Incomplete and preliminary

Skill Mismatches and Unemployment in the United States

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Abstract

The 2008-2009 crisis created large dislocations in the U.S. labor market: some sectors, locations, and occupations were more affected than others. As a result, researchers have been looking at the possibility of structural changes in labor market functioning, which may have created mismatches between available labor and employment opportunities; thus raising equilibrium levels of unemployment. As opposed to previous research that often uses a Beveridge curve framework to analyze the existence of skill mismatches in the labor market or changes in equilibrium unemployment levels, we study changes in the quality of the unemployment pool vis-à-vis the employment pool. We use information from the CPS monthly outgoing rotation groups for 1979-2011 to estimate wage equations based on observable characteristics and use the estimates to impute average wages for employed and unemployed workers, our sufficient statistics for "labor quality". We show that quality differences between these two groups is procyclical and analyze the source of this cyclicality. In addition, we show that this quality differential remains negatively related to the unemployment rate even after controlling for aggregate and state-level variations in output, suggesting a possible noncyclical relationship between these variables. Turning to recent events, quality differentials between employed and unemployed individuals did not decline as much as suggested by the sharp rise in unemployment, suggesting an increase in skill mismatches.

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[1] IMF and Federal Reserve Board, respectively. This paper should not be reported as representing the views of the IMF, the Federal Reserve Board, or any other member of their boards and staff. The views expressed herein are those of the author(s) and do not necessarily represent those of the IMF, Federal Reserve, or Fed and IMF policy.

I. INTRODUCTION

The most recent financial crisis has hit U.S. labor markets and generated large disparities across states and groups of workers. For instance, construction employment has not recovered yet from the beating it took in 2008 and 2009, and unemployment spells remain quite long, even if they have receded somewhat from peak levels in 2009. At the same time, some sectors have continued to post strong employment gains (e.g. health care, including during the crisis years) while some local labor markets improved faster than others since mid 2009.

These gyrations could have created deeper-seated problems in labor markets, including the ability to match unemployed workers to available jobs. Indeed, the last few years have seen a burgeoning literature on possible structural labor market problems in the United States. Available research usually starts with the observation that the Beveridge curve (an equilibrium negative relationship between job vacancy rates and unemployment rates) seemed to have shifted up; i.e. higher job vacancy rates than observed before the crisis are needed to produce a particular level of the unemployment rate. Discussions then tend to center on whether this upward shift in the Beveridge curve represents a structural worsening of the U.S. labor market or a temporary (actually, a usual cyclical) phenomenon, with skill mismatches being a possible cause for either event.

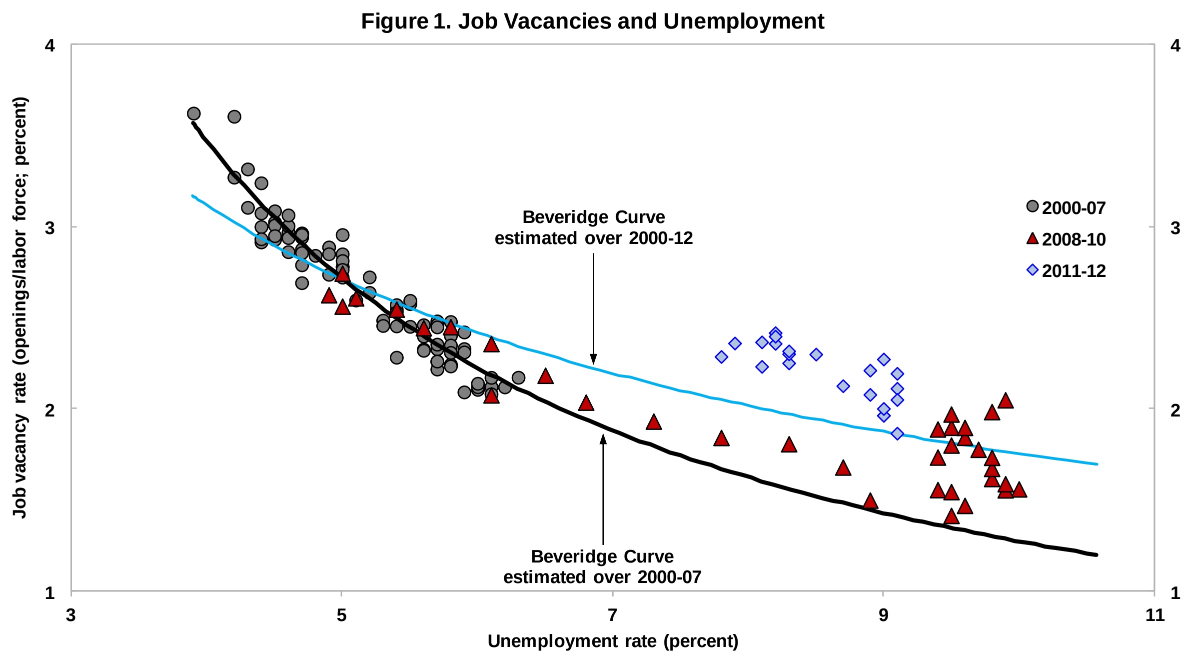
Here we take a different approach. We look at skill mismatches by analyzing changes in the quality of the unemployment pool vis-à-vis the employment pool. Because "skill" is a multifaceted variable, we chose to use a (imputed) wage measure as a sufficient statistic for worker quality. For that, we went back to a literature initiated by the seminal work of Jacob Mincer in the 1960s and estimated wage equations for employed workers based on observable characteristics. We then used the estimated parameters to simulate the wages unemployed workers would receive if hired and imputed wages for employed workers solely based on observable characteristics for both groups of workers. The difference between imputed wages for employed and unemployed workers can be used as a measure of the distance between the average quality of both groups. The estimation uses individual level information from the CPS monthly outgoing rotation groups for 1979-2011 and allows a broad, long-term view of variations in the average quality differential (QD) between employed and unemployed workers in the United States. We relate this information to movements in the unemployment rate and GDP growth, including in a panel data setting for all U.S. states.

