman, James A. and Barry T. Hirsch (2008), "College Majors and the Knowledge Content of Jobs," *Economics of Education Review*, Vol. 27(5), pp. 517-535.

Geis, Wido (2010), "High Unemployment in Germany: Why do Foreigners Suffer Most?" IFO Institute for Economic Research at the University of Munich, Working Paper No. 90.

Gomme, Paul, Richard Rogerson, Peter Rupert, and Randall Wright (2005), "The Business Cycle and the Life Cycle," *NBER Macroeconomics Annual 2004*, Vol. 19: 415-461.

Hoynes, Hilary (2000), "The Employment, Earnings, and Income of Less Skilled Workers Over the Business Cycle" in David Card and Rebecca Blank (Eds.), *Finding Jobs – Work and Welfare Reform*. Russell Sage Foundation, New York, pp. 23-71.

Jaimovich, Nir and Henry E. Siu (2009) "The Young, the Old, and the Restless: Demographics and Business Cycle Volatility," *American Economic Review*, Vol. 99(3): 804-826.

Krussell, Per and Anthony A. Smith Jr. (1999), "On the Welfare Effects of Eliminating Business Cycles," *Review of Economic Dynamics*, Vol. 2(1), pp. 245-272.

Krussell, Per, Toshihiko Mukoyama, Aysegul Sahin, and Anthony A. Smith Jr. (2009) "Revising the Welfare Effects of Eliminating Business Cycles," *Review of Economic Dynamics*, Vol. 12(3), pp. 393-404.

Lucas, Robert (1987), *Models of Business Cycles*, Basil Blackwell, New York.

Maxwell, Nan L. (2008), "Wage Differentials, Skills, and Institutions in Low-Skill Jobs," *Industrial and Labor Relations Review*, Vol. 61(3), pp. 394-409.

Menu, Alessandro (2011), "Labour Force Composition and Aggregate Fluctuations," mimeo.

Mukoyama, Toshihiko and Aysegul Sahin (2006), "Costs of Business Cycles for Unskilled Workers," *Journal of Monetary Economics*, Vol. 53(8), pp. 2179-2193.

Orrenius, Pia and Madeline Zavodny (2010), "Immigrants' Employment Outcomes over the Business Cycle," IZA Discussion Paper No. 5354.

Paggiaro, Adriano (2011), "The Effect of Economic Downturns on the Career of Immigrants," mimeo, Centro Studi Economici Antonveneta.

Peri, Giovanni and Chad Sparber (2009) "Task Specialization, Immigration, and Wages," *American Economic Journal: Applied Economics*, Vol. 1(3): 135-169.

Peri, Giovanni and Chad Sparber (2011) "Highly-Educated Immigrants and Native Occupational Choice," *Industrial Relations*, Vol. 50 (3): 385-411.

Table 1: Unemployment Rates within Education Group and Skill Quartile

Skill Quartile within Education Group	Average Unemployment Rate (%)	Standard Deviation, Unemployment	Standard Deviation, Cyclical Component of Unemployment
		High School or Less Education	
Overall	7.84	2.64	0.96
Top Manual Skill Quartile	8.99	3.87	1.97
Bottom Manual Skill Quartile	5.16	1.84	0.78
Top Communication Skill Quartile	4.59	1.64	0.71
Bottom Communication Skill Quartile	9.46	3.27	1.72
Top Quantitative Skill Quartile	5.68	2.09	0.90
Bottom Quantitative Skill Quartile	9.81	3.01	1.50
		Some College or More Education	
Overall	3.96	1.41	0.46
Top Manual Skill Quartile	4.91	1.89	0.77
Bottom Manual Skill Quartile	3.15	1.12	0.47
Top Communication Skill Quartile	2.82	0.99	0.42
Bottom Communication Skill Quartile	5.96	2.26	0.91
Top Quantitative Skill Quartile	3.47	1.28	0.54
Bottom Quantitative Skill Quartile	4.49	1.56	0.72

Table 2: Skill Values within Broad Education Groups

		High School or Less Education	
Skill	***Manual***	***Communication***	***Quantitative***
Mean	0.64	0.35	0.43
Standard Deviation	0.26	0.26	0.29
Bottom Quartile	0.48	0.13	0.18
Median	0.70	0.27	0.39
Top Quartile	0.86	0.53	0.67
		Some College or More Education	
Skill	***Manual***	***Communication***	***Quantitative***
Mean	0.42	0.59	0.55
Standard Deviation	0.28	0.27	0.29
Bottom Quartile	0.19	0.41	0.29
Median	0.39	0.61	0.56
Top Quartile	0.65	0.82	0.78

