The Education Gap and Unemployment in Metropolitan America: Methodological and Technical Appendix

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Methodological Appendix

Education Gap

To construct the education gap measure, data from the Bureau of Labor Statistics' Occupational Employment Statistics program was used to obtain a record of every job in each metropolitan area classified by occupation for the years 2005, 2007, and 2009. Those occupations were assigned an educational distribution (e.g. a percentage for each level of attainment) based on the amount of education attained by the average worker in the United States, using national data from the U.S. Census Bureau's American Community Survey (ACS), as reported and organized by the Integrated Public Use Microdata Series (IPUMS) for the same years.

The occupations are classified by the Standard Occupational Classification system (SOC). However, since the six-digit ACS occupational codes reported by IPUMS are slightly different than the BLS codes, three-digit occupations were used to make them comparable. This preserved considerable detail: There were 98 unique three-digit occupations in 2007. The educational distribution of these occupations was used to calculate industry demand for education. All respondents in the one-percent microdata samples were included if they were in the labor force—including individuals age 16 and older.

Educational attainment categories (e.g. high school, some college) were assigned a single number for typical years of education completed. The percentage of workers with less than a high school education was multiplied by 10; the share with a high school diploma was multiplied by 12; the share with some college was multiplied by 13; the share with an associate's degree was multiplied by 14; bachelor's degree by 16; master's degree by 18; and doctorate or professional degree by 20. For attainment below a bachelor's degree, those values correspond to the median years of education attained by respondents with those educational categories. For higher degrees, the years of a typical program are considered. Most bachelor's degree programs are four years, though some students complete the coursework faster or slower than that. PhD programs are considered to be four years, even if dissertation research may take longer.

The supply of education was calculated using the percentage of residents aged 25 and older with various levels of education for each metropolitan area, and the same formula described above was used to ascribe years of attainment to each level of education. The attainment data were gathered directly from the ACS for the years 2005, 2007, and 2009 for metropolitan areas. For the national education supply estimates, individual ACS data were obtained via IPUMS and individual weights applied to the population aged 25 and older.

Equation one shows the general approach to creating the education gap measure: The education gap is the level of education demanded by the average metropolitan area (m) job divided by the level of education supplied by the average worker.

$$1.\ Education\ Gap_m = \frac{Average\ Years\ of\ Education\ Demanded_m}{Average\ Years\ of\ Education\ Supplied_m}$$

The equations to calculate education demand are shown in equations two and three. The first step is to determine the share of jobs in a given metropolitan area associated with each level of educational attainment. As explained above, the average educational distribution—meaning the share of workers with each level of educational attainment—was calculated for each occupation using national data from the American Community Survey as reported by IPUMS. These national educational characteristics of each occupation were then matched to metropolitan jobs using the SOC categories.

Equation two shows how the educational distribution of metropolitan jobs was calculated for each area. The number of jobs (N) in a metro (m) associated with level of education (e) are summed over every three-digit occupation (o) in the metro. Dividing this by the total number of jobs (T) yields a measure for the percentage of jobs (ω) that require a given level of education for each metropolitan area. This is repeated for all six attainment categories.

$$2.\ \omega_{m,e} = \frac{1}{T}\sum_{o=1}^{o=98}(N_{o,m,e})$$

The second step is to translate the share of jobs with each level of education to an aggregate metropolitan measure for years of education obtained. To do this, the years of education required (y) for each educational category (e) is multiplied by the share of jobs in the metro area in that category (ω).The sum, across each education level, is equal to the years of education demanded by the average metropolitan job.

$$3. Average\ Years\ of\ Education\ Demanded_{\ m} = \sum_{e=1}^{e=6} (y_e \omega_{m,e})$$

To measure education supply, the percentage of the population with the relevant education level (σ) is multiplied by the years of education required (y). Data from the 2005, 2007, and 2009 American Community Survey was used to construct a measure of the supply of education among adults age 25 and older. The sum is the years of education attained by the average worker in the metropolitan area.

$$4. Average\ Years\ of\ Education\ Supplied_m = \sum_{e=1}^{e=6} (y_e \sigma_{m,e})$$

Industry Demand for Employment

Since unemployment rates are affected by changes in industry demand, and not just the match between the demand and supply of workers, a comprehensive measure of industry demand is needed to control for metropolitan-specific industry composition. The most straightforward way to measure a local economy's industry demand for workers would be to observe how changes in industry employment at the metropolitan scale affect metropolitan unemployment. However, the causality runs both directions, so such an analysis would be fundamentally biased. Instead, the analysis focuses on how national industry changes play out at the metropolitan level. The goal is to predict the changes in an industry's local employment that one would expect given national employment trends in that same industry.

