Geography and Gender: Variation in the Gender Earnings Ratio Across U.S. States*

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Objectives. The gender earnings ratio for year-round full-time (YRFT) workers varies substantially across U.S. states, with a range of 24 percentage points. I examine the sources of this variation to assess to what extent it reflects compositional differences by gender that vary across state and/or nonneutral effects of state of residence on gender earnings. *Methods.* Using CPS data, I estimate earnings models for men and women that incorporate state fixed effects in addition to standard human capital and demographic variables. I use those estimates to compute unadjusted and regression-adjusted estimates of the impact of state residence on the gender earnings ratio. *Results.* I find that nonneutral gender-specific state effects on earnings exist even after controlling for other determinants of earnings and that state of residence appears, therefore, to have a genuine effect on the gender earnings ratio. I also find that states with particularly low overall gender earnings ratios have consistently low ratios even within quite detailed education and occupation categories. *Conclusions.* Variation in the gender earnings ratio for YRFT workers across states is not simply a result of compositional differences. It is unclear, however, what policy instruments or other factors account for these differences.

Earnings differences by gender in the United States have been widely studied for many years, with primary emphasis on human capital issues (Corcoran and Duncan, 1979; O'Neill, 1985), differential marriage and family effects (Waldfogel, 1998), labor market demand shifts (Blau and Kahn, 1997), and a variety of discriminatory mechanisms (Goldin, 1992; Lang, 2007). Two Census Bureau publications (Semega, 2009; Getz, 2010) report that state of residence may be another factor affecting gender earnings differences: while the overall gender median earnings ratio for year-round full-time (YRFT) workers in 2008 was 77.9 percent, the ratio was less than 73 percent in eight states, greater than 83 percent in five states, and had an overall range of almost 24 percentage points. This finding is consistent with two broad explanations, one reflecting possible gender differences across states in relative skills or in demographic characteristics such as race and ethnicity, and the other reflecting

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possible gender-based differences in the market value of skills in state labor markets.

The Census Bureau reports do not attempt to account for the cross-state variation in the gender earnings ratio. In this article, I explore these state-level differences in the gender gap by using CPS data to estimate earnings models for men and women that include the impact of state of residence, first with no other explanatory variables and then with a full set of standard earnings equation explanatory variables. The difference in the estimated state effects across these models shows how much of the state effect remains after adjusting for underlying differences in worker composition by gender. I then focus on states at the extremes—those with the largest positive and negative state effects after controlling for worker traits—and look in further detail by education and occupation to see what is generating the state impacts.

I find that state effects on men's and women's earnings remain, even after controlling for other standard variables that affect earnings, and that because these state effects are not genderneutral, state of residence does affect the gender earnings ratio. Louisiana has the most negative regression-adjusted impact on the gender earnings ratio, meaning that women there earn the least relative to men compared to what would be expected based on worker characteristics and a common labor market value of those characteristics. Maine has the most positive regression-adjusted impact on the gender gap. The District of Columbia has the highest unadjusted earnings ratio, but most of that is due to composition. Utah has a large negative unadjusted impact of the gender earnings ratio, but that, too, is largely due to composition. When I look closely at the states at the extremes, I find a consistent pattern of lower earnings ratios within detailed education attainment and occupation categories. This finding is consistent with a general pattern of more limited opportunities for women in these states.

The outline of this article is as follows. The next section reviews the findings from the Census Bureau report and briefly reviews the relevant gender earnings differences literature. The section entitled "Methods and Data" presents the data and methods I use to examine the issue. The fourth section contains my estimates and analyses and the section entitled "Extensions: A Closer Look at Extremes" presents a brief analysis of gender earnings differences by education and occupation between the states with the largest positive and negative impact on the gender earnings ratio. The "Summary and Conclusions" section provides a brief summary and discussion.

Background and Literature Review

The Census Bureau analyses of state variation in the gender earnings ratio reported in Semega (2009) and Getz (2010) are based on annual earnings data from the American Community Survey (ACS), a very large nationally representative Census Bureau survey. Conducted since 2005, the ACS includes every county in the United States and contains nearly 3 million observations. Data in the ACS include core demographic information as well as information on income, earnings, health insurance, and education. The earnings data used in these two studies are for YRFT workers, who are defined as persons who work at least 35 hours per week and 50 weeks a year.[1] Most discussions of the gender gap in earnings focus on median earnings for YRFT workers (see, e.g., Hegewisch and Williams, 2013; Hoffman and Averett, 2010; Blau, Ferber, and Winkler, 2014) because such earnings comparisons are less affected by gender differences in annual labor supply and also by outliers.

