11-1-2011

# Unemployment, Skills, and the Business Cycle Since 2000

Chad Sparber
*Colgate University*, csparber@colgate.edu

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November 2011

**Abstract**

This paper employs reduced-form microeconometric analysis to examine how yearly changes in aggregate income and GDP growth 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

*Sparber is Assistant Professor of Economics, 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. The standard deviation of quarterly real GDP growth over the period was 0.7%.

Rising unemployment is one of the biggest concerns of macroeconomic contraction. Differences in unemployment rates by education level are well-documented. Between January 2000 and December 2010, the average US unemployment rate among individuals with a high school degree or less education was 7.8%, whereas unemployment equalled just 4.0% 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 2.6 percentage-points for less-educated workers, nearly twice the figure for college-educated labor (1.4 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. 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 changes in individual unemployment outcomes on changes in 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 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 volatility (in hours worked) compared with other demographic groups.[1] 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 semiparametric 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.

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

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.[2] The 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 14400. 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 than for college-educated workers.

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). Suppose labor market outcomes ($Y$) of individual $i$ living in state $s$ at time $t$ are determined by the following:

$$
\begin{aligned}
Y_{i,s,t} &= \alpha_0 + \alpha \cdot T + \beta \cdot M_{s,t} + \gamma_0 \cdot X_i + \gamma \cdot X_i \cdot T + \delta_0 \cdot d_s + \varepsilon_{i,s,t} \qquad (1) \\
\text{where } T &= \text{Time trend} \\
M &= \text{Macroeconomic variable of interest} \\
X &= \text{Time-invariant demographic characteristics} \\
d_s &= \text{State dummy} \\
\varepsilon &= \text{Idiosyncratic error term}
\end{aligned}
$$

By annually first-differencing Equation (1), we can eliminate effects from state (and other fixed) factors, and identify labor market effects driven by *changes* in macroeconomic conditions over the

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

course of a year:

$$(Y_{i,s,t} - Y_{i,s,t-1}) = \alpha + \beta \cdot (M_{s,t} - M_{s,t-1}) + \gamma \cdot X_i + (\varepsilon_{i,s,t} - \varepsilon_{i,s,t-1}) \tag{2}$$

In Equation (2), $\beta$ represents the effect of a change in macroeconomic conditions on an average worker. We can enrich the model further by interacting $(M_{s,t} - M_{s,t-1})$ with various skill measures and/or by allowing slopes specific to skills or education levels.

## 3 Data

The model in Equation (2) 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 mesured in constant 2010 dollars).

The NBER provides monthly CPS-ORG individual-level data 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 biannual longitudinal dataset by identifying individual survey respondents and merging their surveys from years $t$ and $t + 1$. We use this information to construct changes in labor market outcomes (unemployment) for individuals over the course of a calendar year.[3]

The chief contribution of the 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.[4] *O*NET* provides skill measures for each SOC-defined occupation. Each value is

[3] A major limitation of the CPS-ORG files is that it is a household survey. Individuals will leave the sample (and hence cannot be longitudinally matched) if they move. Thus, individual-level regressions using longitudinal individual-level CPS-ORG data could be biased if economic shocks spur labor mobility.

[4] The procedure for calculating skill values is outlined in Peri and Sparber (2009, 2011). Manual skills average responses

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). Discussion of regression results in Table 7 provides further examples of occupational skill values.

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 2010, though first-differencing removes one year of the data. We use data only on residents of the contiguous 48 states and excluding the District 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. 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 sta-

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.

tistics 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 both among 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 Results

## 4.1 Results from Monthly CPS-ORG Data

Table 3 displays results from the most basic regression of Equation (2). The dependent variable measures changes in various individual outcomes, while the independent variable measures changes in macroeconomic conditions. The model controls for gender, a quadratic for age, race, educational attainment, and nativity, but it assumes that macroeconomic shocks affect all individuals equally. Standard errors cluster by state. Columns 1-3 exploit regional variation by adopting (log) 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.[5] Aggregate data is recorded quarterly, but changes are measured over the course of a year. Since the macro variables are measured in logs, changes represent growth rates, and coefficients can be interpreted as effects from percentage-point changes in the macro growth rates.

Column 1 is a linear probability model exploring the determinants of whether an individual in the labor force in year $t-1$ left the sample in year $t$. The CPS-ORG is a household sample, so individuals appearing in year $t-1$ but not year $t$ likely moved (though they may leave the sample for other reasons, such as death). Column 1 uncovers no correlation between mobility and own-state income, but people are roughly 10.9 percentage-points more likely to leave the sample (e.g., move) when neighboring states experience a 1%-point increase in the state personal income growth rate.

Columns 2-3 present estimates for unemployment regressions. Inability to measure outcomes for individuals who leave the CPS-ORG sample between years can lead to a sample selection bias. Columns 2 and 3 therefore best represent the unemployment effects of macroeconomic shocks among people who

[5] More formally, state $s$'s neighboring state macro conditions are represented by $Macro_s^{Neighbor} = \frac{\sum_n^{47}\left(\frac{1}{Dist_n}\right)\cdot Macro_n}{\sum_n^{47}\left(\frac{1}{Dist_n}\right)}$, where $n$ is a contiguous US state other than state $s$, $Dist_n$ is the distance between states $s$ and $n$, and $Macro_n$ is the relevant macroeconomic condition in state $n$.

do not move. In column 2, we include all individuals in the labor force in year $t-1$. Since the dependent variable is measured in first-differences, an unemployed person in $t-1$ who finds employment in year $t$ will record a value of -1. Column 3, in contrast, includes only those who were employed in year $t-1$, so the dependent variable records only values of zero or one – results represent the probability of an employee becoming unemployed. Neighboring state income is associated with unemployment in both regressions. Evidence for own-state income effects occur only in Column 3 – a 1%-point increase in own-state personal income growth rates are associated with 0.14 percentage-point decrease in the probability of an employee becoming unemployed.

Columns 4-6 adopt the same methodology as columns 1-3 but use national real GDP as the measure of macroeconomic performance as a substitute for state and neighboring state personal income. The results are quite comparable. A 1%-point increase in the national GDP growth rate is associated with a 5.5 percentage-point increase in the probability of moving, and a 0.24-0.37 percentage-point decrease in the probability of being unemployed (among those who do not move). For context, the Great Recession of December 2007 through June 2009 saw an output loss of 4%, and is therefore associated with estimated mobility and unemployment effects four times those values.