Equation five shows how predicted industry demand was measured for each metropolitan area. National industry growth rates, *g*, over a given period (t_0 to t_1) for each industry (*i*) sub-sector (i.e. three-digit NAICS) were multiplied by the metropolitan (*m*) share of employment (*p*) in that industry at the start of each period, (t_0). This yields a measure of how national employment trends in each industry would be expected to affect metro employment.

$$4. Industry\ Demand_{m,t_0-t_1} = \sum_{i=1}^{i=n} (g_{i,t_0-t_1} p_{i,m,t0})$$

To conduct the analysis, these two indexes—the education gap and industry demand—were used to predict the level of and changes in unemployment rates across metropolitan areas during various periods in recent economic history. In doing so, the analysis controls for metropolitan demographic variables as well as state characteristics that are common to every metro in that state.[1] Metros that cross state boundaries are assigned to the state of their primary city.

Technical Appendix Tables

The tables in this section show the results of various regressions undertaken to determine the statistical validity of the results in the report. The results of these exercises suggest—but do not entirely prove—that the findings presented above are statistically significant, not the result of omitted variables bias, and not the result of reverse causality. Proving that more definitively would require a natural experiment that is quite rare generally in social science and not really plausible in this specific case.

Predicting average unemployment rates since 2005

Appendix Table 1 shows regression results that are relevant to the first finding that metropolitan areas with higher education gaps suffer from consistently higher unemployment rates. In this table, the main independent variable is the average education gap from 2005 to 2009, and the dependent variable is the average unemployment rate from 2005 to 2010 using annual data for each year. The education gap index is highly significant even controlling for various metropolitan characteristics, including demographic characteristics, the share of workers with a bachelor's degree, and actual job growth from 2005 to 2010 instrumented using predicted job growth.

Including the share of workers with a bachelor's degree in the model lowers the magnitude of the education effect by roughly one third. This is not surprising considering that this variable is highly correlated with the denominator of the education gap index. It indicates, however, that the supply of education is not the only thing that matters. All things being equal in terms of educational attainment, metro areas with more jobs available to less educated workers experience lower unemployment rates.

[1] Specifically, binary variables were included in the analysis equal to one for every metro in the relevant state and zero otherwise. State characteristics that might affect unemployment rates and are common across metros include things like banking laws, union laws, tax rates, the quality of public goods like education system and infrastructure.

Some readers may be concerned that the average education gap could be affected by unemployment rate changes, which would bias the results of regression. To attempt to guard against this possibility, the 2005 measure of the education gap was used as an instrument to first predict the average from 2007 and 2009, since the 2005 measure is unlikely to be affected by subsequent changes in the future. The size and significance of the education gap variable were not substantially changed (ranged from 32 to 34). As a further check, the share of adults aged 25 and older with a bachelor's degree was used as an instrument for the 2005-to-2009 education gap. Bachelor's degree attainment in 2000 is highly predictive of the average education gap between 2005 and 2009. [2] This makes it a plausible instrument so long as unemployment in 2005 and 2010 do not predict bachelor's degree attainment in 2000. The results were again robust, with coefficients ranging from 32 to 49 and p-values less than 0.05. These findings are not shown to conserve space but are available upon request.