In the 2008 ACS data used by Semega, the ratio of median earnings by gender for YRFT workers was 77.9 percent. About half of the states were within approximately 2 or 3 percentage points of this figure, while the other half were scattered, 19 with a median earnings ratio below 75 percent and eight with a ratio above 80 percent; see Online Appendix (Figure 1) for more information. The overall range was from 64.3 percent in Wyoming to 88 percent in the District of Columbia. Results reported in Getz for 2009 are quite similar.

The Census Bureau reports do not attempt to explain the variation in the gender earnings ratio across states. A large body of research in economics and sociology has examined earnings by gender, usually with the goal of explaining differences in means and quantifying the impact of particular factors on earnings differences. Most of the early work on gender earnings differences emphasized human capital issues involving education and especially work experience and continuity (Corcoran and Duncan, 1979; O'Neill, 1985). As educational and work experience differences by gender have diminished substantially, family responsibility issues have received relatively more attention in the family gap literature (Waldfogel, 1998). Because those literatures are well known, I do not review them here except to note that almost all approaches ultimately distinguish between "explained" sources of the wage difference based on average differences by gender in skills or other characteristics and "unexplained" differences reflecting the different labor market value of those skills and characteristics by gender. These traditional explanations of the gender gap could apply to state earnings ratios if the relative qualifications of men and women varied across states and/or if returns by gender vary.

The fact that men's and women's earnings may differ by geographic location is certainly not new. Regional economic differences and urban/rural differences in earnings are longstanding and well studied. But that kind of analysis is quite distinct from the issue of whether men and women might be differentially affected by residence in a particular location. In well-functioning labor markets with sufficient mobility, similarly skilled workers ought to receive similar wages across geographic areas. This might be less true for women if they are less

[1] Paid time off or sick time are treated as weeks worked. Approximately 70 percent of working men and 60 percent of working women work YRFT.

geographically mobile than men or if family location decisions are made with priority given to male employment prospects (Corcoran and Duncan, 1979; Fuller, 2008).

Other than the Census Bureau reports, no research in economics has examined the variation in the gender earnings ratio by state. In the sociological literature, Ryu (2010) has proposed that state policies concerning welfare and family policy, as well as the scale of public-sector employment, could affect relative gender outcomes in the labor market. The analysis is based on the 2000 Census 1 Percent PUMS and utilizes multilevel models. She reports that an ideology score of state government has a positive effect on women's earnings, a measure of commitment to the Family and Medical Leave Act has no effect, and that the size of the state public social service sector has a negative effect. Her research does not focus on the size of state effects nor identify them specifically by state. She does not explore whether compositional differences in skills by gender can account for the earnings differences across states.

To date, then, there appears to be little no research that examines how and why the gender ratio of YRFT workers varies across states and no research that identifies the net impact of residence in specific states on the gender earnings ratio. This article intends to provide such estimates of state effects on men's and women's earnings and the possible causes of those effects.

Methods and Data

My basic approach involves adding state of residence as a covariate to an otherwise standard human capital earnings function. I estimate earnings regressions with state effects separately by gender, first with no controls and then with additional controls for education, potential work experience, race and ethnicity, family and marital status, and other standard covariates. The earnings regressions are of the following form:

$$\text{In}(E_{\text{ij}}) = X_{\text{ij}}\,\beta + S_{\text{j}} + {}_{\mu}\text{ij}, \tag{1}$$

where E_{ij} is the annual earnings of YRFT worker i in state j, X_{ij} represents explanatory variables that vary across specification, β is the corresponding set of parameters, S_{j} is a set of state effects, and μ is a random error term. I estimate this equation separately by gender to produce estimates $\widehat{S}_{jm}$ and$\widehat{S}_{jf}$, which indicate how state of residence affects men's and women's earnings after control for other determinants of earnings. $\widehat{S}_{jm}$ and $\widehat{S}_{jf}$ can be interpreted as percentage earnings effects of residence in state j, conditional on the variables included in X.[2]

[2] I necessarily assume that individuals work in the state in which they reside; the ASEC data do not include separate information on place of work. Obviously, this may not be true in all cases, but it will be true for most workers.