Empirical work in Hoynes (2000), Orrenius and Zavodny (2010), and others notes that economic shocks have a heterogenous 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 and 4 demonstrate a nearly monotonic relationship such that workers with more educational attainment are much more likely to respond to shocks by moving, relative to their less-educated counterparts, though coefficients are insignificant in Column 1. Among people who do not move, however, macroeconomic declines are much more likely to result in job losses among people with little educational attainment. Column 3 suggests that a 1%-point decline in the state personal income growth rate is associated with a 0.31 percentage-point rise in the probability of being unemployed for high school dropouts, but an insignificant effect among those with a graduate degree. Magnitudes are larger when using national-level real GDP as the macro variable (Columns 5 and 6), 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. Recall that skill data is available for all members of the labor force, and is specific to a person's current occupation (or in the case of the unemployed, a person's most recent occupation). Though skills will change if a person changes occupations between years $t-1$ and $t$, we treat them as time-invariant and fixed in year $t-1$. Note that since the model in Equation (2) is expressed in first differences, the coefficients on the skills themselves account for trend behavior. If US manufacturing and manually-intensive occupations are steadily declining, for example, associated unemployment effects will be captured by these control variables. Interaction terms 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. We also introduce 20 aggregated BEA industry fixed effects to control for industry-trends in unemployment over the period.[6]

Column 1 demonstrates that a skilless individual in a state experiencing a 1 percentage-point increase in the aggregate personal income growth rate is 0.36 percentage-points more likely to move (though the coefficient itself is insignificant). This effect is amplified for workers with high communication skills, but dampened by those with high manual skills: For every decile increase in a person's communication skill, effects from the same macro shock increase by 0.05 percentage-points. For every decile increase in a person's manual skill, the effects are mitigated by 0.06 percentage-points.

More interestingly, columns 2 and 3 report results from unemployment regressions. The role of skills is most clearly visible in column 3. First, it finds the typical result that positive macro shocks decrease the probability of an employed person becoming unemployed – a 1 percentage-point decline in income is associated with a 0.23 percentage-point rise in unemployment for the general worker. 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. The median communication worker, for example, experiences only a 0.09 percentage-point rise in unemployment probability for the same income shock. Results for all workers (column 2) are similar, though we also see evidence that workers engaged in manually-intensive work see heightened sensitivity to business cycle fluctuations.

These results are echoed when using national real GDP as the dependent variable (Columns 4-6). Mobility among communication-intense workers is more sensitive to macro shocks than among manual laborers, though there is now evidence that mobility among workers with high quantitative skill is also sensitive to income fluctuations. In both columns 5 and 6, we see that GDP shocks have little effect on employment opportunities of communication-intense workers. Column 5, finds that not only do high manual skill workers experience greater sensitivity to income shocks, but high quantitative skill workers do as well. Both of these effects disappear in column 6.

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

[6] As with occupations, the CPS asks individuals to state their current industry of employment, or in the case of the unemployed, their most recent industry of employment.

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 3, 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 (0.238) remains positive, significant, and similar in magnitude 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 0.024 percentage-point decrease in the negative correlation between state income and a worker's probability of becoming unemployed. Column 5 and 6 results using national GDP find similar effects, with Column 5 mirroring the result in Table 5 that manual and quantitative skills increase unemployment sensitivity to GDP shocks.

Table 7 provides an alternative view of the unemployment estimates of results 3 and 6 in Table 6 by displaying estimates for pairs of occupations similar along two skill dimensions but different along the third. Figures in the final columns represent the estimated percentage-point change in an employed worker becoming unemployed due to a one percentage-point increase in aggregate income growth rates. Estimates vary across educational attainment and skill level, and are presented for both state income and national GDP macro shocks.

The top panel lists occupations with similar manual and communication values, but different quantitative skill. We see no meaningful differences in estimated unemployment probabilities across occupations. This is not surprising given the small coefficients on the quantitative skill interaction terms in Table 6. The middle panel displays occupation pairs with similar manual and quantitative skill, but different communication content. Unlike with quantitative skills, differences in unemployment probabilities can be quite large for workers with different communication skill. For example, a one percentage-point decline in the state income growth rate will increase the probability of an actuary with a bachelors degree becoming unemployed by 0.1 percentage-points. The same shock increases the probability of unemployment for financial analysts – a similar occupation but with greater communication content – by just half of that amount. Workers with similar communication and quantitative skill but different manual ability also exhibit differences in unemployment probabilities. Those differences are much smaller than with communication skill disparities, however. Altogether, the table gives a sense that skills (particularly communication skills) are relevant in determining the unemployment effects of aggregate income shocks.

## 4.2 Industry Controls

Labor market outcomes can vary significantly across industries.[7] 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, will be much more apparent in the manufacturing industry than in educational services. Though our Tables 5-7 included industry fixed-effects to control for industry trends, we 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 rather try to find employment in industries employing many communication workers.

Table 8 addresses industry concerns. Specifications resemble columns 3 and 6 of Tables 5 and 6 – the dependent variable represents the change in probability that an employed person becomes unemployed. 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 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-specific quadratic time trends. These specifications have the advantage of controlling for all time shocks specific to industries, but come at the cost of reducing much data variation and 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 an employee becoming unemployed, but each decile increase in communication skill mitigates this probability by 0.1 percentage points. The magnitude of this effect is similar for US GDP regressions, but larger standard errors make the effect insignificant (p-value of 0.20).

Columns 2-6 focus on the five US industries that together comprise more than 50% of US employment during the period. Regressions continue to include date dummies or quadratic time terms, as well as the usual explanatory variables. Top panel results demonstrates that communication-intensive workers are less-sensitive to business cycle shocks than their coworkers in manufacturing and retail. Quantitative-skill employees in health care and education are similarly protected from state income

[7] The US Beureau 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.

volatility relative to other workers in those industries. Manual labor in education is more sensitive to income fluctuations. Interestingly, however, many of these results disappear in regressions that use national GDP as the macro variable (bottom panel), so these effects are not as robust as in previous regressions.

### 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.[8] 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 (2) to estimate how skills affect the relationship between macroeconomic performance and these labor market outcomes.

The regressions in Table 9 are analogous to the unemployment specifications in Table 5. They control for gender, age, age-squared, education, skill, nativity, and industry (though coefficients on these variables are not displayed). Macroeconomic variables are interacted with skill but not educational attainment. The first two columns adopt the annual change in usual weekly hours worked as the dependent variable; the second two columns analyze the change in inflation-adjusted weekly earnings. Columns 1 and 3 include all members of the labor force that could be identified in periods $t-1$ and $t$. The unemployed are assigned hours worked and earnings values of zero. Columns 2 and 4 only include those employed in both periods. The top panel uses state personal income as the macro variable; the bottom panel uses national GDP.