Table 3: Unemployment and Macroeconomic Shocks

	Dependent Dichotomous Variable: Individual is Unemployed			
	(1)	**(2)**	**(3)**	**(4)**
Macro Variable:	*State Personal Income*		*National GDP*	
State Fixed Effects	*No*	*Yes*	*No*	*Yes*
Time Control	*None*	*Quarter*Year Fixed Effects*	*None*	*Season Fixed Effects + Time Quadratic Trend*
Business Cycle	-0.2262	-0.1886	-0.8125	-0.7035
	(0.0928)**	(0.0461)***	(0.0420)***	(0.0350)***
Business Cycle (Neighbor States)	-0.4159	-0.1877		
	(0.0875)***	(0.2638)		
Female	-0.0031	-0.0032	-0.0032	-0.0032
	(0.0011)***	(0.0011)***	(0.0011)***	(0.0011)***
Age	-0.0066	-0.0065	-0.0066	-0.0065
	(0.0002)***	(0.0002)***	(0.0002)***	(0.0002)***
Age^2	0.0001	0.0001	0.0001	0.0001
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Asian	0.0135	0.0098	0.0135	0.0097
	(0.0027)***	(0.0013)***	(0.0028)***	(0.0014)***
Black	0.0476	0.0489	0.0476	0.0489
	(0.0024)***	(0.0021)***	(0.0024)***	(0.0021)***
Hispanic	0.0079	0.0044	0.0077	0.0044
	(0.0039)*	(0.0025)*	(0.0039)*	(0.0025)*
Other Non-White Race	0.0357	0.0338	0.0359	0.0339
	(0.0035)***	(0.0033)***	(0.0035)***	(0.0033)***
High School Graduate	-0.0382	-0.0401	-0.0383	-0.0401
	(0.0020)***	(0.0019)***	(0.0020)***	(0.0019)***
Some College	-0.0534	-0.0566	-0.0535	-0.0566
	(0.0025)***	(0.0026)***	(0.0025)***	(0.0026)***
Bachelors Degree	-0.0680	-0.0718	-0.0682	-0.0718
	(0.0029)***	(0.0029)***	(0.0029)***	(0.0029)***
Graduate Degree	-0.0727	-0.0765	-0.0728	-0.0765
	(0.0029)***	(0.0031)***	(0.0029)***	(0.0031)***
Foreign-Born	-0.0111	-0.0133	-0.0111	-0.0133
	(0.0015)***	(0.0016)***	(0.0015)***	(0.0016)***
Observations	2264804	2264804	2264804	2264804
R-squared	0.02	0.03	0.02	0.03

* significant at 10%; ** significant at 5%; *** significant at 1%. Individual-level regressions. Dichotomous dependent variable equals one if the individual in the labor force is unemployed. Standard errors are clustered by state. Business Cycle defined by HP Filter of log real quarterly state personal income (Columns 1 & 2) or National GDP (3 & 4) data. Date range January 2000-December 2011. Constant, fixed effects, and time trend coefficients suppressed.

Table 4: Unemployment and Macroeconomic Shocks by Education Level

	Dependent Dichotomous Variable: Individual is Unemployed			
	(1)	**(2)**	**(3)**	**(4)**
Macro Variable:	*State Personal Income*		*National GDP*	
State Fixed Effects	*No*	*Yes*	*No*	*Yes*
Time Control	*None*	*Quarter*Year Fixed Effects*	*None*	*Season Fixed Effects + Time Quadratic Trend*
Cycle * HS Dropout	-0.4869	-0.4522	-1.4231	-1.3248
	(0.1041)***	(0.0708)***	(0.0976)***	(0.0931)***
Cyclec * HS Grad	-0.3386	-0.3059	-1.0110	-0.9045
	(0.1105)***	(0.0644)***	(0.0578)***	(0.0521)***
Cycle * Some College	-0.2068	-0.1671	-0.7424	-0.6317
	(0.0852)**	(0.0389)***	(0.0388)***	(0.0338)***
Cycle* Bachelors	-0.0918	-0.0508	-0.5651	-0.4514
	(0.0877)	(0.0385)	(0.0466)***	(0.0388)***
Cycle * Graduate Deg	0.0756	0.1162	-0.3471	-0.2331
	(0.0808)	(0.0373)***	(0.0288)***	(0.0266)***
Cycle (Neighbor States)	-0.4216	-0.1838		
	(0.0868)***	(0.2599)		
Female	-0.0031	-0.0032	-0.0032	-0.0032
	(0.0011)***	(0.0011)***	(0.0011)***	(0.0011)***
Age	-0.0066	-0.0065	-0.0066	-0.0065
	(0.0002)***	(0.0002)***	(0.0002)***	(0.0002)***
Age^2	0.0001	0.0001	0.0001	0.0001
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Asian	0.0135	0.0097	0.0134	0.0097
	(0.0027)***	(0.0013)***	(0.0027)***	(0.0013)***
Black	0.0476	0.0489	0.0476	0.0489
	(0.0024)***	(0.0021)***	(0.0024)***	(0.0021)***
Hispanic	0.0079	0.0044	0.0077	0.0044
	(0.0039)*	(0.0025)*	(0.0039)*	(0.0025)*
Other Non-White Race	0.0357	0.0338	0.0360	0.0339
	(0.0035)***	(0.0033)***	(0.0035)***	(0.0033)***
High School Graduate	-0.0382	-0.0401	-0.0382	-0.0400
	(0.0020)***	(0.0020)***	(0.0019)***	(0.0019)***
Some College	-0.0534	-0.0566	-0.0533	-0.0564
	(0.0025)***	(0.0026)***	(0.0025)***	(0.0026)***
Bachelors Degree	-0.0680	-0.0718	-0.0680	-0.0716
	(0.0029)***	(0.0029)***	(0.0029)***	(0.0029)***
Graduate Degree	-0.0727	-0.0766	-0.0726	-0.0762
	(0.0030)***	(0.0031)***	(0.0029)***	(0.0031)***
Foreign-Born	-0.0111	-0.0133	-0.0110	-0.0133
	(0.0015)***	(0.0016)***	(0.0016)***	(0.0016)***
Observations	2264804	2264804	2264804	2264804
R-squared	0.02	0.03	0.02	0.03

* significant at 10%; ** significant at 5%; *** significant at 1%. Individual-level regressions. . Dichotomous dependent variable equals one if the individual in the labor force is unemployed. Standard errors are clustered by state. Business Cycle defined by HP Filter of log real quarterly state personal income (Columns 1 & 2) or National GDP (3 & 4) data. Date range January 2000-December 2011. Constant, fixed effects, and time trend coefficients suppressed.