Quality differentials between employed and unemployed workers are procyclical. However, even after controlling for variations in output or the output gap, QD is negatively related to the unemployment rate, suggesting a relationship that goes beyond a common response to variations in production. This fact can be observed in aggregate specifications of Okun's Law and in panel data estimations using state-level data. Turning to recent events, average QD did not decline during the 2008-2009 crisis to the extent projected using estimated parameters, i.e. the unemployment rate rose "too much" given output changes and the usual degree of convergence between the quality of working individuals and the unemployed during recessions. This result is consistent with increased "mismatch" in the labor market. Abrupt reductions in employment levels followed by a reluctance to hire (a so-called “jobless recovery”) could also explain some of the wedge between actual and simulated unemployment rates during and after the crisis, but the relatively small convergence in QD compared to the previous two jobless recoveries (in the early 1990s and early 2000s) suggests significant skill mismatches.

The next section of the paper reviews the recent literature on possible structural problems in the U.S. labor market, with a focus on skill mismatches. Section III describes the method for estimating the quality differential between employed and unemployed workers. Section IV discusses aggregate cyclical movements in QD and section V presents state-level estimates. Section VI shows new estimates for Okun’s Law using aggregate and state-level QD as control variable. Section VII concludes the paper.

II. Recession and “Equilibrium” Unemployment: A Review of the Recent Literature

Unemployment rates increased sharply during the latest crisis and a literature on the structural consequences of such shock has flourished since then. Most of this work starts with the observation that the Beveridge curve (BC, an equilibrium relationship between vacancy and unemployment rates) shifted upwards during the crisis. Data since 2010 are consistent with movements along this new, higher curve. Indeed, rough estimates of the curve using available information until 2012 produces large residuals and, at least optically, the “shift” hypothesis seems convincing. (Figure 1)



Source: BLS, JOLTS data, and authors’ estimations.

An example of the focus on the BC is Minneapolis Federal Reserve Bank President Kocherlakota's 2010 speech, in which he argued that the June 2010 job opening rate of 2.2 percent would be associated with an unemployment rate of about 6.5 percent, not 9.5 percent, and attributed the remaining increase to higher skill mismatch.[2] Tasci and Lindner (2010) note that the BC has always exhibited a counter-clockwise loop during the early stages of a recovery, as job openings adjust much more quickly to changes in labor demand than unemployment. Valletta and Kuang (2010) argues that movements in the BC may be consistent with an increase in the NAIRU of no more than 1¼ percentage points, although they also suggest that—based on cross-industry, cross-occupation, and cross-state evidence—the shift is likely to be only temporary. Daly et al (2011) consider movements in both the BC **and** in the job creation curve, and conclude that the NAIRU may have increased by about a 1 percentage point—though most of this increase would be temporary, according to the authors. Davis, Faberman, and Haltiwanger (2012) suggest that some of the shift in the BC may reflect unobserved changes in recruiting intensity rather than changes in matching efficiency.

Moving a step deeper, Barnichon and Figura (2011) decomposes changes in the unemployment rate into those attributable to changes in matching efficiency (which might contribute to an increase in structural unemployment and a shift in the BC) and those attributable to other factors (firms' hiring and layoff policies, demographics and labor force participation), which might lead to movements along or shifts in the BC. Their analysis suggests some decline in matching efficiency since 2007. Barlevy (2011) estimates Shimer (2007)-style matching functions and finds that the shock to matching efficiency since 2007 could have increased the unemployment rate to at most 7 percent. Veracierto (2011) performs a similar exercise, allowing for a three-state matching model (including non-participants) and letting separation rates vary over time, and finds that the deterioration in matching efficiency could explain at most 1 percentage point of the rise in the unemployment rate.

Other papers explore whether the extent of skill mismatches has increased by examining cross-state, cross-industry, and cross-occupation evidence. Barnichon et al (2011) concludes that most of the outward shift in the Beveridge curve can be attributed to a shortfall in hires per vacancy across **most** industries, although more than half can be explained by construction alone. Şahin et al (2012) estimate deviations in industry-, occupation-, and region-specific Beveridge curves from their historical relationships, and find that mismatch across industries and occupations explains at most one-third of the total observed increase in the unemployment rate, whereas geographical mismatch plays no apparent role (a fact confirmed by some papers focusing on migration patterns, e.g. Molly, Smith, and Wozniak, 2011). Lazear and Spletzer (2012) present a simplified version of the arguments in Sahin et al (2012) and conclude that most of the worsening in labor market outcomes is cyclical.

[2] To arrive at this calculation, he applies Shimer (2007) to estimate the amount of change in unemployment that is attributable to movements along the Beveridge curve.

Using an alternative framework, Estevão and Tsounta (2011) construct an index of skill mismatch for each state, by comparing the "supply" of low-, middle-, and high-skilled persons in the state (as determined by educational attainment for the state's adult population) to the "demand" for those workers (as determined by the share of employed workers in high-, middle-, and low-skilled industries). They show that mismatch appears to be cyclical, although it has risen at a higher rate in the current episode than in past downturns. They find that changes in state-level unemployment rates are linked to skill mismatches and housing market performance even after controlling for cyclical effects (using state-level output data). This result suggests some causality going from mismatches and housing conditions to unemployment rates. The numerical estimates imply that the structural unemployment rate in 2010 was about 1¾ percentage points higher than at the end of 2006, although only a third of this value could be attributed solely to "skill mismatch". Rothstein (2012) examines changes in real wages since the start of the recession and finds declines for most demographic characteristics and industries, suggesting only a small industry-specific mismatch.

Additional evidence related to whether structural unemployment has increased comes from the literature on the scarring effects of unemployment—that is, if unemployment spells have historically resulted in lower employment probabilities, then the recent dramatic increase in unemployment (particularly, long-term unemployment) may be associated with permanently higher unemployment rates. von Wachter, Song, and Manchester (2012) use longitudinal payroll tax data from the Social Security Administration to estimate the effect of a mass-layoff event in 1982 on displaced workers' earnings as well as the probability of reporting positive earnings over the next twenty years. The authors find that displaced workers experience persistently lower earnings over the rest of their career. Additionally, even twenty years following the displacement, non-displaced workers were more likely than displaced workers to report positive earnings—suggesting that displaced workers also experienced adverse long-term effects on employment stability. Kahn (2010) and Oreopoulos, von Wachter, and Heisz (2012)—the latter using Canadian data—find that individuals who graduated during a recession had persistent losses in income. Oreopoulos, von Wachter, and Heisz (2012) find that although these graduates also had a higher propensity to be unemployed initially, after four years, unemployment rates between the groups converged, suggesting a minimal amount of hysteresis in the medium-term.