Appendix Table 1. Medium-term Metropolitan Area Unemployment Regressed on Metropolitan Education Gap and Other Characteristics at the Start of the Recession

Average Unemployment Rate from 2005 to 2010	1	2	3	4
Industry Predicted Job Growth 1970-2000	-1.115	-1.318	-1.086	-1.367***
	(1.124)	(0.990)	(1.022)	(0.465)
Industry Predicted Job Growth 2005-2010	-0.942	-6.822	-5.209	
	(9.525)	(7.757)	(8.083)	
Average Education gap (2005, 2007, 2009)	32.09***	29.56***	22.16**	29.06***
	(7.358)	(7.611)	(8.649)	(2.438)
White Share of Population, 2005		2.255	2.242	2.228
		(2.443)	(2.321)	(1.550)
Black Share of Population, 2005		5.765***	5.856***	5.013***
		(1.854)	(1.741)	(1.653)
Foreign-Born Share of Population, 2005		6.073***	7.166***	6.343***
		(1.666)	(1.881)	(1.406)
Elderly (65 and older) Share of Population, 2005		25.76***	22.80***	24.48***
		(5.689)	(5.606)	(3.698)
Median Age of Population, 2005		-0.173**	-0.156**	-0.187***
		(0.0719)	(0.0691)	(0.0370)
Share of Adults 25 and older with Bachelor's Degree or Higher, 2005			-3.292	

[2] The correlation is -0.87, with a F-stat of 582 in a regression of the gap on attainment with state effects.

			(2.491)	
Actual Job Growth 2005-2010 (instrumented)				-5.318*
				(2.883)
Constant	-24.71***	-21.95***	-14.23	-21.00***
	(6.916)	(7.659)	(8.958)	(3.258)
Observations	358	354	354	354
Adjusted R-squared	0.631	0.689	0.690	0.705

Robust standard errors in parentheses, clustered on states (except column 4). *** p<0.01, ** p<0.05, * p<0.1. All regressions include state fixed effects. Columns 4 uses predicted job growth as an instrument for actual job growth.

The Education Gap by Education Level

Appendix Table 2 goes one step further and asks: Which education gap matters most in explaining unemployment rates? To assess this, education gaps were calculated for each level of education for 2005, and those indexes were independent variables in a regression predicting average unemployment from 2005 to 2010. The results show that bachelor's degree and master's degree attainment gaps are the most significant, and other "gaps" become insignificant. Moreover, master's degree attainment gaps remain significant even after controlling for the share of the population with a bachelor's degree, suggesting that unmet demand for master's degree workers has a significant effect on unemployment. master's degree earners in engineering and science play important roles in innovation and technical fields, which may partly explain the finding; similarly MBA's may be better entrepreneurs than those holding a bachelor's degree alone.

Column 3 of the table breaks down the supply and demand variables further still and drops the gap measures. In other words, Column 3 controls for the share of jobs that demand each level of education (except associate's degree) and the share of the adult population that has attained each of those degrees (except associate's). The results confirm the previous findings. On the supply side, it is important that a metro's population has high rates of bachelor's and master's degree attainment. But some of the demand side variables are also significant: the share of occupations requiring a high school diploma and the share requiring a PhD or professional degree. The first indicates that elevated demand for less educated workers does seem to decrease subsequent unemployment. The second is probably related to the stability provided by "eds and meds." Metro areas dominated by large universities (e.g. Ithaca, NY and State College, PA) and metro areas with a high concentration of workers in hospitals exhibit high demand for PhDs and professional degrees, and both of these industries grew during the recession.

Appendix Table 2. Medium-term Metropolitan Area Unemployment Regressed on Specific Education gaps

	Average Unemployment Rate from 2005 to 2010		
	1	2	3
Industry Predicted Job Growth 1970-2000	-1.423	-0.997	-0.143
	(1.028)	(0.999)	(1.052)
Industry Predicted Job Growth 2005-2010	-8.041	-5.460	-18.81***
	(7.807)	(7.563)	(5.626)
White Share of Population, 2005	2.974	2.598	0.791
	(2.596)	(2.395)	(1.470)
Black Share of Population, 2005	7.058***	6.926***	5.821***
	(2.417)	(2.164)	(1.083)
Foreign-Born Share of Population, 2005	9.215***	9.391***	4.121***
	(1.831)	(2.021)	(1.415)
Elderly (65 and older) Share of Population, 2005	20.52***	16.26***	9.452
	(4.761)	(4.445)	(5.724)
Median Age of Population, 2005	-0.114**	-0.0838*	-0.0240
	(0.0433)	(0.0449)	(0.0571)
Demand for Less than High School Educations/Supply of Less than High School Educations	0.0795	0.321	
	(0.196)	(0.201)	
Demand for High School Educations/Supply of High School Educations	-0.248	0.450	
	(0.467)	(0.504)	
Demand for Some College Educations/Supply of Some College Educations	-0.149	0.0503	
	(0.507)	(0.515)	
Demand for Assoc.'s Degree Educations/Supply of Assoc.'s Degree Educations	-0.140	0.0569	
	(0.232)	(0.259)	
Demand for Bachelor's Degree Educations/Supply of Bachelor's Degree Educations	2.703**	2.215	
	(1.301)	(1.428)	
Demand for Master's Degree Educations/Supply of Master's Degree Educations	1.090***	0.948**	
	(0.360)	(0.385)	
Demand for Doctorate Degree Educations/Supply of Doctorate Degree Educations	-0.289	-0.334	
	(0.335)	(0.338)	
Share of Adults 25 and older with Bachelor's Degree or Higher, 2005		-5.037*	
		(2.521)	