Table 5: Unemployment and Macroeconomic Shocks by Skill

	Dependent Dichotomous Variable: Individual is Unemployed			
	(1)	(2)	(3)	(4)
Macro Variable:	*State Personal Income*		*National GDP*	
State Fixed Effects	*No*	*Yes*	*No*	*Yes*
Time Control	*None*	*Quarter*Year Fixed Effects*	*None*	*Season Fixed Effects + Time Quadratic Trend*
Business Cycle	-0.3371	-0.2997	-1.0072	-0.9055
	(0.1075)***	(0.0637)***	(0.0823)***	(0.0799)***
Business Cycle (Neighbor States)	-0.4045	-0.1409		
	(0.0876)***	(0.2428)		
Cycle * Manual	-0.1577	-0.1559	-0.4067	-0.3921
	(0.0489)***	(0.0487)***	(0.0622)***	(0.0630)***
Cycle * Communication	0.4739	0.4966	0.8817	0.9172
	(0.0607)***	(0.0622)***	(0.0683)***	(0.0690)***
Cycle * Quantitative	-0.0835	-0.1056	-0.0478	-0.0750
	(0.0393)**	(0.0362)***	(0.0630)	(0.0622)
Manual Skill	0.0039	0.0037	0.0038	0.0036
	(0.0017)**	(0.0019)*	(0.0017)**	(0.0019)*
Communication Skill	-0.0439	-0.0436	-0.0437	-0.0432
	(0.0014)***	(0.0013)***	(0.0014)***	(0.0013)***
Quantitative Skill	-0.0097	-0.0094	-0.0097	-0.0095
	(0.0010)***	(0.0011)***	(0.0010)***	(0.0011)***
Observations	2217500	2217500	2217500	2217500
R-squared	0.02	0.03	0.02	0.03

* significant at 10%; ** significant at 5%; *** significant at 1%. Individual-level regressions. Dichotomous dependent variable equals one if the individual in the labor force is unemployed. Standard errors are clustered by state. Business Cycle defined by HP Filter of log real quarterly state personal income (Columns 1 & 2) or National GDP (3 & 4) data. Date range January 2000-December 2011. Regressions include gender, age, age-squared, race, education, and nativity controls. Those estimates, a constant, fixed effects, and time trend coefficients are suppressed.

Table 6: Unemployment and Macroeconomic Shocks by Education Level and Skill

	Dependent Dichotomous Variable: Individual is Unemployed			
	(1)	**(2)**	**(3)**	**(4)**
Macro Variable:	*State Personal Income*		*National GDP*	
State Fixed Effects	*No*	*Yes*	*No*	*Yes*
Time Control	*None*	*Quarter*Year Fixed Effects*	*None*	*Season Fixed Effects + Time Quadratic Trend*
Cycle * HS Dropout	-0.4689	-0.4358	-1.3272	-1.2392
	(0.1097)***	(0.0747)***	(0.1114)***	(0.1080)***
Cyclec * HS Grad	-0.3910	-0.3581	-1.0639	-0.9648
	(0.1208)***	(0.0748)***	(0.0867)***	(0.0840)***
Cycle * Some College	-0.3061	-0.2650	-0.9071	-0.8009
	(0.1029)***	(0.0600)***	(0.0834)***	(0.0818)***
Cycle* Bachelors	-0.2376	-0.1937	-0.8553	-0.7433
	(0.1030)**	(0.0595)***	(0.0911)***	(0.0893)***
Cycle * Graduate Deg	-0.1182	-0.0790	-0.7370	-0.6306
	(0.0956)	(0.0569)	(0.0846)***	(0.0845)***
Business Cycle (Neighbor States)	-0.4074	-0.1392		
	(0.0872)***	(0.2403)		
Cycle * Manual	-0.0828	-0.0782	-0.2958	-0.2766
	(0.0496)	(0.0499)	(0.0617)***	(0.0630)***
Cycle * Communication	0.3589	0.3776	0.7028	0.7315
	(0.0619)***	(0.0616)***	(0.0793)***	(0.0785)***
Cycle * Quantitative	-0.0871	-0.1097	-0.0633	-0.0918
	(0.0395)**	(0.0363)***	(0.0632)	(0.0623)
Manual Skill	0.0039	0.0037	0.0038	0.0036
	(0.0017)**	(0.0019)*	(0.0017)**	(0.0019)*
Communication Skill	-0.0439	-0.0436	-0.0437	-0.0433
	(0.0014)***	(0.0013)***	(0.0014)***	(0.0013)***
Quantitative Skill	-0.0097	-0.0094	-0.0097	-0.0095
	(0.0010)***	(0.0011)***	(0.0011)***	(0.0011)***
Observations	2217500	2217500	2217500	2217500
R-squared	0.02	0.03	0.02	0.03

* significant at 10%; ** significant at 5%; *** significant at 1%. Individual-level regressions. . Dichotomous dependent variable equals one if the individual in the labor force is unemployed. Standard errors are clustered by state. Business Cycle defined by HP Filter of log real quarterly state personal income (Columns 1 & 2) or National GDP (3 & 4) data. Date range January 2000-December 2011. Regressions include gender, age, age-squared, race, education, and nativity controls. Those estimates, a constant, fixed effects, and time trend coefficients are suppressed.