III. Estimating the Quality Difference between Employed and Unemployed

The papers reviewed in the previous section tend to use a search theoretical framework, which underlies the construction and analysis of Beveridge curves. While using it as inspiration, we move away from an analysis of shifts in the BC and take a direct look at how the quality of the workforce has evolved in the past 30 years or so, with a focus on the differences between employed and unemployed workers. The key idea behind this procedure is that sectoral, regional and other shocks would cause changes in the skill structure of the unemployment pool. The absorption of unemployed workers back into jobs would thus depend on the type of demand for labor being generated. By looking at the differential in labor quality between the currently-employed and unemployed workers, we would be answering the question: “How easily could unemployed workers be hired if labor demand evolves according to the current skill distribution among employed workers?”

To operationalize this idea, we estimate a single dimensional measure of quality (as determined by the labor market) for employed and unemployed individuals, and then compare average quality for the employed and unemployed populations. We first assume that real hourly wages (estimated in microdata from the CPS monthly outgoing rotation group respondents) is a suitable proxy for quality, and further assume that unemployed and employed individuals with the same observable characteristics (age, education, gender, etc.) are of similar quality. Conditional on this assumption, and also assuming linearity in the combined contribution of these characteristics, we can estimate the contribution of observable characteristics to quality for the employed population, and impute quality for the unemployed.

More specifically, our procedure is:

1) Using CPS microdata from the outgoing rotation groups (MORG) for 1979-2011, we calculate real hourly wages for employed persons. For workers who are paid by the hour, we use reported hourly wages; for salaried workers, we impute hourly wages as weekly wages divided by hours worked per week. (We have not extended our analysis for earlier years because MORG microdata extracts are only available beginning in 1979; also, prior to 1979 some smaller states are not identifiable.)

2) Separately by year we estimate OLS regressions of log hourly wages on: age and age squared; dummies for Hispanic, white, and black; a dummy for gender; dummies for educational attainment (14 categories); dummies for marital status; dummies for three digit industry and occupation; state dummies; and dummies for calendar month. For some specifications, we also estimate the regressions separately by state.

3) We use these coefficients to predict log wages for employed and unemployed persons. (Note that this requires unemployed respondents to report previous industry and occupation, which excludes new entrants.)

4) Finally, we calculate QD as the difference in average predicted log wages between employed and unemployed persons (the averages are weighted by BLS person weights). Note that this comparison excludes those who report not being in the labor force.

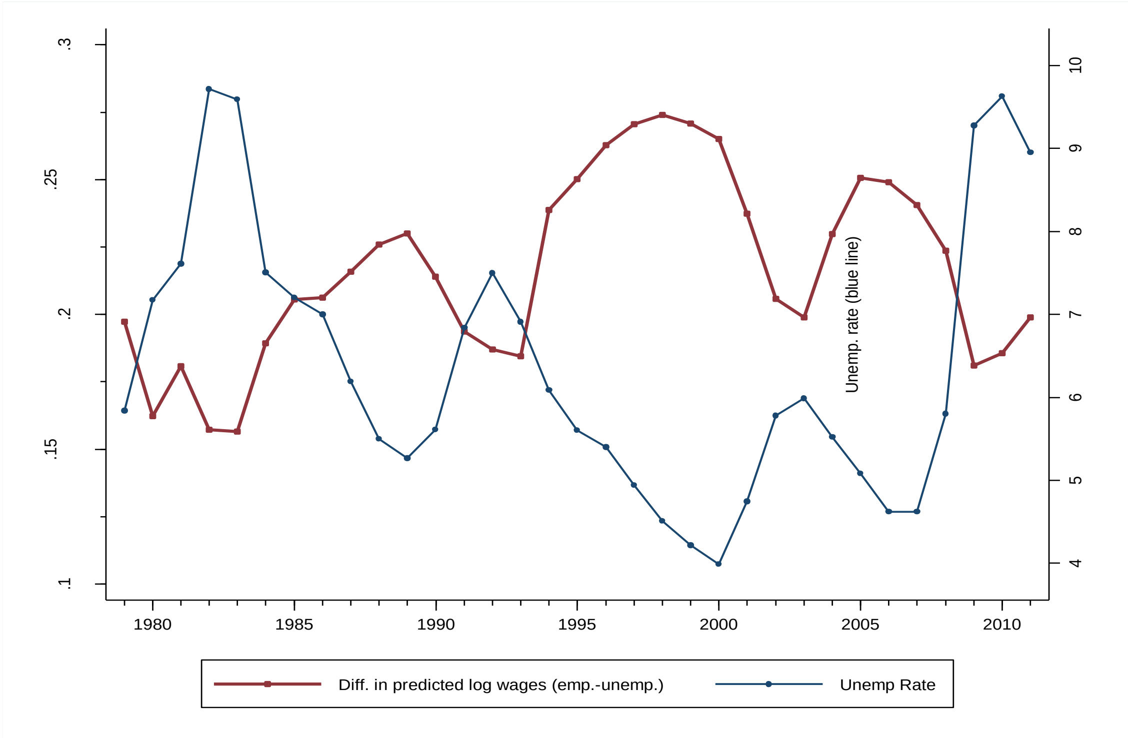
IV. THE CYCLICALITY IN QD AND ITS RECENT MOVEMENTS

Figure 2 plots the time series of QD against the national unemployment rate. QD is very clearly counter-cyclical. That is, during recessions the difference in quality between the employed and unemployed populations converges—the average unemployed person looks more like an employed person than during an expansion. This is not surprising. During tight labor markets, persons who have more difficulty finding jobs are likely of much different (lower) quality than employed workers. When a downturn comes, the labor market gets flooded with individuals that are closer in quality to employed people and the composition of the unemployment pool gets more similar to the employed pool. When a recovery starts, unemployed individuals with better skills tend to be picked up first, creating a wider gap between the quality of the employed and the unemployed pool of workers. These movements are exacerbated by the fact that the size of the unemployment pool is much smaller than the size of the employed pool of workers, thus a given flow of workers affect the average quality of unemployed workers more than the average quality of employed workers. Cyclical changes in the coefficients associated with each demographic characteristic would also influence the cyclical movements in QD.

As in the earlier recessions in this panel, during the most recent recession QD also displayed some convergence. However, compared with other recessionary episodes in this sample, it appears that QD may have converged less than one might expect given the dramatic rise in the unemployment rate. If so, one potential explanation may be that some degree of mismatch exists between the skills demanded by firms (and possessed by those who remain employed) and the unemployed (which are demanded by a lesser amount), thus preventing QD to converge by its "usual" amount.