Share of occupations Not Requiring High School, 2005			-10.83
			(39.69)
Share of occupations Requiring High School, 2005			-118.5***
			(28.78)
Share of occupations requiring some college, 2005			-47.14
			(36.69)
Share of occupations requiring Bachelor's degree, 2005			-86.50*
			(44.93)
Share of occupations requiring Master's degree, 2005			3.853
			(31.58)
Share of occupations requiring PhD or Professional degree, 2005			-138.3**
			(54.99)
Share of adults over 25 with less than high school, 2005			3.029
			(4.677)
Share of adults over 25 with high school, 2005			-4.880
			(4.094)
Share of adults over 25 with some college, 2005			-8.019
			(5.043)
Share of adults over 25 with Bachelor's, 2005			-15.02**
			(6.328)
Share of adults over 25 with Master's, 2005			-17.15***
			(5.949)
Share of adults over 25 with PhD or Professional degree, 2005			-3.819
			(6.755)
Constant	2.157	2.115	75.65**
	(3.434)	(3.276)	(31.21)
Observations	354	354	354
Adjusted R-squared	0.712	0.716	0.735

Robust standard errors in parentheses, clustered on states. *** p<0.01, ** p<0.05, * p<0.1. All regressions include state fixed effects.

Unemployment changes from the pre-recession minimum

Appendix Table 3 examines the relationship between the education gap, industry demand, and the increase in unemployment rates since the start of the recession (taking the starting point as the minimum annual unemployment rate between 2006 and 2010, including May of 2011). The year of minimum unemployment rate was typically 2006 or 2007. In only 6 of 358 cases was it later than 2007 (2008 in each case).

In these regressions, change variables are included for the education gap and the demographic characteristics. The first regression uses only change variables, but few are significant. The other regressions include controls for the pre-recession starting points using the level of 2007 variables. Many of these variables are significant, including the level and change in education gap, as well as predicted industry demand from the beginning of the recession to the first quarter of 2011.

These regressions were repeated using the 2007 to 2009 unemployment rate change as the dependent variable. The results were very similar to those shown, but the education gap effect was somewhat smaller relative to predicted industry demand. In other words, during the worst period of the recession, the education gap had less predictive power than the interplay of regional industry composition and national trends.

Likewise, a regression that looked at the "recovery" period—defined as the first quarter of 2010 until the first quarter of 2011—found no significant effects from the education gap index. As for predicted industry changes, stronger growth performance during the worst of the recession (2007 to 2009) was highly correlated with larger increases in unemployment rates during the recovery period, whereas predicted growth for the year ending in the first quarter of 2011 was associated with lower increases in unemployment. In other words, reductions in unemployment rates over the last year were largely characterized by a rebound effect—as workers in the hardest-hit metro areas were re-absorbed into the labor market more quickly than their counterparts in less affected metro areas.