Table 7: Changes in Unemployment Probability by Education and Skill Level

	(1) Median Skill Set (0.5 for all skills)	(2) Top Quartile Manual	(3) Top Quartile Communication	(4) Top Quartile Quantitative
	Macro Variable: State Personal Income			
High School Dropout	-0.341	-0.361	-0.247	-0.368
High School Graduate	-0.263	-0.283	-0.169	-0.291
Some College	-0.170	-0.190	-0.076	-0.198
Bachelors Degree	-0.099	-0.118	-0.004	-0.126
Graduate Degree	0.016	-0.004	0.110	-0.012
	Macro Variable: National GDP			
High School Dropout	-1.058	-1.127	-0.875	-1.081
High School Graduate	-0.783	-0.852	-0.600	-0.806
Some College	-0.619	-0.689	-0.436	-0.642
Bachelors Degree	-0.562	-0.631	-0.379	-0.585
Graduate Degree	-0.449	-0.518	-0.266	-0.472

Table displays the estimated percentage-point change in unemployment probability due to income being 1% above potential. Figures are based upon individual-level regression coefficient estimates from columns 2 and 4 in Table 6. Median skill workers have manual, communication, and quantitative skill values of 0.5. Subsequent columns increase specified skill value to a top quartile value of 0.75, holding other skill values at the median.

Table 8: Asymmetric Effects During Recessions and Expansions

	Dependent Dichotomous Variable: Individual is Unemployed			
	(1)	(2)	(3)	(4)
Macro Variable:	*State Personal Income*		*National GDP*	
State Fixed Effects	*Yes*		*Yes*	
Time Control	*Quarter*Year Fixed Effects*		*Season Fixed Effects + Time Quadratic Trend*	
Economic Conditions:	*Recession*	*Expansion*	*Recession*	*Expansion*
Cycle * HS Dropout	-0.3091	-0.4849	-1.1335	-1.4590
	(0.2524)	(0.1482)***	(0.2518)***	(0.2350)***
Cyclec * HS Grad	-0.2909	-0.3637	-0.8192	-1.1814
	(0.1836)	(0.1199)***	(0.2145)***	(0.1714)***
Cycle * Some College	-0.2559	-0.2819	-0.5633	-1.0008
	(0.1867)	(0.1145)**	(0.2076)***	(0.1790)***
Cycle* Bachelors	-0.0958	-0.1833	-0.4322	-0.8998
	(0.1754)	(0.1003)*	(0.2099)**	(0.1707)***
Cycle * Graduate Deg	-0.0123	-0.0522	-0.2367	-0.4271
	(0.1919)	(0.0917)	(0.2230)	(0.1793)**
Business Cycle (Neighbor States)	0.0746	-0.5740		
	(0.3299)	(0.3459)		
Cycle * Manual	-0.4782	-0.0124	-0.4859	-0.2771
	(0.1391)***	(0.0984)	(0.1341)***	(0.1576)*
Cycle * Communication	0.6324	0.1941	1.2481	0.6212
	(0.1846)***	(0.0980)*	(0.2107)***	(0.1330)***
Cycle * Quantitative	-0.2470	-0.0680	-0.0938	0.0651
	(0.0873)***	(0.0657)	(0.1331)	(0.1007)
Manual Skill	-0.0038	0.0050	-0.0007	0.0055
	(0.0024)	(0.0022)**	(0.0022)	(0.0030)*
Communication Skill	-0.0393	-0.0420	-0.0335	-0.0456
	(0.0023)***	(0.0021)***	(0.0027)***	(0.0021)***
Quantitative Skill	-0.0118	-0.0093	-0.0095	-0.0110
	(0.0017)***	(0.0015)***	(0.0021)***	(0.0016)***
Observations	1135539	1081961	1088886	1128614
R-squared	0.03	0.03	0.03	0.03

* significant at 10%; ** significant at 5%; *** significant at 1%. Individual-level regressions estimated separately for recessions and expansions. . Dichotomous dependent variable equals one if the individual in the labor force is unemployed. Standard errors are clustered by state. Business Cycle defined by HP Filter of log real quarterly state personal income (Columns 1 & 2) or National GDP (3 & 4) data. Date range January 2000-December 2011. Regressions include gender, age, age-squared, race, education, and nativity controls. Those estimates, a constant, fixed effects, and time trend coefficients are suppressed.

Table 9: Longitudinal Results

	Dependent Dichotomous Variable: Individual is Unemployed			
	(1)	**(2)**	**(3)**	**(4)**
Macro Variable:	*State Personal Income*		*National GDP*	
Time Control	*Quarter*Year Fixed Effects*		*Season Fixed Effects + Time Quadratic Trend*	
Individual Fixed Effects	*No*	*Yes*	*No*	*Yes*
Cycle * HS Dropout	-0.4367	-0.1004	-1.1805	-0.6155
	(0.0758)***	(0.1160)	(0.0953)***	(0.1778)***
Cyclec * HS Grad	-0.3173	-0.0134	-0.8965	-0.4660
	(0.0817)***	(0.1062)	(0.0754)***	(0.1575)***
Cycle * Some College	-0.2753	0.0021	-0.7834	-0.4100
	(0.0774)***	(0.1160)	(0.0683)***	(0.1634)**
Cycle* Bachelors	-0.2086	0.0571	-0.7202	-0.3488
	(0.0694)***	(0.0976)	(0.0678)***	(0.1775)*
Cycle * Graduate Deg	-0.0900	0.1216	-0.6121	-0.3225
	(0.0615)	(0.1326)	(0.0527)***	(0.1507)**
Business Cycle (Neighbor States)	-0.0169	0.0043		
	(0.2692)	(0.3355)		
Cycle * Manual	-0.0887	-0.1856	-0.2403	-0.1614
	(0.0564)	(0.1082)*	(0.0662)***	(0.1305)
Cycle * Communication	0.4144	0.1976	0.6984	0.3299
	(0.0444)***	(0.1277)	(0.0475)***	(0.1638)**
Cycle * Quantitative	-0.1136	-0.0821	-0.1074	-0.0833
	(0.0408)***	(0.0647)	(0.0533)**	(0.0864)
Manual Skill	0.0019		0.0017	
	(0.0019)		(0.0019)	
Communication Skill	-0.0393		-0.0385	
	(0.0013)***		(0.0013)***	
Quantitative Skill	-0.0065		-0.0066	
	(0.0007)***		(0.0007)***	
Observations	1520281	1520281	1520281	1520281
R-squared	0.03	0.8	0.03	0.8