As a simple test of this, in table 1 we regress the time series of QD on the unemployment rate (column 1), the unemployment rate and the GDP gap as measured using the CBO's estimate of potential GDP (column 2), and additionally the unemployment rate interacted with a dummy for post-2007 (column 3). This simple regression confirms that QD is strongly counter-cyclical and that increases in the unemployment rate in the post-2007 period were associated with less convergence in QD than in earlier years (the interaction term is positive). Figure 3 plots the predicted value of QD from a regression of QD on the unemployment rate and GDP gap, using data from 1979-2007. During the recession, QD converged less than would have been expected given the usual historical relationship between QD, the unemployment rate, and the GDP gap.

Figure 2: Quality differential and the unemployment rate



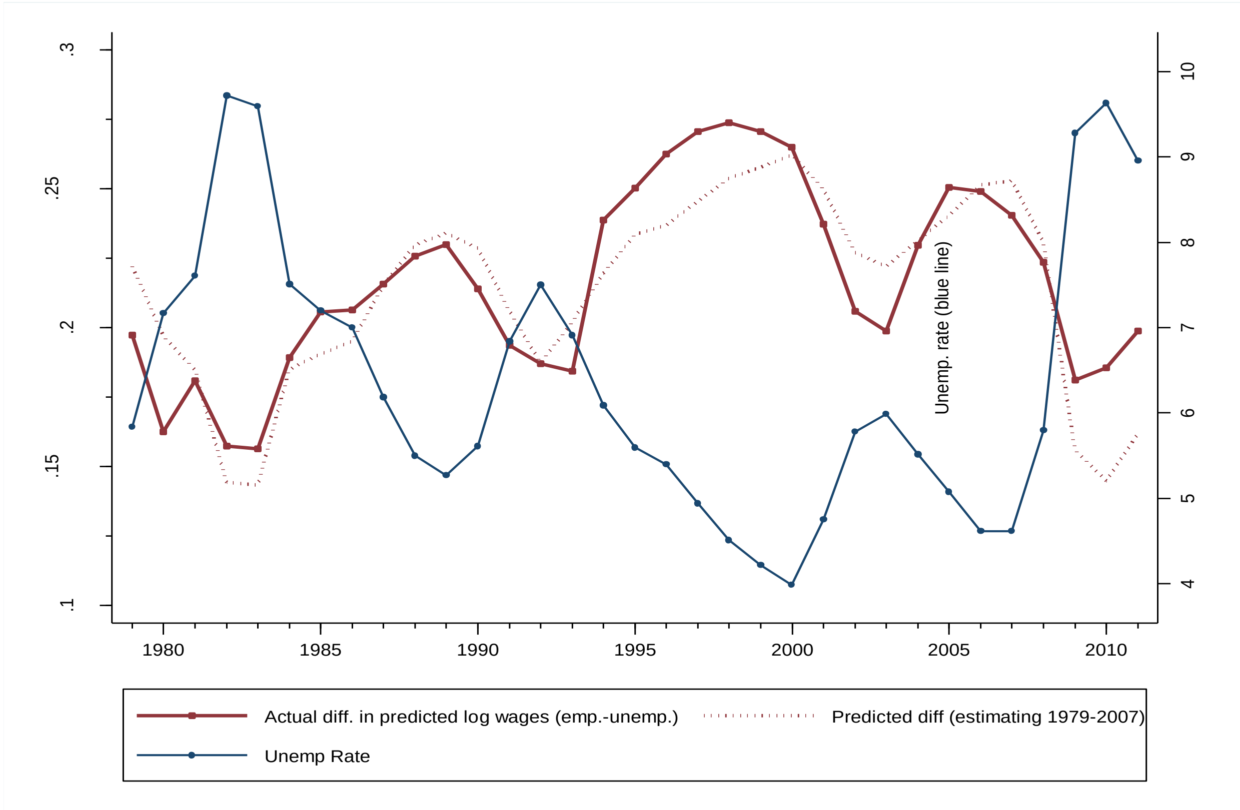
Note: Predicted log wage for employed and unemployed from regression of log wage on age, age squared, gender dummies, race dummies, marital status dummies, educational attainment dummies, industry and occupation dummies, state dummies, and month dummies. Regressions are estimated separately by year. Regressions use microdata from the UNICON CPS monthly outgoing rotation group extracts.

Table 1: Relationship between QD and unemp. rate, output gap

	(1)	(2)	(3)
Dependent variable: national QD			
Unemp. rate	-0.018	-0.026	-0.025
	(0.002)	(0.005)	(0.005)
GDP gap		-0.006	-0.003
		(0.004)	(0.004)
Year>=2008			-0.074
			(0.048)
(Year>=2008)*(unemp. rate)			0.012
			(0.006)
R-square adj.	0.72	0.73	0.78

Note: Table displays coefficients from OLS regression of the difference in log average predicted wages for emp. and unemp. persons on listed variables. Standard errors are in parentheses. Observations are years; sample includes 1979-2011, N=33. GDP gap is the percent difference between real GDP and potential GDP (based on current CBO estimates for potential GDP).