Because I am using linear regression, I am implicitly capturing state effects relative to mean earnings, rather than median earnings. The distribution of state gender ratios for mean earnings is similar, though not identical, to the distribution of the medians. Not surprisingly, the gender ratios of mean earnings are typically lower than the medians, since the top tail of the earnings distribution is typically fatter for men than women. Still, like the ratio of median earnings, the ratio of mean earnings has substantial variation across states. I provide more information on the distribution of the mean gender earnings ratio by state in the next section.

I use the estimated state effects from Equation (1) to compute a state's gender earnings ratio (R_{j}) as a function of how male and female earnings in that state vary relative to the national average:

$$R_{\mathrm{j}} = [\overline{Y}_F \times (1 + \hat{S}_{jf})] / [\overline{Y}_M \times (1 + \hat{S}_{jm})] = \lambda \times (1 + \hat{S}_{jf})/(1 + \hat{S}_{jm}). \tag{2}$$

In Equation (2) $\overline{Y}_{\mathrm{F}}$ and $\overline{Y}_{\mathrm{M}}$ are average national earnings for YRFT women and men and λ is the corresponding national ratio of average gender earnings ($\overline{Y}_{\mathrm{F}}/\overline{Y}_{\mathrm{M}}$). I compute R_{j} first using the estimated state effects from a regression with no covariates and then using the corresponding estimates controlling for demographic factors and human capital measures. The latter estimate is a far more appropriate and economically meaningful measure of the impact of state residence on the gender earnings ratio. The difference between the unadjusted and adjusted ratios indicates what portion of the difference in the ratio across states reflects composition effects and what portion reflects more structural permanent effects that vary across state. If compositional differences largely explain the observed state differences in the gender earnings ratio, then the adjusted state effects will be considerably smaller in absolute value than the unadjusted effects. If the two are similar, then measured compositional effects are not important.

I use data from the 2008 and 2009 CPS March Supplements, also known as the Annual Social and Economic Census (ASEC). I use the CPS rather than the ACS because it is the most widely used data set for annual earnings analysis and also because earnings in each state are measured over the same calendar year time period.[3] The ASEC provides data on annual earnings for YRFT workers as well as measures of individual characteristics regularly used in earnings equations. For some purposes, hourly wage data might be preferable because that is a measure of earnings over a consistent time period

[3]In the ASEC, annual earnings refer to the previous calendar year, while the ACS provides information about work and earnings in the previous 12 months. Because the ACS conducts interviews continuously throughout the calendar year, the 2008 survey year ACS earnings data span a 23-month time period from January 2007 (interviews taken in January 2008) through November 2008 (interviews in December 2008). As a result, the 2008 ACS overlaps data from the March CPS for both 2007 and 2008. The overall gender median earnings ratio in the 2008 ACS was 77.9 percent and in the CPS it was 77.1 percent (2008) and 77.8 percent (2007).

and is often interpreted as the price of labor. But wage data are not available in large national data sets and are available even then only for persons paid by the hour.[4] Annual earnings for YRFT workers, which are used widely in gender earnings analyses, have many of the attractive features of hourly wage data in that earnings are measured over a consistent number of hours worked for both men and women.

I pool two years in order to provide a larger sample to estimate the state effects. This is particularly important for smaller states and it is unlikely to cause a problem since state effects on earnings by gender are likely to be stable across two years. I limit the sample to YRFT workers age 18 to 65. The only further modification I make to the data is to exclude observations with YRFT earnings less than \$2,500 or more than \$500,000 in order to reduce the impact of outliers. This eliminates 353 observations for men and 303 for women (about 0.5 percent of each sample). The resulting sample includes 79,371 men and 59,285 women. For men, state samples range from 638 to 7,460, while for women the range is from 471 to 4,967. All regressions use the appropriate CPS sample survey weights.