Appendix Table 3. Unemployment Rate Increase from Pre-recession Minimum Regressed on Education gap and Industry Demand

	(Unemployment Rate in May 2011) - (Lowest Unemployment Rate before Recession)				
	1	2	3	4	5
Industry Predicted Job Growth, 2008q1 to 2011q1	-15.25*	-19.86***	-16.92***		
	(8.516)	(5.789)	(6.218)		
Industry Predicted Job Growth, 2010q1 to 2011q1					-74.80***
					(21.23)
Industry Predicted Job Growth, 2008q1 to 2010q1					-22.52***
					(5.591)

Instrumented Actual Job Growth, 2008q1 to 2011q1				-15.96***	
				(3.418)	
Change in Education gap Index, 2007 to 2009	1.420	20.20**	17.50**	17.72***	20.36**
	(5.290)	(8.192)	(7.407)	(5.267)	(8.153)
Change in White Share of Population, 2007 to 2009	0.199	-4.249	-4.569	-4.083**	-4.967
	(1.185)	(3.110)	(3.133)	(1.806)	(3.063)
Change in Black Share of Population, 2007 to 2009	1.916	2.953	2.211	11.46*	1.991
	(9.217)	(8.348)	(7.967)	(6.577)	(7.819)
Change in Foreign-born Share of Population, 2007 to 2009	9.685	19.14*	21.24*	14.92***	19.08*
	(10.45)	(10.55)	(11.10)	(5.056)	(10.71)
Change in Share of Elderly Share of Population, 2007 to 2009	-40.26**	2.128	0.655	10.31	-4.996
	(16.01)	(19.01)	(18.02)	(11.90)	(18.72)
Change in Median age of Population, 2007 to 2009	0.366***	0.257**	0.260**	0.142**	0.282***
	(0.0844)	(0.101)	(0.0972)	(0.0663)	(0.103)
Education gap, 2007		17.42***	6.023	17.06***	17.13***
		(4.862)	(7.468)	(1.776)	(4.587)
White Share of Population, 2007		0.715	0.771	0.861	0.425
		(1.442)	(1.432)	(1.260)	(1.483)
Black Share of Population, 2007		3.136*	3.432**	2.410*	2.814*
		(1.587)	(1.631)	(1.343)	(1.639)
Foreign-Born Share of Population, 2007		5.944**	7.789**	5.710***	6.193**
		(2.537)	(3.273)	(1.142)	(2.639)
Elderly (65 and older) Share of Population, 2007		14.15**	10.25*	13.88***	13.10**
		(6.520)	(5.504)	(3.173)	(6.404)
Median Age of Population, 2007		-0.127**	-0.0999*	-0.145***	-0.111**
		(0.0534)	(0.0521)	(0.0259)	(0.0506)
Share of Adults 25 and older with Bachelor's Degree or Higher, 2007			-4.695*		
			(2.381)		
Constant	3.416***	-12.97***	-0.950	-11.39***	-12.50***
	(0.452)	(3.977)	(6.739)	(2.339)	(3.798)
Observations	354	354	354	354	354
Adjusted R-squared	0.694	0.778	0.782	0.803	0.783

Robust standard errors in parentheses, clustered on states (except column 4). *** p<0.01, ** p<0.05, * p<0.1. All regressions include state fixed effects. Column 4 uses predicted industry growth to instrument for actual growth.

Metropolitan Fixed Effects

The results so far have looked at how well the education gap and industry demand indexes explain unemployment rates *across* different metropolitan areas. Appendix Table 4, on the other hand, analyzes how these indexes explain unemployment rates over time *within* the same metropolitan area. To do this, a panel was created for every metropolitan area in the database (358 in total) for the periods 2005, 2007, and 2009. The industry demand index was calculated to predict job growth during the three-year period ending in the year observed (e.g. 2002 to 2005 for the 2005 measurement).

Metropolitan fixed effects were used to adjust for unmeasured metropolitan characteristics that were constant over time (such factors would include weather, local laws, infrastructure, and state laws). Time effects were also included in some of the regressions, as indicated, to account for national trends that affected all metros. All regressions shown calculated heteroskedastic-robust standard errors (meaning the errors can vary as predictive variables change in size across metros). Finally, in the last regression, these controls were combined with a technique that is robust to correlation over time in the regression errors. In other words, this approach adjusts for the possibility that the model's unexplained variation could be cumulative in its effect within metros and might be correlated with variables of interest.

The results of this analysis show that the education gap remains highly significant and is robust to these various econometric adjustments. The predictive power of the education gap is reduced, but this is partly because the variation within metros over time is very small, compared to the variation in predicted industry changes.