Figure 3: QD and predicted QD



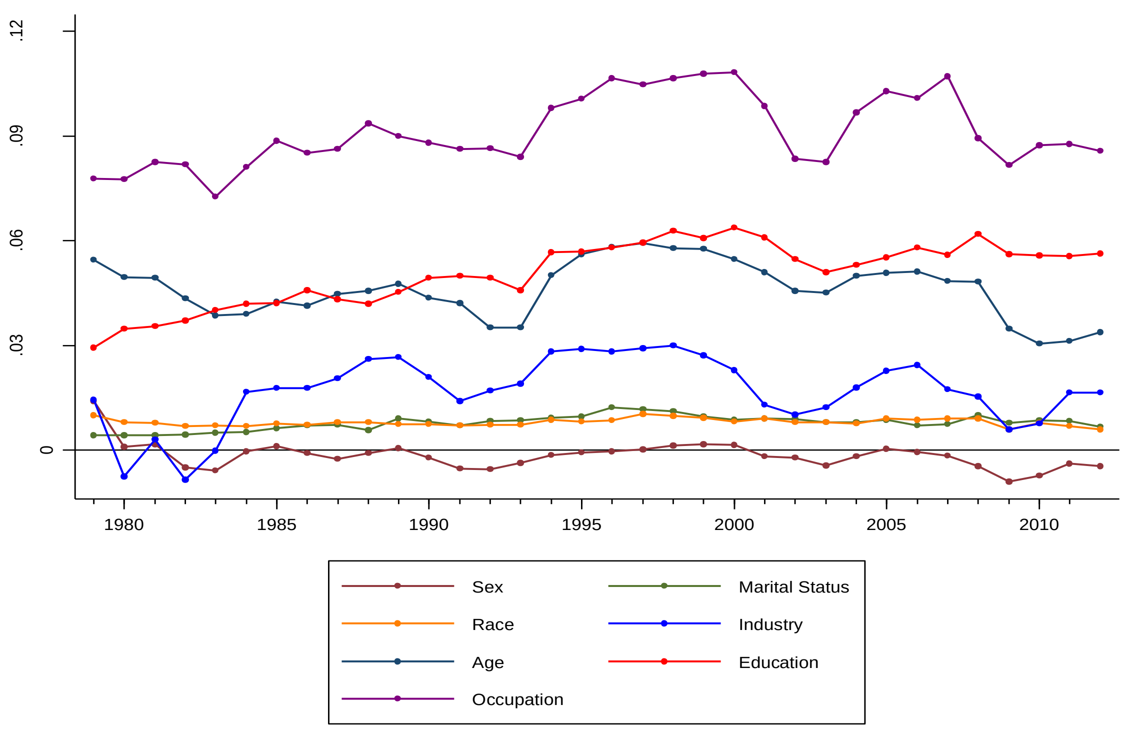
Note: Maroon solid line is the QD, estimated as described in the note to figure 1. The dotted line is the predicted value for QD, as predicted from the regression represented in column 2 of table 1 (estimated from 1979-2007).

Figure 4 explores the contribution of various characteristics to the level and cyclicality of QD. As before, we regress (separately by year) an employed individual's log wage on the full set of characteristics as described in section 2. We then predict wages for employed and unemployed persons based solely on one class of characteristics (e.g. age or gender), and compute QD based only on the contribution of these characteristics.

These series should be interpreted as differences between the employed and unemployed populations in terms of their distribution of each characteristic interacted with the market returns to this characteristic. Similarly, cyclicality in QD for a particular characteristic may be driven by cyclicality in the difference of the distributions for employed relative to unemployed persons, cyclicality in the returns to these characteristics, or both.

Sex, race, and marital status contribute little to overall differences in quality between employed and unemployed persons (conditional on the other characteristics). Age (the blue line) has a larger contribution, and this contribution is cyclical. (We have explored the source of this cyclicality, and it appears to be because the prime-age share of the employed and unemployed populations converge during recessions; cyclicality in the returns to age is much less important.) Education (the red line) is an important contributor to QD, but its contribution is surprisingly acyclical. Finally, QD in industry and occupation are important components of the aggregate QD, and drive much of its overall cyclicality. (As with age, this appears to be due to cyclicality of convergence in the occupation/industry distributions rather than cyclicality in the returns to particular industries or occupations.) The next version of this paper will focus more on the cyclical behavior of QD.

Figure 4: Contribution of specific characteristics to QD



Note: Each series represents the difference in predicted log wages for employed and unemployed as implied by the coefficients from the listed variable. Coefficients are from separate regressions by year of log wage on age, age squared, gender dummies, race dummies, marital status dummies, educational attainment dummies, industry and occupation dummies, state dummies, and month dummies. Regressions use microdata from the UNICON CPS monthly outgoing rotation group extracts.

V. State-Level Estimates of QD

We are interested in understanding whether the lack of usual cyclicality in QD in the most recent recessionary episode may be a reflection of skills mismatch, and hence structural unemployment, or something else. To do so, it will be useful to form state-specific estimates of QD and relate these to state characteristics that may be related to mismatch (e.g. impact of the housing crunch, concentration of employment in construction or finance, etc.).

To begin, we estimate log wage regressions similar to those described in section 2 except estimated separately by state. Figure 5A displays the average QD (across state, weighted by population), which looks very similar to the QD as measured when log wage regressions are estimated for the full sample (unconditional on state). Figure 5B depicts the coefficient of variation in QD (standard deviation of QD across states divided by the mean QD across states), which is one measure of dispersion in QD. Interestingly, dispersion in QD across states rises during recessions, suggesting that the convergence in quality between employed and unemployed individuals is not uniform across states (and becomes less uniform as the labor market worsens).

Table 2 displays estimates from state-year level regressions of QD, analogous to the national-level regressions from Table 1. As shown in column 1-3, QD remains strongly countercyclical within states (after controlling for state fixed effects, column 2), and states with higher unemployment rates tend to have lower QD (controlling for year fixed effects as well, column 3). When controlling for state-specific effects, there is strong evidence that post-2007 QD decreased on average less in response to a given rise in unemployment than in previous episodes (the interaction term in column 4 is strongly positive), though after controlling for year fixed effects this interaction term becomes insignificant (column 5). (This may be because after controlling for year fixed effects there is little independent variation in the post-2007 period to estimate the interaction effect.)

Clearly, one important direction to push this analysis is exploring what state characteristics are associated with QD and changes in QD since 2007. We have only begun this part of the analysis, and are working to relate changes in QD over this period to various state characteristics (such as the extent the state was affected by the housing crunch). As a taste of what this sort of analysis might reveal, figures 6A and 6B plot changes from 2007-2009 (panel A) and 2007-2011 (panel B) in QD against changes in the unemployment rate. There is no discernable relationship between changes in QD and the unemployment rate. Also curious, states that one might a priori expect to have experienced greater increases in mismatch (“house bubble states” like Florida, Nevada, Arizona; or, manufacturing-intensive states like Michigan) don’t appear to be outliers. We hope to extend this analysis by exploring more carefully which states and regions experience more atypical degrees of convergence in QD.