Covariates include measures used regularly in the earnings function literature: race and ethnicity (non-Hispanic white, non-Hispanic black, Hispanic); marital status (currently married and never married); number of children under age 18; educational attainment (dummy variables for high school, some college, college degree, and postgraduate degree); residence in a metropolitan area; and linear and quadratic terms for potential years of work experience.[5] In additional specifications, I also include measures of whether a worker is self-employed and a measure of hours worked in the survey week. It is certainly possible that hours worked may differ by gender even among YRFT workers, all of whom work at least 35 hours per week. The hours of work measure in the ASEC data is, unfortunately, somewhat problematic because it refers to usual hours in the survey week rather than over the previous calendar year, which is the timeframe for the reported YRFT earnings.

Estimates

The overall gender earnings ratio in the CPS for 2008–2009 is 71.2 percent, which is 6 to 7 percentage points lower than the corresponding ratios of median earnings in the CPS and ACS. The mean earnings ratio by state ranges from 57.8 to 82.6 percent with an *SD* of 4.01 percentage points. The District

[4]The MORG files of the CPS are the primary source of such data. They are used, for example, in analyses of the wage impact of minimum wage legislation (BLS, 2013).

[5]This is based on an assumed age at completion of schooling. Controlling for age and education implicitly controls for age as well. I do not include controls for occupation in the regression models because this is an intervening variable that may bias the effect of variables such as education. I examine the impact of occupation descriptively in the section entitled “Extensions: A Closer Look at Extremes.”

of Columbia still has the highest earnings ratio at 82.6 percent, but it is substantially lower than its 88 percent ratio of median earnings and it is the only state with a ratio above 80 percent. Other states with relatively high mean earnings ratios are California, Oregon, Alaska, Hawaii, and Florida, all between 75 and 77 percent. Louisiana replaces Wyoming as the state with the lowest gender earnings ratio; it is the only state with a ratio below 60 percent; other low ratio states include Utah, Alabama, North Dakota, and Idaho. See the Online Appendix (Figure 2) for the full distribution of the gender mean earnings ratio across states.

Online Appendix Table 1 presents weighted sample means for annual earnings and selected independent variables for men and women. The women are considerably more likely than the men to be black (14.1 vs. 9.4 percent) and to have at least some college, and to a lesser degree, to be a college graduate or have a graduate degree. They are considerably less likely to be married and Hispanic and they have fewer children than the men.

For the analysis of state differences in gender earnings ratios, it is critical that there be variation across states in relative skills by gender. This is clearly true for many of the covariates. For workers with some college, the female-to-male gender ratio ranges from 0.98 (Minnesota, the only state where women are less likely than men to have exactly that level of education) to 1.45 (Kentucky). For the proportion who are college graduates, the range is from 0.81 (Utah) to 1.45 (Wyoming) and in 12 states, the female-to-male ratio exceeds 1.2. For the gender ratio of workers with postgraduate education, the extreme female-to-male ratios are again Utah (0.59) and Indiana (1.63)[6] and 14 states have a ratio above 1.2. Similarly, race and ethnicity also vary across states. The proportion white non-Hispanic ranges from less than 25 percent (Hawaii) to more than 96 percent (Maine), while the proportion Hispanic ranges from less than 1 percent (North Dakota) to 35–40 percent in New Mexico. Since gender earnings ratios vary by race and ethnicity—from 85 to 86 percent for blacks and Hispanics at approximately 85–86 percent, with Asians slightly lower (82 percent) and white non-Hispanics lowest at 73 percent (U.S. Census Bureau, 2012)—states with larger black or Hispanic populations would likely have higher overall gender earnings ratios even if earnings by race and ethnicity were uniform across states. See Table 1 in the Online Appendix for information on the *SD* of gender ratio for each covariate across states.

Regression results are summarized in Table 1. To make the table as tractable as possible, given the large number of state estimates, I do not include the coefficients for the covariates; see Table 2 in the Online Appendix for the underlying coefficient estimates. The first column shows the state impact on the gender mean earnings ratio estimated from a model that includes only a year dummy for 2009 as an additional covariate. Because this model is only used as a baseline reference, I do not show the underlying coefficients for men

[6]Men in Indiana have a lower than average proportion of YRFT workers with postgraduate education, while women are above average, although not in the top quartile.