To summarize this section, there is no evidence that the results discussed in the main body of the report are statistical artifacts of omitted variables bias or endogeneity. It appears that the education gap and the industry demand indexes used here are valid and important predictors of metropolitan unemployment rates.

Appendix Table 4. Panel Analysis of Metropolitan Unemployment Rate and Education gap using 2005, 2007, and 2009 Observations

	Metropolitan Unemployment Rate					
	1	2	3	4	5	6
Education Gap	21.17***	8.065	36.75***	14.79**	17.88***	11.54***
	(5.549)	(5.631)	(7.048)	(7.476)	(2.603)	(1.523)
Predicted Job Growth Over Last Three Years	-53.91***	-47.93***	-52.55***	-47.77***	- 51.92***	-51.55***

	(1.280)	(8.556)	(1.267)	(8.546)	(1.640)	(1.413)
Median Age of Population	0.266***	0.375***	0.285***	0.373***	0.403***	0.404***
	(0.0567)	(0.0633)	(0.0555)	(0.0624)	(0.0177)	(0.0162)
Black Share of Population	24.32***	12.48	21.75***	12.64	8.535***	8.718***
	(8.252)	(8.084)	(7.929)	(8.058)	(2.152)	(2.178)
Share of Population Foreign Born	-8.402	-11.08	-9.133	-11.08	-11.24***	-11.47***
	(7.935)	(7.256)	(7.688)	(7.223)	(1.871)	(1.674)
White Share of Population	0.484	1.725	0.481	1.607	1.395	1.200
	(2.423)	(2.431)	(2.399)	(2.424)	(0.933)	(0.914)
Share of Population 65 Years or Older	26.24***	-21.34*	14.49	-21.23*	-25.44***	-25.24***
	(9.235)	(12.87)	(10.05)	(12.77)	(4.198)	(3.874)
Share of Working-age Population with Bachelor's Degree or Higher			16.38***	5.851	4.852***	
			(4.594)	(4.568)	(1.491)	
Constant	-29.63***	-13.45**	-48.15***	-21.51**	-24.87***	-17.25***
	(6.504)	(6.708)	(8.201)	(9.016)	(3.013)	(1.892)
Observations	1,065	1,065	1,065	1,065	1,064	1,064
R-squared	0.855	0.864	0.858	0.865		
Number of MSAs	358	358	358	358	357	357
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	No	Yes	No	Yes	Yes	Yes
Auto-correlation within panels	No	No	No	No	Yes	Yes

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All regressions control for metropolitan area fixed effects and are robust to heteroskedasticity. Year effect controls are indicated when used. Columns five and six use generalized least squares and MSA binary variables to adjust for auto-correlation within MSAs over time. Columns 1-4 were re-estimated with errors clustered on MSAs without changing the significance of the estimates for education gap or industry demand. Specifically, the standard errors became slightly smaller when year effects were omitted and slightly larger when year effects were included.

Unemployment Rates by Education Group

Appendix Table 5 provides the formal analysis behind the finding that the education gap explains higher unemployment rates for workers with a high school diploma or less but does not predict unemployment rates for workers with some college or post-secondary degrees. The analysis here is restricted to 2009 unemployment rates because that is the latest available data on unemployment rates by education group from the Census Bureau (the BLS does not report this data at the metropolitan scale). The same control variables are used to adjust for general metropolitan conditions.

Appendix Table 5. 2009 Unemployment Rates by Education Group Regressed on Education Gap