Figure 5A: Average QD (across states)

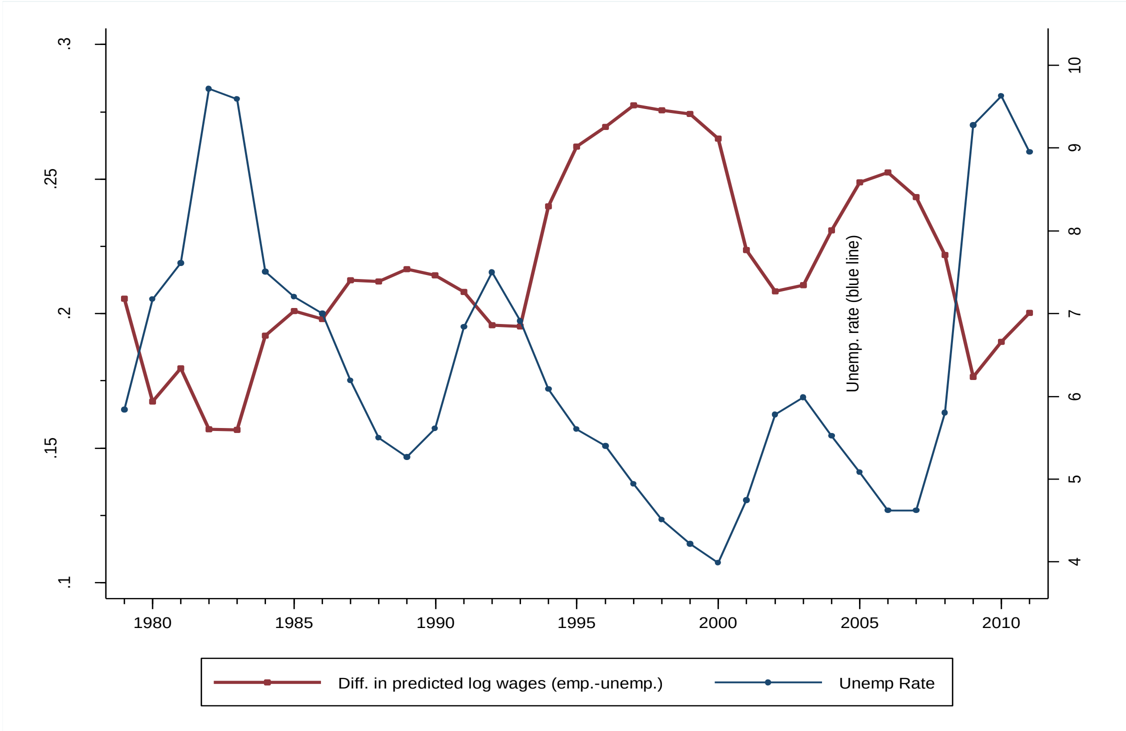
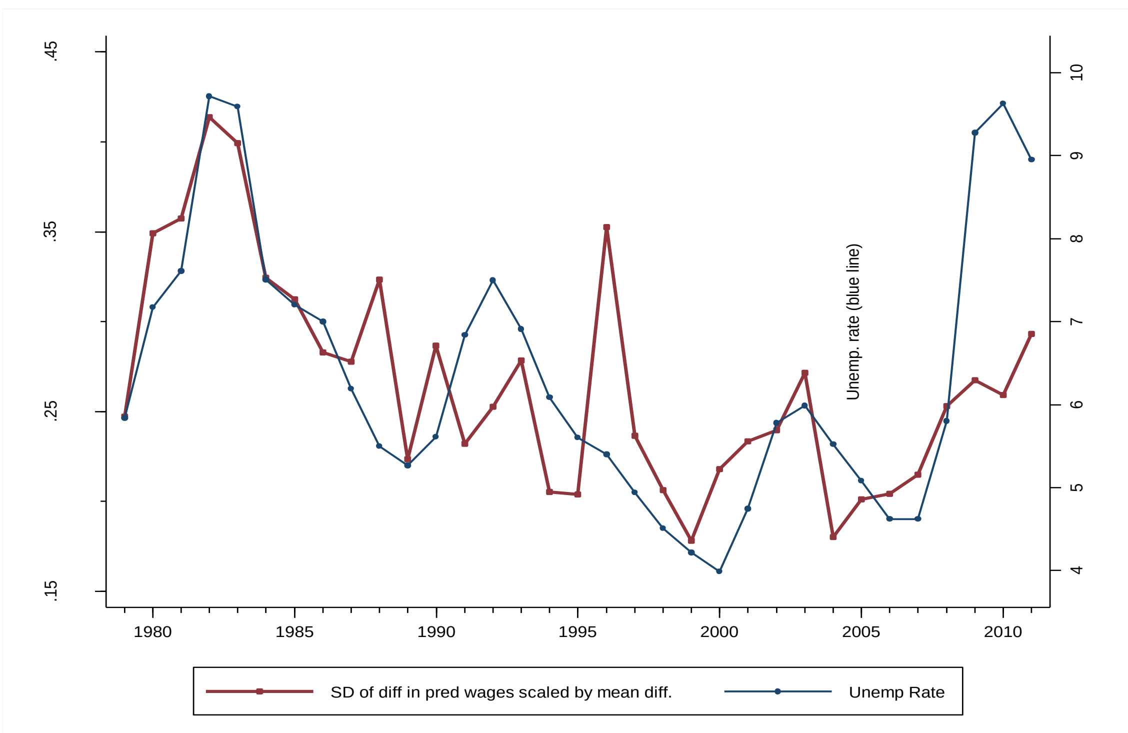


Figure 5B: Coeff. of variation in QD (across states)



Note: Predicted log wage for employed and unemployed from regression, separately by state, of log wage on age, age squared, gender dummies, race dummies, marital status dummies, educational attainment dummies, industry and occupation dummies, and month dummies. Regressions are estimated separately by state and year. Regressions use microdata from the UNICON CPS monthly outgoing rotation group extracts. Panel A shows the average difference across states, and panel B shows the standard deviation scaled by the mean. (All statistics are weighted by state population for that year).