The results for usual hours worked are broadly consistent with those in previous regressions. In Column 1, we see that increases in own-state and neighboring state personal income are associated with increases in usual hours worked – a one percentage-point increase in own-state personal income growth is associated with a 0.086 hour increase in hours worked. This relationship is weakened, however, for workers with high communication skills – workers at the 64th percentile of communication skill experience no estimated effect from own-state shocks. Estimates from national GDP shocks are similar. A one percentage-point increase in national GDP is associated with a 0.29 rise in hours worked for a person without skills, but this effect decreases by a factor of ten for workers in the most communication-intensive occupations.

While Column 1 examined effects for the labor force, Column 2 includes only those who were

[8] See Mennuni (2011), Balleer 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.

employed in years $t-1$ and $t$. By effectively eliminating individuals with zero hours worked, the magnitudes of the coefficient estimates decline markedly. For regressions using state personal income, coefficients on own-state income and the interaction with communication skills become insignificant. For regressions using national GDP, coefficients on the macro shock and communication-interaction variables decrease by more than one half, though it remains true that hours worked among employees using communication skills are less sensitive to economic fluctuations.

Evidence for effects on real weekly earnings (Columns 3 and 4) is less clear. Coefficients on own-state income, neighboring-state income, and national GDP are insignificant but usually positive in sign. When the entire labor force is included, the negative and significant coefficients on the communication interaction terms, when coupled with the positive though insignificant coefficients on the macro variables alone, indicate that communication-intensive workers are again less-sensitive to macro conditions. Significant results for the communication interaction term disappear, however, when dropping unemployed individuals from the regression.

Results for hours worked and earnings regressions allowing interaction terms with education levels (analogous to Table 6's unemployment specifications) deliver comparable results and are available upon request. Workers in communication-intensive occupations experience less volatility in hours worked from macroeconomic shocks than other workers do, especially in regressions that include both employed and unemployed workers. Estimates from earnings regressions are less clear. Altogether, however, we believe that the results in this section largely concur with those from earlier sections. Macroeconomic fluctuations have a weaker association with labor market outcomes for communication-intensive workers.

# 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 income growth is associated with roughly a 0.2 to 0.3 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 unemployment 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 re-training programs geared toward developing communication skills to reduce new entrants into cyclical unemployment.

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**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 |

Values represent proportion of workers who use less of a given skill.

## Table 3: Unemployment and Macroeconomic Shocks

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Dependent Variable:* | *Left Sample* | *Δ Unemployed* | *Δ Unemployed* | *Left Sample* | *Δ Unemployed* | *Δ Unemployed* |
| *Regression Includes Those Who Were:* | *In Labor Force in t-1* | *In Labor Force in t-1* | *Employed in t* | *In Labor Force in t-1* | *In Labor Force in t-1* | *Employed in t* |
| | | *In Sample in t* | *In Sample in t* | | *In Sample in t* | *In Sample in t* |
| *Macro Variable:* | *State Personal Income* | *State Personal Income* | *State Personal Income* | *National GDP* | *National GDP* | *National GDP* |
| *Frequency of Macro Variable* | *Monthly* | *Monthly* | *Monthly* | *Monthly* | *Monthly* | *Monthly* |
| Δln(Macro) | 0.358 | -0.008 | -0.144 | 5.474 | -0.371 | -0.238 |
| | (0.710) | (0.043) | (0.039)*** | (0.063)*** | (0.029)*** | (0.025)*** |
| Δln(Macro), Neighboring States | 10.892 | -0.418 | -0.222 | | | |
| | (0.830)*** | (0.054)*** | (0.052)*** | | | |
| Female | -0.010 | -0.007 | -0.006 | -0.010 | -0.007 | -0.006 |
| | (0.001)*** | (0.001)*** | (0.001)*** | (0.001)*** | (0.001)*** | (0.001)*** |
| Age | -0.029 | 0.003 | -0.003 | -0.030 | 0.003 | -0.003 |
| | (0.001)*** | (0.000)*** | (0.000)*** | (0.001)*** | (0.000)*** | (0.000)*** |
| Age^2 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** |
| Asian | 0.013 | 0.000 | 0.006 | 0.022 | 0.000 | 0.006 |
| | (0.008) | (0.002) | (0.002)*** | (0.005)*** | (0.002) | (0.002)*** |
| Black | 0.051 | -0.013 | 0.014 | 0.053 | -0.013 | 0.014 |
| | (0.006)*** | (0.003)*** | (0.001)*** | (0.005)*** | (0.003)*** | (0.001)*** |
| Hispanic | 0.018 | -0.001 | 0.005 | 0.029 | -0.002 | 0.005 |
| | (0.010)* | (0.003) | (0.002)*** | (0.008)*** | (0.003) | (0.002)*** |
| Other Race | 0.055 | -0.005 | 0.017 | 0.077 | -0.006 | 0.016 |
| | (0.009)*** | (0.005) | (0.003)*** | (0.008)*** | (0.005) | (0.003)*** |
| High School Graduate | -0.028 | 0.013 | -0.012 | -0.030 | 0.013 | -0.012 |
| | (0.003)*** | (0.002)*** | (0.001)*** | (0.003)*** | (0.002)*** | (0.001)*** |
| Some College | -0.037 | 0.015 | -0.017 | -0.036 | 0.014 | -0.017 |
| | (0.003)*** | (0.002)*** | (0.002)*** | (0.004)*** | (0.002)*** | (0.002)*** |
| Bachelors Degree | -0.048 | 0.017 | -0.024 | -0.047 | 0.016 | -0.024 |
| | (0.004)*** | (0.002)*** | (0.002)*** | (0.004)*** | (0.002)*** | (0.002)*** |
| Graduate Degree | -0.045 | 0.017 | -0.027 | -0.046 | 0.017 | -0.027 |
| | (0.004)*** | (0.002)*** | (0.002)*** | (0.004)*** | (0.002)*** | (0.002)*** |
| Foreign-Born | 0.021 | 0.001 | -0.002 | 0.021 | 0.001 | -0.002 |
| | (0.004)*** | (0.001) | (0.001) | (0.004)*** | (0.001) | (0.001) |
| Constant | 0.960 | -0.083 | 0.116 | 1.043 | -0.082 | 0.115 |
| | (0.014)*** | (0.005)*** | (0.005)*** | (0.015)*** | (0.005)*** | (0.005)*** |
| Observations | 1101600 | 537972 | 516236 | 1101600 | 537972 | 516236 |
| R-squared | 0.19 | 0.00 | 0.01 | 0.09 | 0.00 | 0.01 |

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Individual-level regressions. Left Sample is a dichotomous variable measuring whether individuals left the sample between periods *t-1* and *t*. Unemployed is a dichotomous variable measuring whether a person was unemployed. Standard errors are clustered by state. Date range for time *t*: January 2001-December 2010.