TABLE 1

Unadjusted and Adjusted State Effect Estimates on Gender Earnings Differences and Earnings Ratio, YRFT Workers, Age 18–65, 2008–2009

State	(1) Unadjusted Gender Earnings Ratio Effect	(2) Adjusted State Effect, Men	(3) Adjusted State Effect, Women	(4) Adjusted Gender Earnings Ratio Effect
Alabama	−0.060	−0.019	−0.079	−0.044
Alaska	0.017	0.064	0.101	0.024
Arizona	0.015	0.014	0.009	−0.004
Arkansas	0.012	−0.152	−0.124	0.024
California	0.050	0.087	0.105	0.012
Colorado	0.021	0.023	0.052	0.020
Connecticut	−0.015	0.110	0.127	0.010
DC	0.075	0.137	0.180	0.027
Delaware	−0.001	0.011	0.013	0.002
Florida	0.023	−0.049	−0.039	0.007
Georgia	−0.017	−0.002	−0.011	−0.006
Hawaii	0.022	0.067	0.019	−0.032
Idaho	−0.060	−0.066	−0.083	−0.013
Illinois	−0.027	0.028	−0.008	−0.025
Indiana	0.020	−0.100	−0.043	0.045
Iowa	−0.014	−0.068	−0.054	0.011
Kansas	−0.060	−0.083	−0.102	−0.015
Kentucky	−0.050	−0.062	−0.096	−0.026
Louisiana	−0.123	0.010	−0.153	−0.115

continued

TABLE 1—continued

State	(1) Unadjusted Gender Earnings Ratio Effect	(2) Adjusted State Effect, Men	(3) Adjusted State Effect, Women	(4) Adjusted Gender Earnings Ratio Effect
Maine	0.044	−0.122	−0.028	0.077
Maryland	0.021	0.075	0.110	0.024
Massachusetts	0.005	0.034	0.098	0.044
Michigan	−0.039	−0.023	−0.043	−0.014
Minnesota	−0.006	−0.033	0.027	0.044
Mississippi	−0.020	−0.078	−0.105	−0.021
Missouri	−0.027	−0.066	−0.062	0.003
Montana	−0.028	−0.086	−0.100	−0.011
New Hamp.	−0.004	0.034	0.059	0.018
Nebraska	0.016	−0.100	−0.072	0.022
Nevada	−0.024	0.075	0.074	−0.001
New Jersey	−0.033	0.126	0.100	−0.016
New Mexico	−0.034	0.078	0.008	−0.046
New York	0.032	0.014	0.014	0.000
North Carolina	0.017	−0.098	−0.072	0.021
North Dakota	−0.043	−0.125	−0.140	−0.013
Ohio	−0.030	−0.032	−0.044	−0.009
Oklahoma	−0.039	−0.068	−0.113	−0.034
Oregon	0.045	−0.073	0.001	0.057

continued

TABLE 1—continued

State	(1) Unadjusted Gender Earnings Ratio Effect	(2) Adjusted State Effect, Men	(3) Adjusted State Effect, Women	(4) Adjusted Gender Earnings Ratio Effect
Pennsylvania	–0.008	–0.001	–0.006	–0.004
Rhode Island	–0.027	0.017	0.029	0.009
South Carolina	–0.010	–0.097	–0.090	0.006
South Dakota	–0.019	–0.113	–0.095	0.015
Tennessee	–0.011	–0.092	–0.090	0.002
Texas	0.027	0.003	–0.002	–0.004
Utah	–0.095	0.005	–0.010	–0.010
Vermont	0.011	–0.071	–0.027	0.034
Virginia	–0.015	0.039	0.035	–0.002
Washington	–0.032	0.048	0.060	0.008
West Virginia	–0.040	–0.094	–0.125	–0.025
Wisconsin	0.003	–0.064	–0.025	0.029
Wyoming	–0.053	0.033	–0.043	–0.053
Sample Size		79,371	59,285	
Adj. R^2.		0.340	0.296	
Avg. Abs. Value	0.030	0.062	0.065	0.022
Minimum	–0.123	–0.152	–0.153	–0.115
Maximum	0.075	0.137	0.180	0.077

NOTE: All effects are scaled relative to the overall population mean. Col. (1) based on estimates from model that includes only a year dummy for 2009. Cols. (2)–(4) based on model that includes race, ethnicity, education, metro residence, and family status variables; see text for details. See Online Appendix Table 2 for coefficients for all covariates.
SOURCE: 2008 and 2009 March CPS.