	Unemployment Rate- Less than High School	Unemployment Rate- High School	Unemployment Rate-Some College	Unemployment Rate- Bachelor's or higher	Unemployment Rate- High School or Less minus BA or higher
	1	2	3	4	5
Education Gap in 2009	0.572***	0.210**	0.0643	0.0126	0.315***
	(0.135)	(0.0975)	(0.0613)	(0.0291)	(0.0919)
Predicted Job Growth, 2007-2009	0.273	-0.351**	-0.518***	-0.0520	-0.161
	(0.318)	(0.142)	(0.121)	(0.0962)	(0.139)
White Share of Population, 2009	0.170***	0.0693*	-0.0108	0.00934	0.0912***
	(0.0624)	(0.0393)	(0.0322)	(0.0209)	(0.0227)
Black Share of Population, 2009	0.270***	0.131***	0.0307	0.00901	0.165***
	(0.0782)	(0.0430)	(0.0419)	(0.0255)	(0.0265)
Foreign-born Share of Population, 2009	-0.0912	0.0775*	0.0432	0.0911***	-0.0159
	(0.0650)	(0.0392)	(0.0310)	(0.0215)	(0.0368)
Share of population aged 65 or older, 2009	0.171	0.102	0.120	0.0890*	0.0814
	(0.205)	(0.111)	(0.0909)	(0.0461)	(0.0945)
Median age of population, 2009	0.000570	0.000309	0.000130	0.000294	-0.000565
	(0.00179)	(0.000797)	(0.000542)	(0.000400)	(0.000899)
Constant	-0.598***	-0.226***	-0.0311	-0.0144	-0.327***
	(0.154)	(0.0843)	(0.0640)	(0.0281)	(0.0859)
Observations	354	354	354	354	354
Adjusted R-squared	0.332	0.526	0.512	0.363	0.375

Robust standard errors in parentheses, clustered on states. All regressions include state fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

State Policies

The results reported in the main section of this report and in the analysis discussed above use state fixed effects, an econometric technique that effectively creates binary variables for whether the metropolitan area is in a given state or not. In practice, this adjusts for the average effect of being in a specific state, given other variables. It adjusts for unchanging factors that are common to each metropolitan area in the state. These include weather, geography, state policies, and history. To be clear, these variables are not controlled for directly, but they are effectively absorbed by using state effects insofar as they are common across metro areas in the same state.

Because the use of state effects controls for the characteristics common to all metropolitan areas in a state, one cannot control for state fixed effects and specific state policies at the same time. And yet, state policies might inform the analysis. Therefore, for this last section, state effects are dropped and three state policies are considered: banking regulation, union regulation, and the state and local tax burden.

The only variable that proved to be significant in the regressions presented here was banking regulation. The education gap measure and the predicted industry change index remained significant after adding these variables.

The analysis considered the effects of state branching deregulation, using data from a recent academic paper on the subject. [3] Before 1970, most states did not allow chartered banks to open new branches within the state or to merge and acquire other banks. This promoted community banks, which operated akin to local monopolies.[4] Economists from the IMF have found that branching regulation had a strong causal effect on housing prices during the housing bubble through more lenient lending standards and a larger number of loans.[5] Indeed, an analysis performed here shows that state foreclosure rates are significantly higher in states with more years of bank deregulation.[6] Evidently, a longer period of deregulation has allowed further penetration of large banks into regional markets, further mergers and acquisitions, and an elevated supply of risky housing loans during the housing boom.

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[3] Thorsten Beck, Ross Levine, and Alexey Levkov, “Big Bad Banks? The Winners and Losers from Bank Deregulation in the United States,” *Journal of Finance* 65 (5) (2010): 1637-1667. Data is available at Beck’s World Bank website.
[4] Randall Kroszner and Philip Strahan, “What Drives Deregulation? Economics and Politics of the Relaxation of Bank Branching Deregulation,” *Quarterly Journal of Economics* 114 (1999): 1437-67.
[5] Giovanni Favara and Jean Imbs, “Credit Supply and the Price of Housing” Discussion Paper 8129 (Center for Economic Policy Research, 2010).
[6] State foreclosure data was obtained from the Federal Reserve Bank of New York for February 2009.

Appendix Table 6 shows the results of regression analysis that includes these variables. The number of years since banking deregulation is strongly and significantly correlated with higher unemployment rates. The average state deregulated in 1980. States such as California, Rhode Island, and Nevada were the first to deregulate, as far back as 1960, and those states have suffered disproportionately from foreclosures and a corresponding upswing in unemployment rates. Iowa, which has one of the lowest increases in unemployment, was the last to deregulate in 1999. Likewise, Texas, which has seen only a modest increase in unemployment, deregulated late—in 1988. On average, ten years of deregulation correspond to an unemployment rate increase that is between 0.34 and 0.39 percentage points larger, even adjusting for industry composition. This does not mean that banking deregulation was necessarily a mistake, since it may have benefits that compensate for the costs identified here. It does however suggest that stricter lending standards associated with later banking deregulation may have mitigated the recession's impact in some states.