## Table 4: Unemployment and Macroeconomic Shocks by Education Level

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Dependent Variable:* | *Left Sample* | *Δ Unemployed* | *Δ Unemployed* | *Left Sample* | *Δ Unemployed* | *Δ Unemployed* |
| *Regression Includes Those Who Were:* | *In Labor Force in t-1* | *In Labor Force in t-1* | *Employed in t* | *In Labor Force in t-1* | *In Labor Force in t-1* | *Employed in t* |
| | | *In Sample in t* | *In Sample in t* | | *In Sample in t* | *In Sample in t* |
| *Macro Variable:* | *State Personal Income* | *State Personal Income* | *State Personal Income* | *National GDP* | *National GDP* | *National GDP* |
| *Frequency of Macro Variable* | *Monthly* | *Monthly* | *Monthly* | *Monthly* | *Monthly* | *Monthly* |
| Δln(Macro)*HS Dropout | -0.049 | -0.138 | -0.314 | 4.960 | -0.641 | -0.439 |
| | (0.671) | (0.087) | (0.069)*** | (0.139)*** | (0.093)*** | (0.084)*** |
| Δln(Macro)*HS Graduate | 0.231 | -0.024 | -0.186 | 5.443 | -0.454 | -0.303 |
| | (0.721) | (0.058) | (0.053)*** | (0.084)*** | (0.057)*** | (0.033)*** |
| Δln(Macro)*Some Coll | 0.466 | -0.019 | -0.147 | 5.550 | -0.358 | -0.236 |
| | (0.718) | (0.047) | (0.034)*** | (0.055)*** | (0.037)*** | (0.032)*** |
| Δln(Macro)*Bachelors | 0.495 | 0.009 | -0.092 | 5.543 | -0.273 | -0.159 |
| | (0.716) | (0.043) | (0.039)** | (0.070)*** | (0.052)*** | (0.045)*** |
| Δln(Macro)*Graduate | 0.816 | 0.159 | 0.026 | 5.887 | -0.173 | -0.089 |
| | (0.729) | (0.062)** | (0.041) | (0.070)*** | (0.036)*** | (0.033)*** |
| Δln(Macro), Neighboring States | 10.884 | -0.421 | -0.227 | | | |
| | (0.830)*** | (0.053)*** | (0.050)*** | | | |
| Female | -0.010 | -0.007 | -0.006 | -0.010 | -0.007 | -0.006 |
| | (0.001)*** | (0.001)*** | (0.001)*** | (0.001)*** | (0.001)*** | (0.001)*** |
| Age | -0.029 | 0.003 | -0.003 | -0.030 | 0.003 | -0.003 |
| | (0.001)*** | (0.000)*** | (0.000)*** | (0.001)*** | (0.000)*** | (0.000)*** |
| Age^2 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** |
| Asian | 0.013 | 0.000 | 0.006 | 0.022 | 0.000 | 0.006 |
| | (0.008) | (0.002) | (0.002)*** | (0.005)*** | (0.002) | (0.002)*** |
| Black | 0.051 | -0.013 | 0.014 | 0.053 | -0.013 | 0.014 |
| | (0.006)*** | (0.003)*** | (0.001)*** | (0.005)*** | (0.003)*** | (0.001)*** |
| Hispanic | 0.018 | -0.001 | 0.005 | 0.029 | -0.002 | 0.005 |
| | (0.010)* | (0.003) | (0.002)*** | (0.008)*** | (0.003) | (0.002)*** |
| Other | 0.055 | -0.005 | 0.017 | 0.077 | -0.006 | 0.016 |
| | (0.009)*** | (0.005) | (0.003)*** | (0.009)*** | (0.005) | (0.003)*** |
| HS Grad | -0.032 | 0.012 | -0.013 | -0.038 | 0.010 | -0.014 |
| | (0.005)*** | (0.002)*** | (0.001)*** | (0.004)*** | (0.002)*** | (0.002)*** |
| Some Coll | -0.045 | 0.013 | -0.019 | -0.046 | 0.011 | -0.020 |
| | (0.004)*** | (0.002)*** | (0.001)*** | (0.004)*** | (0.002)*** | (0.002)*** |
| Bachelors | -0.056 | 0.015 | -0.026 | -0.057 | 0.011 | -0.027 |
| | (0.005)*** | (0.002)*** | (0.001)*** | (0.005)*** | (0.002)*** | (0.002)*** |
| Graduate Deg | -0.058 | 0.015 | -0.031 | -0.061 | 0.011 | -0.032 |
| | (0.005)*** | (0.002)*** | (0.002)*** | (0.005)*** | (0.002)*** | (0.002)*** |
| Foreign-Born | 0.021 | 0.001 | -0.002 | 0.021 | 0.001 | -0.002 |
| | (0.005)*** | (0.001) | (0.001) | (0.004)*** | (0.001) | (0.001) |
| Constant | 0.967 | -0.081 | 0.118 | 1.052 | -0.078 | 0.118 |
| | (0.015)*** | (0.005)*** | (0.005)*** | (0.016)*** | (0.005)*** | (0.005)*** |
| Observations | 1101600 | 537972 | 516236 | 1101600 | 537972 | 516236 |
| R-squared | 0.19 | 0.00 | 0.01 | 0.09 | 0.00 | 0.01 |
| Robust standard errors in parentheses | | | | | | |
| * significant at 10%; ** significant at 5%; *** significant at 1% | | | | | | |

Individual-level regressions. Left Sample is a dichotomous variable measuring whether individuals left the sample between periods *t-1* and *t*. Unemployed is a dichotomous variable measuring whether a person was unemployed. Standard errors are clustered by state. Date range for time *t*: January 2001-December 2010.