* significant at 10%; ** significant at 5%; *** significant at 1%. Panel regressions include only individuals observed in the labor force in both year t and t+1. Standard errors are clustered by state. Business Cycle defined by HP Filter of log real quarterly state personal income (Columns 1 & 2) or National GDP (3 & 4) data. Date range January 2000-December 2011. Regressions include gender, age, age-squared, race, education, and nativity controls. Those estimates, a constant, fixed effects, and time trend coefficients are suppressed.

Table 10: Unemployment and Macroeconomic Shocks by Education Level and Skill, Industry Fixed Effects

	Dependent Dichotomous Variable: Individual is Unemployed					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Industry	*All*	*Health Care*	*Manufacturing*	*Retail*	*Education*	*Construction*
Macro Variable:			*State Personal Income*			
Cycle * Manual	-0.0782	0.0646	-0.3671	0.1813	0.1909	-0.8202
	(0.0499)	(0.0992)	(0.1757)**	(0.1956)	(0.1174)	(0.3219)**
Cycle * Communication	0.3776	0.2130	0.4441	-0.0825	0.2547	0.1568
	(0.0616)***	(0.0757)***	(0.2114)**	(0.2283)	(0.1887)	(0.4026)
Cycle * Quantitative	-0.1097	-0.0483	0.1534	0.1696	-0.4762	-0.2430
	(0.0363)***	(0.0666)	(0.1581)	(0.1323)	(0.1368)***	(0.2181)
Macro Variable:			*National GDP*			
Cycle * Manual	-0.2597	0.0128	-0.6856	0.1681	-0.0326	-1.4385
	(0.0638)***	(0.1143)	(0.2030)***	(0.2557)	(0.1459)	(0.2508)***
Cycle * Communication	0.6889	0.2244	0.5936	0.0123	0.2492	0.5738
	(0.0778)***	(0.1072)**	(0.2255)**	(0.2957)	(0.1966)	(0.4078)
Cycle * Quantitative	-0.0746	-0.0570	0.5768	0.2978	-0.4566	-0.2262
	(0.0647)	(0.1046)	(0.2031)***	(0.2023)	(0.1876)**	(0.3563)
Observations	2217500	274246	270078	244972	197554	174178

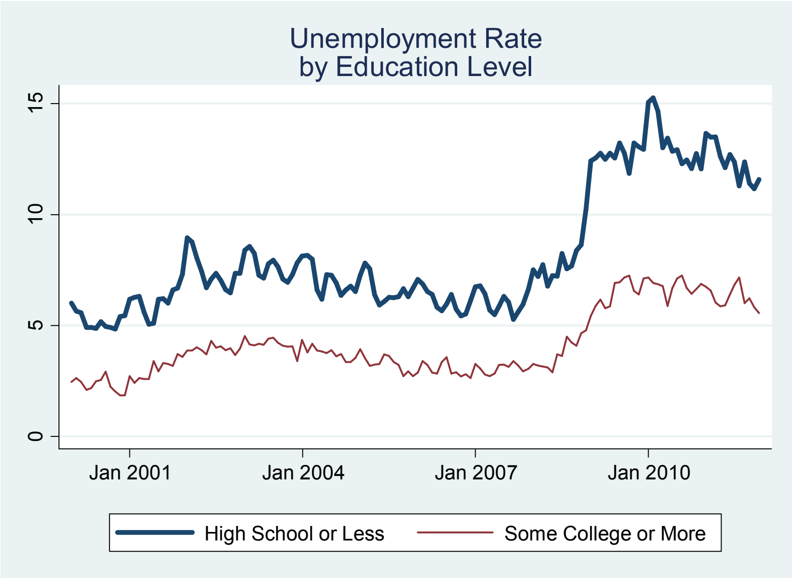
* significant at 10%; ** significant at 5%; *** significant at 1%. Individual-level regressions. . Dichotomous dependent variable equals one if the individual in the labor force is unemployed. Standard errors are clustered by state. Business Cycle defined by HP Filter of log real quarterly state personal income (top panel) or National GDP (bottom panel) data. Date range January 2000-December 2011. Column (1) includes industry-specific time controls. Regressions in columns (2)-(6) include time controls and are performed within specific industries. All regressions include gender, age, age-squared, race, education, skill, and nativity controls, plus interactions of education with business cycles. Those estimates, a constant, fixed effects, and time trend coefficients are suppressed.