2007 data on the marginal rate of overall state and local government taxation for each was compiled from the Tax Foundation, a nonpartisan tax research group based in Washington DC. This variable adjusts for the fact that some states collect more in revenue because they are richer and focuses on the burden as it related to economic activity. The Democratic Party strongholds of New Jersey, New York, Connecticut, and California had the highest rates. Nevada and Texas are among the state with the lowest rates. As for the rate's predictive power, many of the northeastern states were just about average on unemployment rate changes, and Nevada and California were the first and third worst hit states in terms of unemployment rate changes from 2006 to 2010, and yet they were on opposite ends of the tax distribution in 2007. Florida, too, experienced very large unemployment rate increases despite having a low tax burden. With that in mind it is not surprising that the tax burden variable does not predict changes in the unemployment rates of metropolitan areas.

The National Right to Work Legal Defense Foundation provided the data on state right to work laws, which govern whether or not unions can forbid workers from getting a job unless they agree to be part of the union. Union organization is significantly higher in non-right-to-work states. This variable had no predictive power in explaining unemployment rates. Some states with favorable laws towards union organizing such as California and Michigan do have high unemployment rates, but states like Vermont, New Hampshire, and Minnesota had low unemployment rates despite laws favorable towards unions, and Florida and Nevada are right-to-work states with high unemployment rates.

Appendix Table 6. Unemployment Rate Increase from Pre-recession Minimum Regressed on State Policies, the Education gap, and Industry Demand

	1	2	3
Industry Predicted Job Growth, 2008q1 to 2011q1	-29.54***		

	(7.721)		
Industry Predicted Job Growth, 2010q1 to 2011q1			-134.1***
			(38.26)
Industry Predicted Job Growth, 2008q1 to 2010q1			-34.75***
			(7.171)
Instrumented Actual Job Growth, 2008q1 to 2011q1		-19.98***	
		(3.523)	
Change in Education gap Index, 2007 to 2009	16.47	12.43*	17.14
	(11.05)	(6.976)	(11.21)
Change in White Share of Population, 2007 to 2009	-8.201***	-6.268***	-8.701***
	(2.742)	(2.374)	(2.520)
Change in Black Share of Population, 2007 to 2009	5.875	15.52*	5.357
	(7.393)	(8.804)	(7.048)
Change in Foreign-born Share of Population, 2007 to 2009	16.69**	14.47**	18.07**
	(8.307)	(6.469)	(8.624)
Change in Share of Elderly Share of Population, 2007 to 2009	18.07	11.34	6.674
	(21.07)	(15.45)	(21.60)
Change in Median age of Population, 2007 to 2009	0.262*	0.154**	0.300*
	(0.153)	(0.0765)	(0.152)
Education gap, 2007	13.06**	14.02***	12.84**
	(5.884)	(2.249)	(5.388)
White Share of Population, 2007	-0.774	0.426	-0.618
	(1.888)	(1.112)	(1.858)
Black Share of Population, 2007	1.867	2.235*	2.220
	(2.110)	(1.176)	(2.069)
Foreign-Born Share of Population, 2007	12.43***	10.60***	12.72***
	(2.388)	(1.375)	(2.327)
Elderly (65 and older) Share of Population, 2007	24.47***	20.80***	22.97***
	(5.282)	(3.694)	(5.303)
Median Age of Population, 2007	-0.152***	-0.162***	-0.128**
	(0.0562)	(0.0301)	(0.0528)
Years since Bank Deregulation (from 2006)	0.0387***	0.0337***	0.0342**
	(0.0134)	(0.00603)	(0.0130)

Years of having a right-to-work law (from 2006)	0.00705	0.00469*	0.00499
	(0.00698)	(0.00283)	(0.00691)
State overall marginal tax rate	-4.781	-11.84*	-9.387
	(17.94)	(6.566)	(17.00)
Constant	-9.386*	-8.934***	-8.813*
	(5.336)	(2.720)	(5.000)
Observations	354	354	354
Adjusted R-squared	0.518	0.641	0.536

Robust standard errors in parentheses, clustered on states. *** p<0.01, ** p<0.05, * p<0.1.