## Table 5: Unemployment and Macroeconomic Shocks by Skill

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Dependent Variable:* | *Left Sample* | *Δ Unemployed* | *Δ Unemployed* | *Left Sample* | *Δ Unemployed* | *Δ Unemployed* |
| *Regression Includes Those Who Were:* | *In Labor Force in t-1* | *In Labor Force in t-1* | *Employed in t* | *In Labor Force in t-1* | *In Labor Force in t-1* | *Employed in t* |
| | | *In Sample in t* | *In Sample in t* | | *In Sample in t* | *In Sample in t* |
| *Macro Variable:* | *State Personal Income* | *State Personal Income* | *State Personal Income* | *National GDP* | *National GDP* | *National GDP* |
| *Frequency of Macro Variable* | *Monthly* | *Monthly* | *Monthly* | *Monthly* | *Monthly* | *Monthly* |
| Δln(Macro) | 0.356 | 0.056 | -0.231 | 5.215 | -0.364 | -0.300 |
| | (0.664) | (0.080) | (0.063)*** | (0.209)*** | (0.081)*** | (0.080)*** |
| Δln(Macro), Neighboring States | 10.890 | -0.418 | -0.233 | | | |
| | (0.817)*** | (0.052)*** | (0.051)*** | | | |
| Δln(Macro)*Manual | -0.585 | -0.191 | -0.110 | -0.333 | -0.237 | -0.107 |
| | (0.147)*** | (0.073)** | (0.080) | (0.181)* | (0.080)*** | (0.081) |
| Δln(Macro)*Communication | 0.498 | 0.160 | 0.285 | 0.478 | 0.338 | 0.222 |
| | (0.203)** | (0.096) | (0.059)*** | (0.183)** | (0.099)*** | (0.074)*** |
| Δln(Macro)*Quantitative | 0.070 | -0.098 | 0.005 | 0.385 | -0.115 | 0.004 |
| | (0.072) | (0.071) | (0.048) | (0.099)*** | (0.059)* | (0.047) |
| Manual Skill | 0.018 | 0.000 | 0.004 | 0.017 | 0.001 | 0.004 |
| | (0.004)*** | (0.002) | (0.001)** | (0.003)*** | (0.002) | (0.002)** |
| Communication Skill | -0.018 | 0.005 | -0.012 | -0.018 | 0.002 | -0.013 |
| | (0.005)*** | (0.003)* | (0.002)*** | (0.005)*** | (0.003) | (0.002)*** |
| Quantitative Skill | -0.015 | 0.006 | -0.006 | -0.019 | 0.006 | -0.006 |
| | (0.003)*** | (0.001)*** | (0.001)*** | (0.002)*** | (0.002)*** | (0.001)*** |
| Observations | 897520 | 532026 | 511146 | 897520 | 532026 | 511146 |
| R-squared | 0.19 | 0.00 | 0.01 | 0.09 | 0.00 | 0.01 |
| Robust standard errors in parentheses | | | | | | |
| * significant at 10%; ** significant at 5%; *** significant at 1% | | | | | | |

Individual-level regressions. Left Sample is a dichotomous variable measuring whether individuals left the sample between periods *t-1* and *t*. Unemployed is a dichotomous variable measuring whether a person was unemployed. Standard errors are clustered by state. Date range for time *t*: January 2001-December 2010. Regressions include gender, age, age-squared, race, education, and nativity controls, as well as industry fixed effects that are suppressed in the table.

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

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Dependent Variable:* | *Left Sample* | *Δ Unemployed* | *Δ Unemployed* | *Left Sample* | *Δ Unemployed* | *Δ Unemployed* |
| *Regression Includes Those Who Were:* | *In Labor Force in t-1* | *In Labor Force in t-1*<br>*In Sample in t* | *Employed in t*<br>*In Sample in t* | *In Labor Force in t-1* | *In Labor Force in t-1*<br>*In Sample in t* | *Employed in t*<br>*In Sample in t* |
| *Macro Variable:* | *State Personal Income* | *State Personal Income* | *State Personal Income* | *National GDP* | *National GDP* | *National GDP* |
| *Frequency of Macro Variable* | *Monthly* | *Monthly* | *Monthly* | *Monthly* | *Monthly* | *Monthly* |
| ∆ln(Macro)*HS Dropout | 0.096 | -0.007 | -0.320 | 4.835 | -0.503 | -0.427 |
| | (0.661) | (0.093) | (0.076)*** | (0.285)*** | (0.110)*** | (0.096)*** |
| ∆ln(Macro)*HS Graduate | 0.329 | 0.072 | -0.227 | 5.270 | -0.388 | -0.320 |
| | (0.668) | (0.088) | (0.065)*** | (0.201)*** | (0.087)*** | (0.078)*** |
| ∆ln(Macro)*Some Coll | 0.475 | 0.049 | -0.225 | 5.308 | -0.332 | -0.279 |
| | (0.673) | (0.088) | (0.067)*** | (0.219)*** | (0.085)*** | (0.084)*** |
| ∆ln(Macro)*Bachelors | 0.408 | 0.036 | -0.213 | 5.226 | -0.305 | -0.240 |
| | (0.669) | (0.077) | (0.065)*** | (0.196)*** | (0.101)*** | (0.100)** |
| ∆ln(Macro)*Graduate | 0.662 | 0.181 | -0.119 | 5.487 | -0.240 | -0.189 |
| | (0.682) | (0.104)* | (0.069)* | (0.209)*** | (0.086)*** | (0.097)* |
| ∆ln(Macro), Neighboring States | 10.888 | -0.419 | -0.235 | | | |
| | (0.818)*** | (0.052)*** | (0.050)*** | | | |
| ∆ln(Macro)*Manual | -0.503 | -0.174 | -0.083 | -0.264 | -0.191 | -0.065 |
| | (0.146)*** | (0.073)** | (0.079) | (0.187) | (0.077)** | (0.078) |
| ∆ln(Macro)*Communication | 0.347 | 0.126 | 0.238 | 0.346 | 0.262 | 0.153 |
| | (0.195)* | (0.100) | (0.059)*** | (0.171)** | (0.102)** | (0.087)* |
| ∆ln(Macro)*Quantitative | 0.063 | -0.093 | 0.005 | 0.376 | -0.118 | 0.001 |
| | (0.072) | (0.074) | (0.051) | (0.095)*** | (0.058)** | (0.047) |
| Manual Skill | 0.017 | 0.000 | 0.003 | 0.016 | 0.001 | 0.003 |
| | (0.004)*** | (0.002) | (0.001)** | (0.004)*** | (0.002) | (0.002)* |
| Communication Skill | -0.015 | 0.005 | -0.012 | -0.016 | 0.003 | -0.012 |
| | (0.005)*** | (0.003)* | (0.002)*** | (0.005)*** | (0.003) | (0.002)*** |
| Quantitative Skill | -0.015 | 0.006 | -0.006 | -0.019 | 0.006 | -0.006 |
| | (0.003)*** | (0.001)*** | (0.001)*** | (0.002)*** | (0.002)*** | (0.001)*** |
| Observations | 897520 | 532026 | 511146 | 897520 | 532026 | 511146 |
| R-squared | 0.19 | 0.00 | 0.01 | 0.09 | 0.00 | 0.01 |
| Robust standard errors in parentheses | | | | | | |
| * significant at 10%; ** significant at 5%; *** significant at 1% | | | | | | |

Individual-level regressions. Left Sample is a dichotomous variable measuring whether individuals left the sample between periods *t-1* and *t*. Unemployed is a dichotomous variable measuring whether a person was unemployed. Standard errors are clustered by state. Date range for time *t*: January 2001-December 2010. Regressions include gender, age, age-squared, race, education, and nativity controls, as well as industry fixed effects that are suppressed in the table.