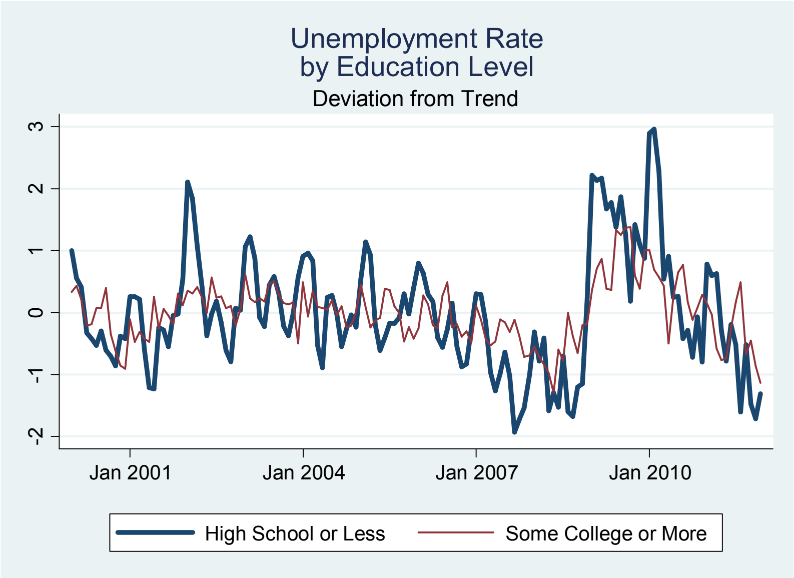
Table 11: Usual Hours Worked per Week, Weekly Earnings, and Macroeconomic Shocks by Skill

	(1)	(2)	(3)	(4)
Dependent Variable:	**ln(Earnings)**	**Usual Hours**	**ln(Earnings)**	**Usual Hours**
Macro Variable:	*State Personal Income*		*National GDP*	
State Fixed Effects	*Yes*		*Yes*	
Time Control	*Quarter*Year Fixed Effects*		*Season Fixed Effects + Time Quadratic Trend*	
Cycle * HS Dropout	0.7415	6.7960	0.9580	19.9356
	(0.2662)***	(2.8457)**	(0.2259)***	(3.2645)***
Cyclec * HS Grad	0.7475	6.5807	0.7342	18.9334
	(0.2068)***	(2.4017)***	(0.1894)***	(3.2840)***
Cycle * Some College	0.8970	6.5495	0.8531	19.1071
	(0.2019)***	(2.5125)**	(0.1855)***	(3.1047)***
Cycle* Bachelors	0.8525	1.8784	0.8212	13.9661
	(0.1937)***	(2.3520)	(0.2098)***	(3.0368)***
Cycle * Graduate Deg	0.6297	3.6821	0.6091	15.6269
	(0.2288)***	(2.8647)	(0.2333)**	(3.2180)***
Business Cycle (Neighbor States)	0.0971	6.0396		
	(0.6915)	(4.9052)		
Cycle * Manual	-0.0993	3.7232	-0.2464	6.4533
	(0.1317)	(1.6277)**	(0.1943)	(2.5374)**
Cycle * Communication	-0.8178	-6.8075	-1.4367	-18.3922
	(0.1385)***	(2.2745)***	(0.1522)***	(2.9896)***
Cycle * Quantitative	-0.0886	-1.5908	0.0344	-0.9269
	(0.1554)	(1.5079)	(0.1722)	(2.4862)
Manual Skill	-0.1013	0.9202	-0.1013	0.9212
	(0.0090)***	(0.1160)***	(0.0090)***	(0.1156)***
Communication Skill	0.3934	3.8857	0.3932	3.8829
	(0.0098)***	(0.0737)***	(0.0099)***	(0.0732)***
Quantitative Skill	0.1645	3.0328	0.1643	3.0324
	(0.0063)***	(0.0784)***	(0.0063)***	(0.0784)***
Observations	1846904	1933151	1846904	1933151
R-squared	0.31	0.12	0.31	0.12

* significant at 10%; ** significant at 5%; *** significant at 1%. Individual-level regressions. Standard errors are clustered by state. Business Cycle defined by HP Filter of log real quarterly state personal income (Columns 1 & 2) or National GDP (3 & 4) data. Date range January 2000-December 2011. Regressions include gender, age, age-squared, race, education, and nativity controls. Those estimates, a constant, fixed effects, and time trend coefficients are suppressed.