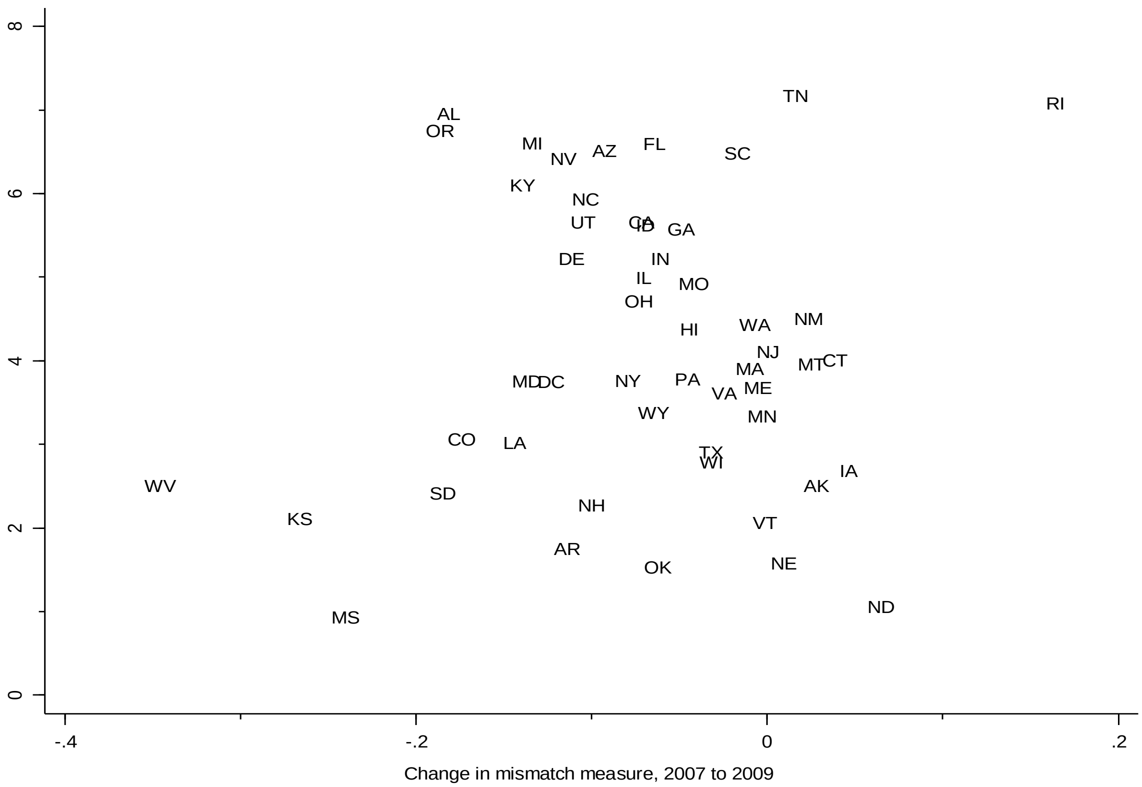
Table 2: State-level relationship between QD and unemployment

	(1)	(2)	(3)	(4)	(5)
		Dependent variable: QD			
Unemp. rate	-0.012	-0.014	-0.008	-0.016	-0.007
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year>=2008				-0.041	0.015
				(0.015)	(0.024)
(Year>=2008)*(Unemp. rate)				0.646	-0.039
				(0.148)	(0.227)
R-square adj.	0.15	0.40	0.49	0.41	0.49
Year fixed effects	NO	NO	YES	NO	YES
State fixed effects	NO	YES	YES	YES	YES

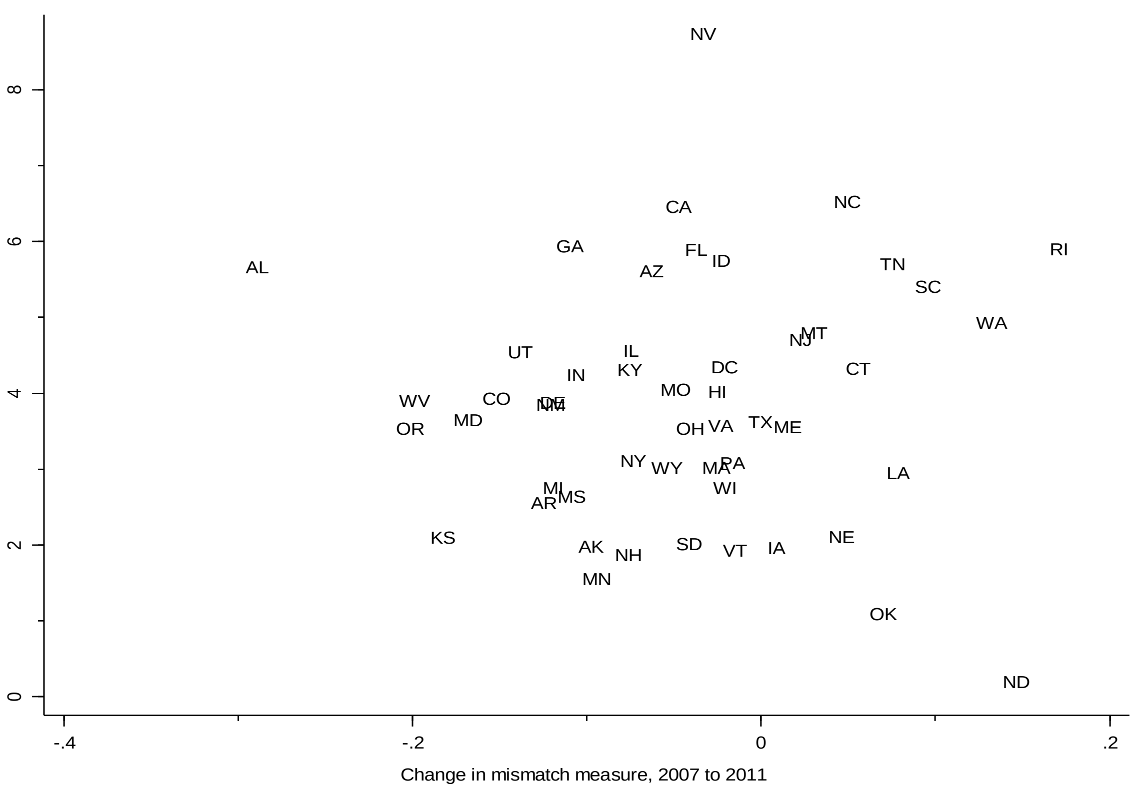
Note: Table displays coefficients from OLS regressions of the difference in log average predicted wages for emp. and unemp. persons on listed variables. Standard errors clustered at the state level are in parentheses. Observations are state-years; sample includes 1979-2011, all states and the District of Columbia, N=1683.