## Table 7: Estimated Changes in Unemployment Probability by Occupation, Education, and Skill

| Occupation | Manual | Communication | Quantitative | High School Graduates: Effect from Own State Income | High School Graduates: Effect from US Real GDP | Bachelors Degree: Effect from Own State Income | Bachelors Degree: Effect from US Real GDP |
|---|---|---|---|---|---|---|---|
| *Similar Manual & Communication Skills; Different Quantitative Skill* | | | | | | | |
| Securities, Commodities, and Financial Services Sales Agents | 0.10 | 0.78 | 0.78 | -0.046 | -0.206 | -0.032 | -0.126 |
| Bill and Account Collectors | 0.11 | 0.74 | 0.31 | -0.058 | -0.214 | -0.044 | -0.134 |
| Stock Clerks and Order Fillers | 0.53 | 0.16 | 0.37 | -0.231 | -0.330 | -0.217 | -0.250 |
| Barbers | 0.54 | 0.17 | 0.05 | -0.231 | -0.329 | -0.217 | -0.249 |
| Driver/Sales Workers and Truck Drivers | 0.94 | 0.25 | 0.67 | -0.242 | -0.342 | -0.228 | -0.262 |
| Automotive Service Technicians and Mechanics | 0.95 | 0.27 | 0.29 | -0.240 | -0.340 | -0.226 | -0.260 |
| *Similar Manual and Quantitative Skill; Different Communication Skill* | | | | | | | |
| Financial Analysts | 0.01 | 0.66 | 0.93 | -0.066 | -0.219 | -0.052 | -0.139 |
| Actuaries | 0.01 | 0.45 | 0.94 | -0.116 | -0.251 | -0.102 | -0.171 |
| Crossing Guards | 0.58 | 0.22 | 0.01 | -0.223 | -0.324 | -0.209 | -0.244 |
| Rail-Track Laying and Maintenance Equipment Operators | 0.58 | 0.01 | 0.05 | -0.273 | -0.356 | -0.259 | -0.276 |
| Radio and Telecommunications Equipment Installers and Repairers | 0.77 | 0.08 | 0.20 | -0.271 | -0.358 | -0.257 | -0.278 |
| Nursing, Psychiatric, and Home Health Aides | 0.78 | 0.61 | 0.18 | -0.146 | -0.277 | -0.132 | -0.197 |
| *Similar Communication and Quantitative Skill; Different Manual Skill* | | | | | | | |
| Animal Trainers | 0.89 | 0.26 | 0.32 | -0.237 | -0.338 | -0.223 | -0.258 |
| Ushers, Lobby Attendants, and Ticket Takers | 0.44 | 0.26 | 0.35 | -0.200 | -0.308 | -0.186 | -0.228 |
| First-Line Supervisors/Mgrs of Construction & Extraction | 0.63 | 0.49 | 0.77 | -0.159 | -0.285 | -0.145 | -0.205 |
| Appraisers and Assessors of Real Estate | 0.37 | 0.50 | 0.79 | -0.135 | -0.267 | -0.121 | -0.187 |
| Aircraft Pilots and Flight Engineers | 0.81 | 0.57 | 0.68 | -0.155 | -0.285 | -0.141 | -0.205 |
| Reservation and Transportation Ticket Agents and Travel Clerks | 0.37 | 0.57 | 0.71 | -0.119 | -0.256 | -0.105 | -0.176 |

Table displays the estimated percentage-point change in an employed worker becoming unemployed due to a one percentage-point increase in aggregate income growth rates. Figures are based upon individual-level regression coefficient estimates from columns 3 and 6 in Table 6.

**Table 8: Unemployment and Macroeconomic Shocks by Education Level and Skill, Industry Fixed Effects**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Dependent Variable:* | | | *Δ Unemployed* | | | |
| *Regression Includes Those Who Were:* | | | *In Labor Force in t-1* | | | |
| | | | *In Sample in t* | | | |
| *Industry* | *All* | *Manufacturing* | *Health Care* | *Retail* | *Education* | *Construction* |
| *Macro Variable:* | | | *State Personal Income* | | | |
| *Frequency of Macro Variable* | | | *Monthly* | | | |
| Δln(Macro)*Manual | -0.093 | -0.289 | 0.133 | 0.040 | -0.283 | -0.126 |
| | (0.075) | (0.225) | (0.101) | (0.225) | (0.141)* | (0.353) |
| Δln(Macro)*Communication | 0.126 | 0.459 | -0.029 | 0.398 | -0.253 | 0.360 |
| | (0.068)* | (0.189)** | (0.131) | (0.206)* | (0.185) | (0.667) |
| Δln(Macro)*Quantitative | 0.067 | 0.289 | 0.349 | -0.205 | 0.346 | 0.263 |
| | (0.057) | (0.230) | (0.068)*** | (0.213) | (0.203)* | (0.350) |
| *Macro Variable:* | | | *National GDP* | | | |
| *Frequency of Macro Variable* | | | *Monthly* | | | |
| Δln(Macro)*Manual | -0.051 | -0.691 | 0.163 | -0.194 | -0.179 | 0.073 |
| | (0.078) | (0.225)*** | (0.116) | (0.235) | (0.152) | (0.506) |
| Δln(Macro)*Communication | 0.115 | -0.083 | -0.002 | -0.492 | -0.187 | 0.417 |
| | (0.088) | (0.195) | (0.142) | (0.264)* | (0.148) | (0.818) |
| Δln(Macro)*Quantitative | 0.027 | 0.415 | 0.322 | 0.368 | -0.140 | 0.091 |
| | (0.047) | (0.251) | (0.094)*** | (0.221) | (0.246) | (0.481) |
| Observations | 511146 | 66635 | 65752 | 52576 | 49585 | 38069 |
| Robust standard errors in parentheses | | | | | | |
| * significant at 10%; ** significant at 5%; *** significant at 1% | | | | | | |

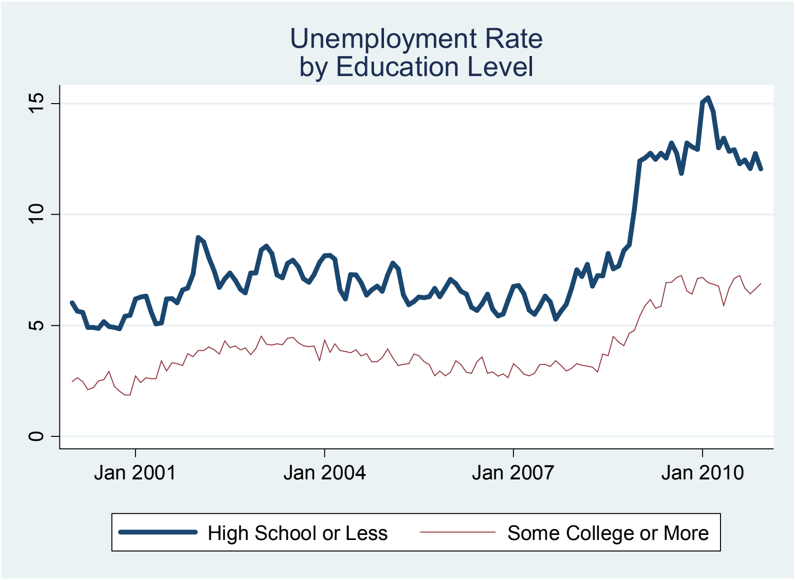
Individual-level regressions. Unemployed is a dichotomous variable measuring whether a person was unemployed. Standard errors are clustered by state. Date range for time *t*: January 2001-December 2010. Regressions include gender, age, age-squared, race, education, and nativity controls, as well as industry fixed effects that are suppressed in the table. Regressions also include industry*time indicators (top panel) or industry-specific quadratic trends (bottom panel).