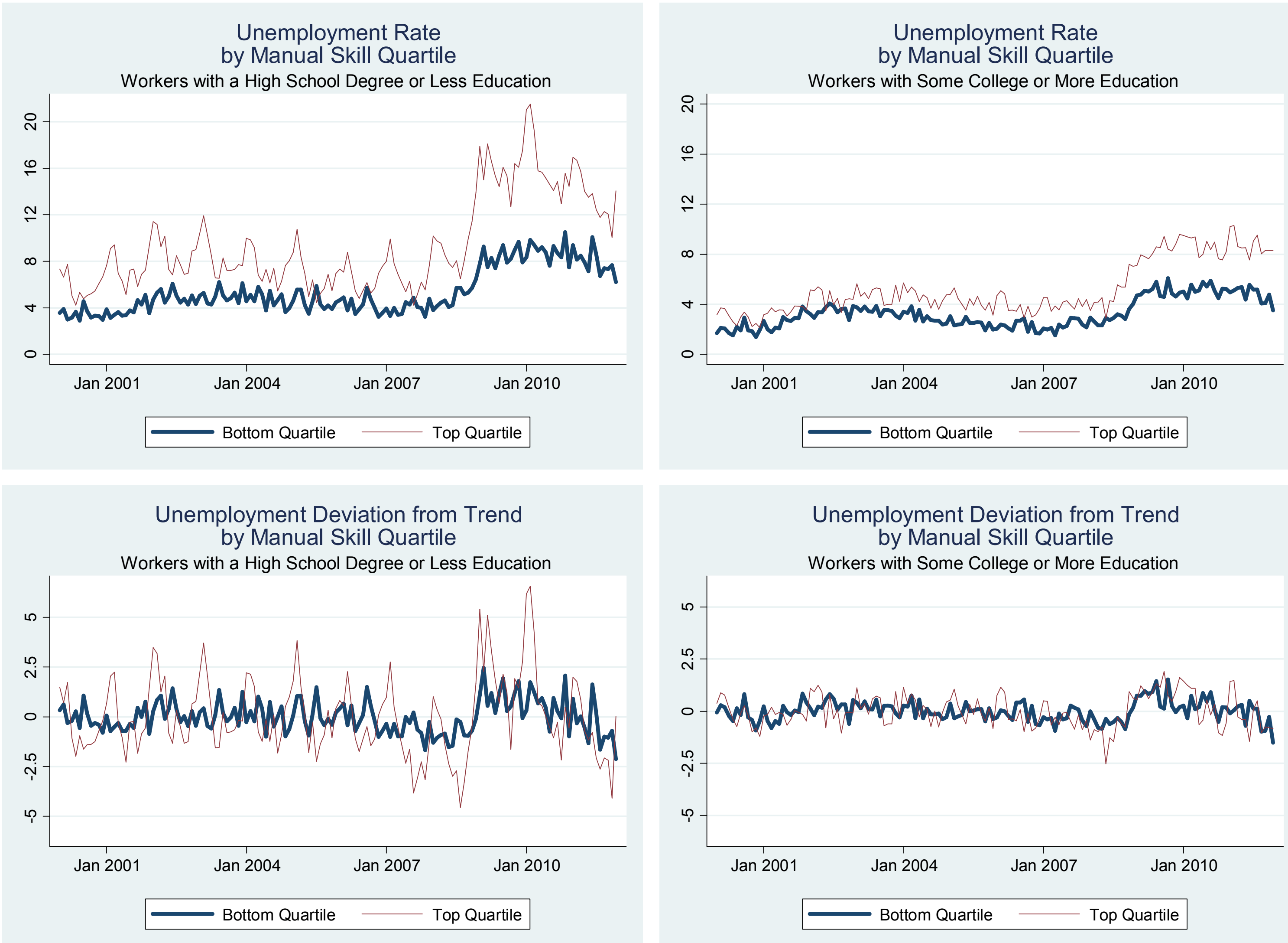
Figure 1





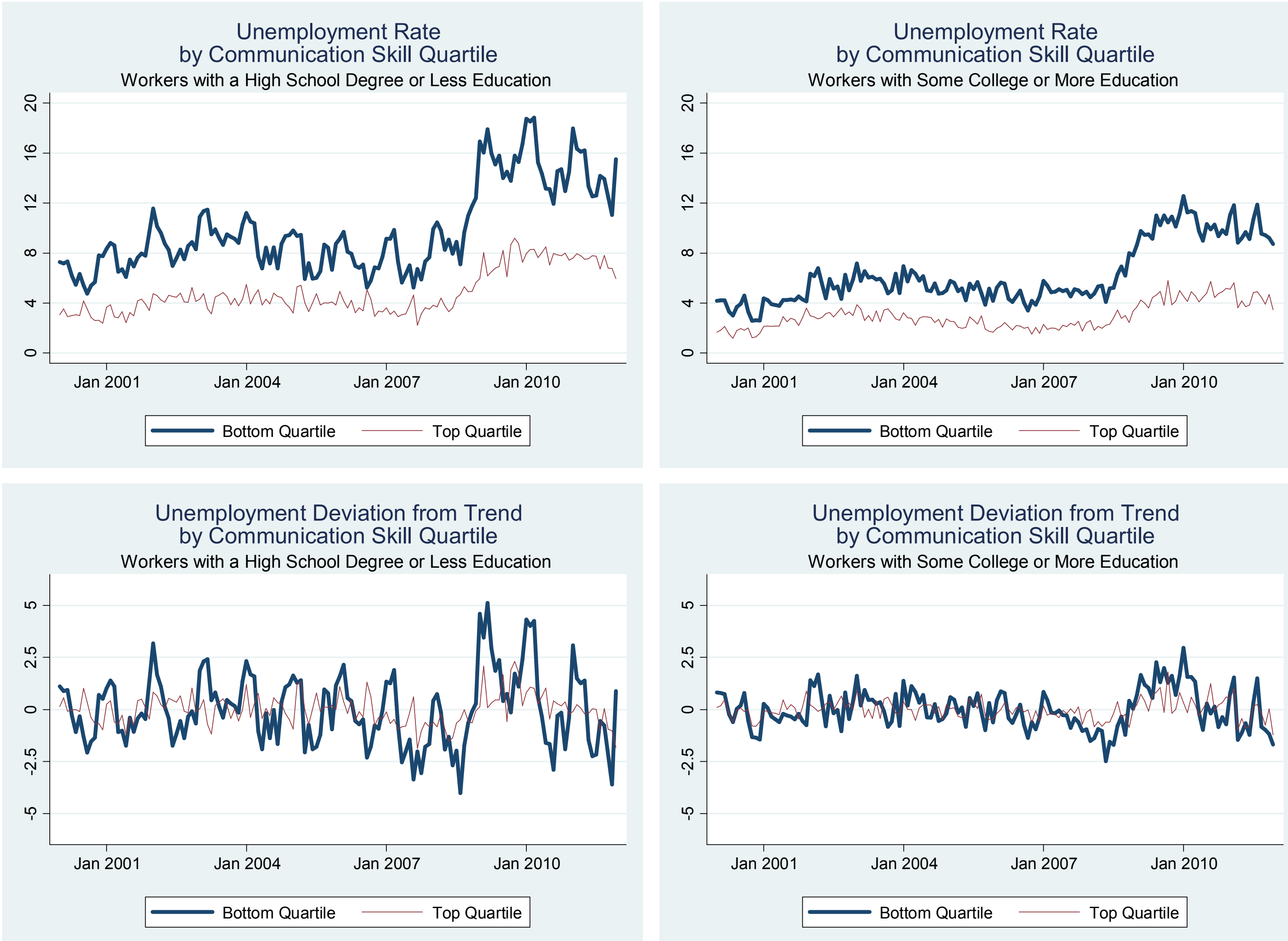
Source: Monthly CPS-ORG files. Cyclical component calculated using the HP Filter with a smoothing parameter for monthly data of 14,400.