Fig 6: Cross-state relationship between changes in unemp. rate and QD

Panel A: 2007 to 2009



Panel B: 2007 to 2011



VI. QD IN OKUN'S LAW-TYPE RELATIONSHIPS

Finally, one might wonder whether QD helps explains movements in unemployment rate in an Okun's Law type framework. (Of course this exercise should be treated as merely descriptive, as variation in QD is surely not exogenous.) Table 3 shows estimates from national-level regressions in which the dependent variable is now the unemployment rate. The coefficient on the GDP gap (-0.44) is within the range usually found when estimating Okun's Law, and QD remains highly countercyclical.[3] QD dispersion across states (Table 3, cont.) is positive correlated with unemployment rates even after controlling for GDP gap and aggregate QD.

Table 3: Okun's Law-type relationship (national)

	(1)	(2)	(4)
Dependent variable: national unemp. rate			
GDP gap	-0.609	-0.441	-0.426
	(0.041)	(0.047)	(0.066)
Quality differential		-16.673	-16.775
		(3.462)	(3.834)
Year>=2008			4.918
			(2.856)
(Year>=2008)*(diff)			-24.974
			(13.982)
R-square adj.	0.87	0.93	0.93

Note: Table displays coefficients from OLS regression of the unemployment rate on listed variables. Standard errors are in parentheses. Observations are years; sample includes 1979-2011, N=33. GDP gap is the percent difference between real GDP and potential GDP (based on current CBO estimates for potential GDP).

[3] For evidence on the size of this coefficient for the United States and OECD countries, as well as the usual coefficients in alternative specifications of Okun's Law (including the difference specification used in the state-level panel data estimations in this paper), see Batini, Estevão, and Keim (2010).

Table 3 (cont.): Okun's Law including QD dispersion

	(1)	(2)	(3)
Dependent variable: national unemp. rate			
GDP gap	-0.441	-0.537	-0.435
	(0.047)	(0.044)	(0.046)
Quality differential	-16.673		-14.279
	(3.462)		(3.877)
Coeff of variation of QD across states		5.309	2.288
		(1.832)	(1.743)
R-square adj.	0.93	0.90	0.93

Note: Table displays coefficients from OLS regression of the unemployment rate on listed variables. Standard errors are in parentheses. Observations are years; sample includes 1979-2011, N=33. GDP gap is the percent difference between real GDP and potential GDP (based on current CBO estimates for potential GDP). Coeff of variation is the weighted cross-state average of QD divided by the cross-state st dev of QD.

Table 4 estimates similar regressions at the state level. Columns 1 and 2 again show the counter-cyclicality in QD even after controlling for state and year fixed effects. To embed QD in an Okun's Law-type framework at the state level, one seemingly needs an estimate of the output gap—and hence potential output—at the state level. As estimates of trend output at the state level are highly sensitive to specification, an equivalent specification—assuming that potential output evolves smoothly—is to estimate the relationship between the unemployment rate, QD, and state-level real GDP in differences. To estimate GDP by state, we take the BEA's estimate of annual GDP by industry and assume that a state's share of that industry's GDP is proportional to the share of that industry's workforce that is employed in the given state. Of course this will be imprecise since industries may use a different mix of capital and labor in some states, but it is probably a reasonable approximation. Estevão and Tsounta (2011) report that a measure of this type captures state-specific GDP variations better than BEA's state GDP statistics. Indeed, the latter uses information on where companies are incorporated, which is often different form where companies operate.

Column 3 shows estimates from a simple state-year version of Okun's law. The coefficient on GDP is somewhat smaller than the national regression, but this is probably to be expected given the significant degree of measurement error in state GDP (leading to attenuation bias). Column 4 includes QD, which remains highly counter-cyclical, even after including state fixed effects (column 5)—note that because this is equation is estimated in differences, this is equivalent to including state-specific time trends in a levels specification. The relationship between QD and the unemployment rate mostly goes away after controlling for year effects, which is to say that within a year, on average it does not appear true that states with higher levels of unemployment have smaller quality differences between the employed and unemployed. Finally, in column 7 we instrument for the change in GDP with the BEA's estimate of the percent change in personal income to correct for possible attenuation bias caused by measurement error in the state-level GDP variable. In this specification, the Okun's Law coefficient on GDP returns to the same magnitude as in the national-level regressions, though the coefficient on QD is now much less precisely estimated.

Table 4: Okun's Law-type relationship (state)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Dependent variable:			
	Unemp. rate		**Change in unemp. rate**				
Quality differential	-12.54	-3.76					
	(2.15)	(0.97)					
Percent change in GDP			-0.20	-0.19	-0.20	-0.08	-0.48
			(0.02)	(0.02)	(0.02)	(0.01)	(0.04)
Change in quality differential				-2.58	-2.52	0.09	-0.82
				(0.56)	(0.57)	(0.26)	(0.70)
OLS/IV	OLS	OLS	OLS	OLS	OLS	OLS	IV
Year fixed effects	NO	YES	NO	NO	NO	YES	NO
State fixed effects	NO	YES	NO	NO	YES	YES	YES

Note: Table displays coefficients from regression of the state unemp. rate (cols 1 and 2) or changes in the state unemployment rate (cols 3-7) on the level or change in the state quality differential measure, and percent change in state GDP (cols 3-7). Standard errors clustered at the state level are in parentheses. Observations are state-years; sample includes 1979-1980 difference to 2010-2011 difference; N=1683 in cols 1 and 2, and 1632 in cols 3-7. In the IV regressions, the percent change in the state's real GDP is instrumented by the percent change in the state's real level of personal income.

VII. CONCLUSIONS

A direct look at how labor skills evolved in the United States teaches us several facts. First, differences between the skills of employed workers and unemployed workers are procyclical. This can be explained by movements in and out of unemployment of workers with more similar characteristics to average employed individuals, and the relative size of the unemployment pool. Second, the cyclicality in quality differentials is mostly driven by movements in occupation/industry distributions, although age distributions also matter. A future version of this paper will develop this analysis further. Third, quality differentials continue to be related to the unemployment rates even after controlling for cyclicality in output, although a specification using state-level data and time-specific dummies soaks up much of this effect. Deviations from the usual relationship between unemployment rates and quality differentials could be interpreted as changes in skill mismatches, as they would represent either slower- or faster-than-usual convergence in the distribution of skills between employed and unemployed workers. Future research will (i) relate QD, unemployment rate and other state-level variables (i.e. housing market conditions) in search of a broader understanding of the shocks driving the latest labor market developments; and (ii) explore further the relationship between state-level dispersion in quality differentials and aggregate labor market outcomes.

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