**Table 9: Usual Hours Worked per Week, Weekly Earnings, and Macroeconomic Shocks by Skill**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Dependent Variable:* | *Δ Usual Hours Worked* | | *Δ Weekly Earnings* | |
| *Regression Includes Those Who Were:* | *In Labor Force in t-1 & t* | *Employed in t-1 & t* | *In Labor Force in t-1 & t* | *Employed in t-1 & t* |
| *Macro Variable:* | *State Personal Income* | | | |
| *Frequency of Macro Variable* | *Monthly* | | | |
| Δln(Macro) | 8.556 | 4.665 | 208.439 | 193.901 |
| | (4.373)* | (3.503) | (158.969) | (146.604) |
| Δln(Macro), Neighboring States | 20.782 | 5.820 | 180.750 | -140.175 |
| | (1.898)*** | (1.235)*** | (112.939) | (114.365) |
| Δln(Macro)*Manual | 6.509 | 0.888 | -123.691 | -213.873 |
| | (4.784) | (3.302) | (123.389) | (117.926)* |
| Δln(Macro)*Communication | -13.363 | -2.999 | -332.115 | -142.643 |
| | (3.819)*** | (2.586) | (150.932)** | (156.021) |
| Δln(Macro)*Quantitative | -2.008 | -4.581 | 347.304 | 178.471 |
| | (4.083) | (2.389)* | (218.813) | (212.394) |
| *Macro Variable:* | *National GDP* | | | |
| *Frequency of Macro Variable* | *Monthly* | | | |
| Δln(Macro) | 29.301 | 11.639 | 45.858 | -242.284 |
| | (4.529)*** | (3.091)*** | (160.119) | (167.133) |
| Δln(Macro)*Manual | 7.467 | 0.855 | 325.436 | 255.812 |
| | (4.898) | (3.251) | (175.767)* | (165.087) |
| Δln(Macro)*Communication | -26.210 | -11.228 | -423.454 | -150.891 |
| | (4.686)*** | (2.919)*** | (176.646)** | (192.351) |
| Δln(Macro)*Quantitative | 2.799 | 0.564 | 359.795 | 147.818 |
| | (3.714) | (2.435) | (120.037)*** | (132.991) |
| Observations | 442103 | 415152 | 428911 | 401249 |
| Robust standard errors in parentheses | | | | |
| * significant at 10%; ** significant at 5%; *** significant at 1% | | | | |

Individual-level regressions. Earnings converted to real 2010 dollars. Standard errors are clustered by state. Date range for time *t*: January 2001-December 2010. Regressions include gender, age, age-squared, race, education, and nativity controls, as well as industry fixed effects that are suppressed in the table.

**Figure 1**


Unemployment Rate
by Education Level
15
10
5
0
Jan 2001
Jan 2004
Jan 2007
Jan 2010
High School or Less
Some College or More

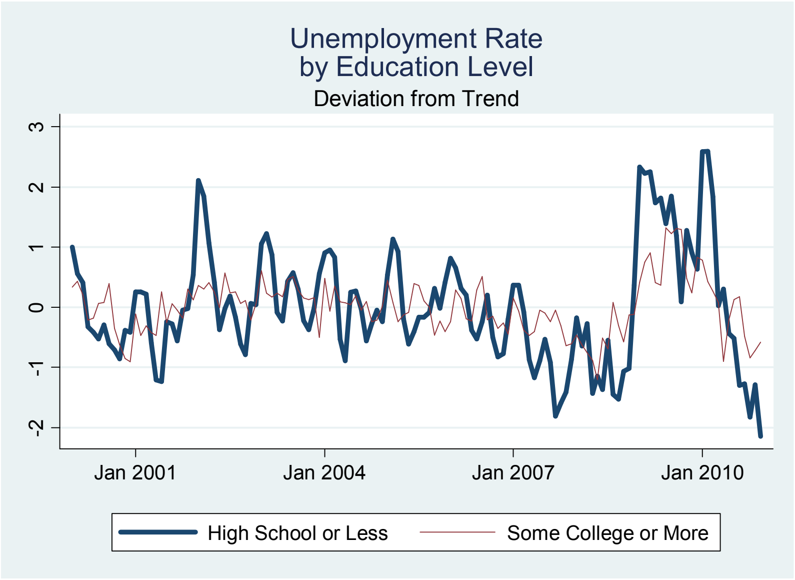

Unemployment Rate
by Education Level
Deviation from Trend
3
2
1
0
-1
-2
Jan 2001
Jan 2004
Jan 2007
Jan 2010
High School or Less
Some College or More