Figure 2: Unemployment Rates by Education and Manual Skill Quartile



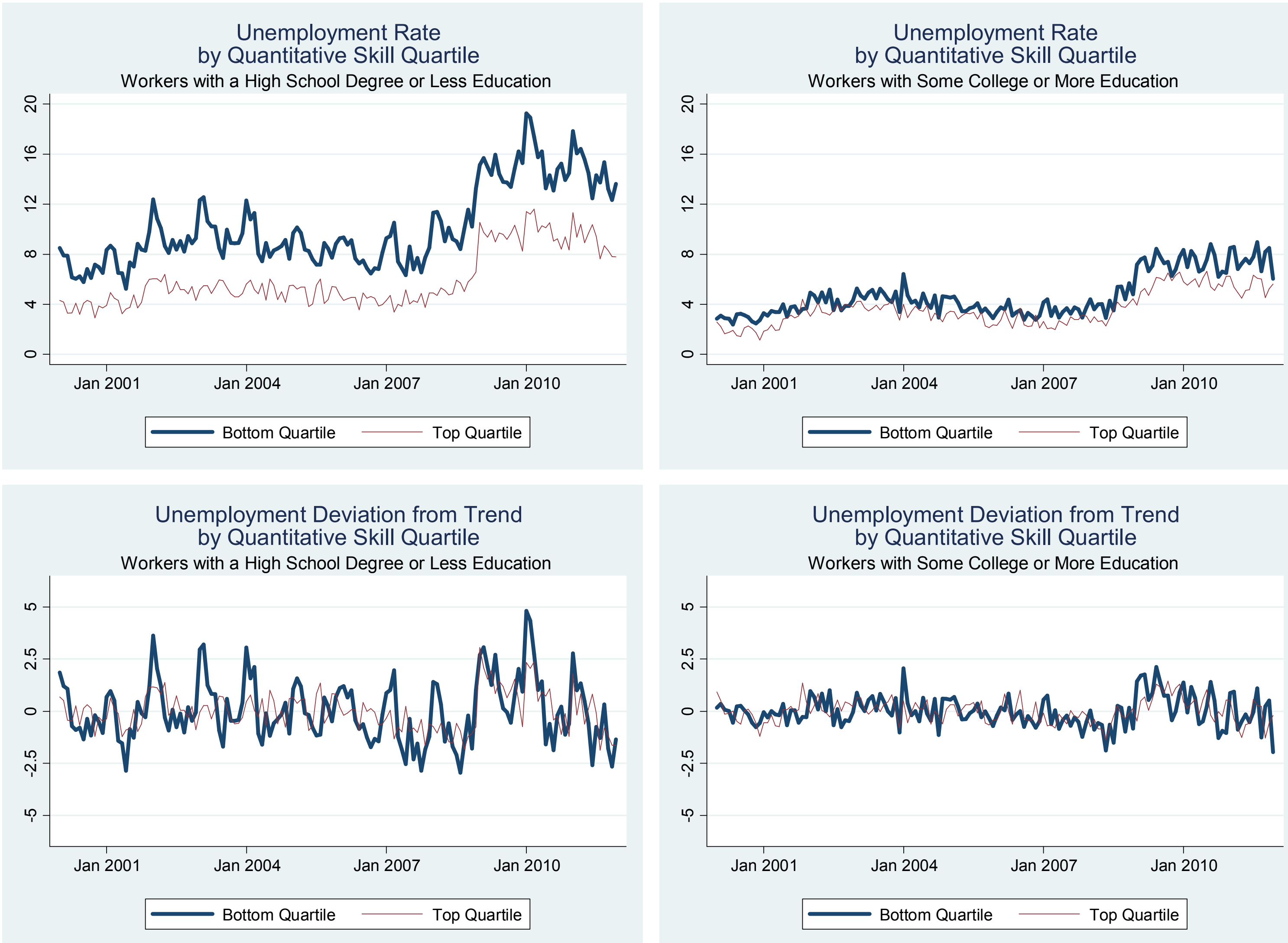
Source: Monthly CPS-ORG files. Cyclical component calculated using the HP Filter with a smoothing parameter for monthly data of 14,400.

Figure 3: Unemployment Rates by Education and Communication Skill Quartile



Source: Monthly CPS-ORG files. Cyclical component calculated using the HP Filter with a smoothing parameter for monthly data of 14,400.

Figure 4: Unemployment Rates by Education and Quantitative Skill Quartile



Source: Monthly CPS-ORG files. Cyclical component calculated using the HP Filter with a smoothing parameter for monthly data of 14,400.