**Figure 2: Unemployment Rates by Education and Manual Skill Quartile**

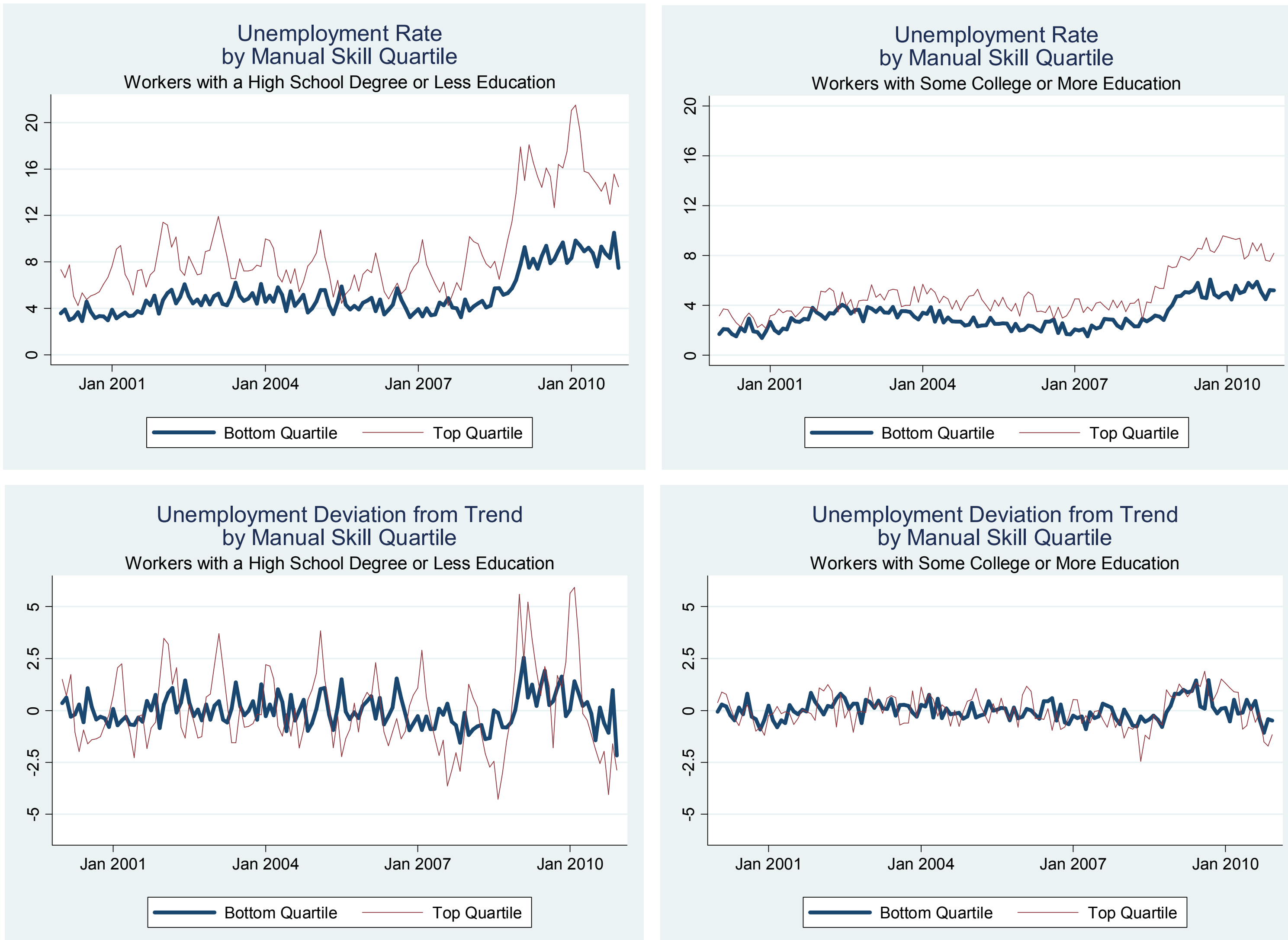


**Figure 3: Unemployment Rates by Education and Communication Skill Quartile**

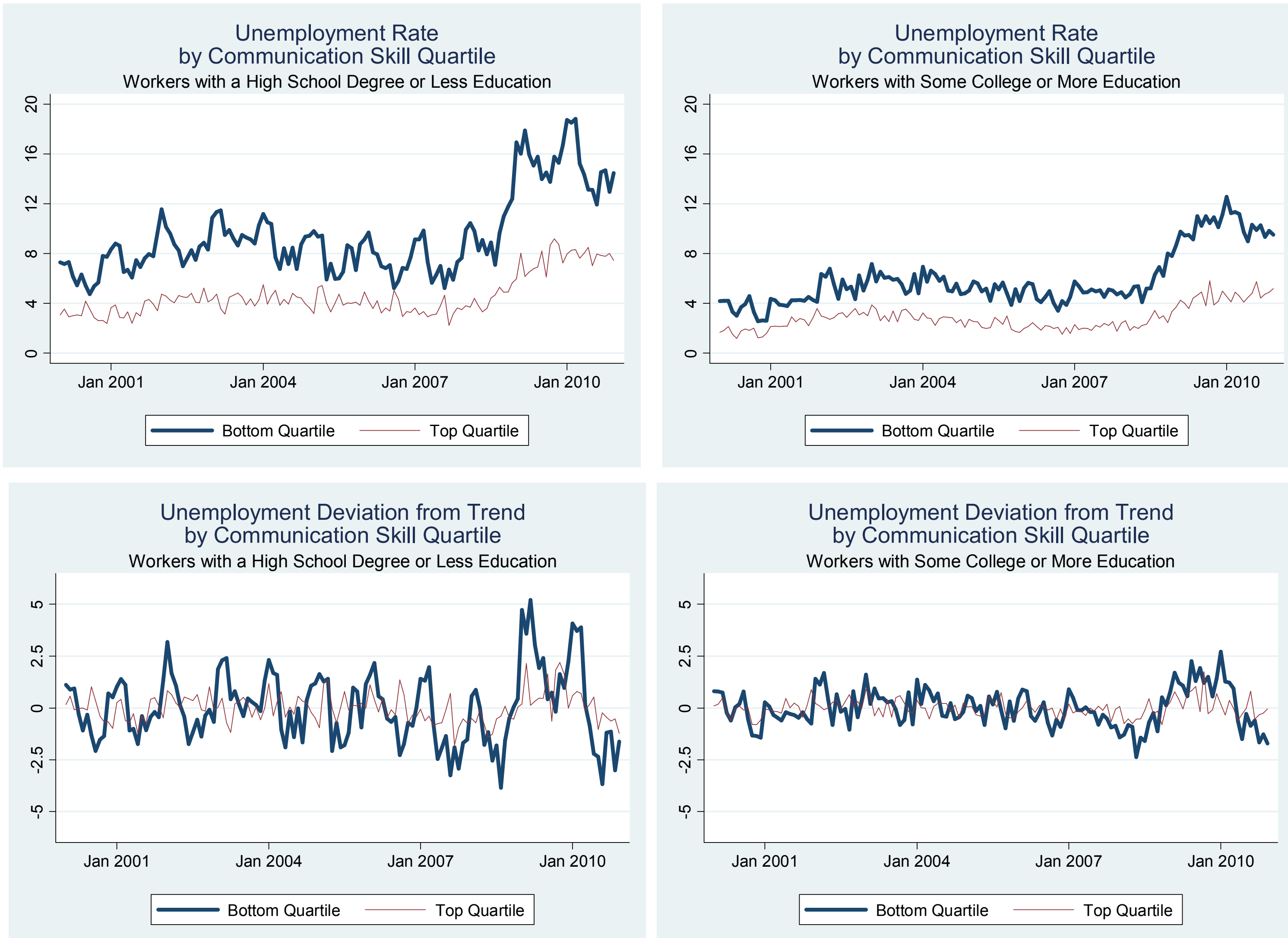


**Figure 4: Unemployment Rates by Education and Quantitative Skill Quartile**