and women separately, but only their joint impact on the earnings ratio. I refer to this as the unadjusted gender earnings ratio. Columns (2) and (3) show the estimated state effects from a model that adds the core explanatory variables and column (4) shows the net impact on the gender earnings ratio of these estimates; I refer to these figures as the adjusted state ratio. All the entries in the table are rescaled as a difference from the overall sample mean, so positive entries indicate either that the state gender earnings ratio is above the national average (columns (1) and (4)) or that men (or women) earn more than the national average, given their characteristics (columns (2) and (3)). The difference between the figures in columns (1) and (4) indicates the quantitative importance of compositional differences on the earnings ratio.

The unadjusted state effects in column (1) range from −0.123 for Louisiana to 0.075 for DC. To get a sense of the calculations, consider the −0.060 entry for Alabama. With no controls except year, men in Alabama earned 4.7 percent less than the average and women earned 12.7 percent less (these figures not shown in Table 1). The overall gender mean earnings ratio was 0.712, which implies, using Equation (2) above, that the earnings ratio in Alabama was $0.712 \times (1 - 0.127)/(1 - 0.047) = 0.652$. Expressed as a difference from the overall earnings ratio, this yields the −0.060 entry for the unadjusted Alabama state effect. The large positive effect for DC reflects a 14.9 percent earnings premium for men and a 27.0 percent earnings premium for women. The large negative effect for Louisiana is the result of a 2.9 percent earnings deficit for men and a 19.7 percent earnings deficit for women.

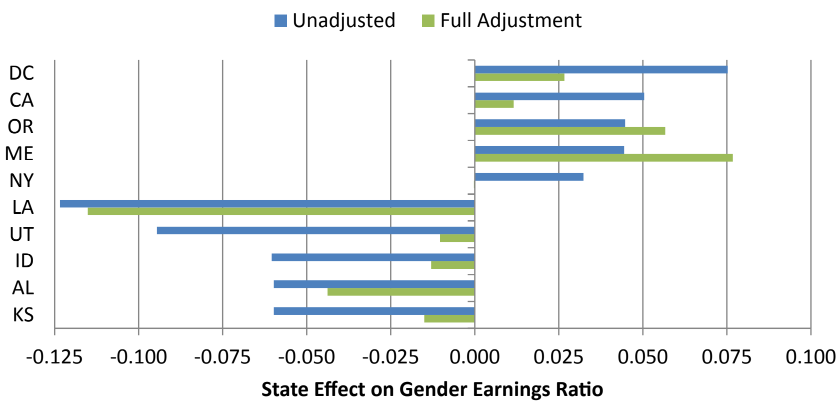
The state effects in columns (2) and (3), which include control for covariates, show a wide range of impacts. For men, the earnings effects range from −0.152 to 0.137 for Arkansas and DC, respectively, while for women the range is even greater, from −0.153 (Louisiana) to 0.180 (DC again). The average state effect (absolute value) is 0.062 for men and 0.065 for women. The state effects for the men and women are highly, but not perfectly, correlated ($r = 0.840$), which is why they do have an effect on the gender earnings ratio, as shown in column (4). After controlling for covariates, the state effects range from −0.115 (Louisiana) to 0.077 (now Maine), with an average absolute value of 0.022.

In general, controlling for covariates reduces the state effect, but this is not universal: 17 states have adjusted impacts that are larger in absolute value than the unadjusted impacts. The biggest positive change as a result of the adjustment for covariates is for Utah, where the state impact increases from 9.5 percentage points below the average to just 1.0 percent below. The largest negative change is for Hawaii, which goes from a gender ratio 2.2 points above average to one 3.2 points below.

The easiest way to assess the estimates in the table is visually. Figure 1 shows the unadjusted and regression-adjusted state effects for the five states with the largest negative and positive unadjusted effects. The comparisons show a full range of situations. Louisiana has the lowest unadjusted gender ratio of

FIGURE 1

Selected States with Large Effects on Gender Earnings Ratio, YRFT Workers



mean earnings for YRFT workers and literally none of the effect is due to any kind of compositional differences. Indeed, its adjusted effect is almost as negative as its unadjusted effect. Louisiana has a higher than average gender ratio for the proportion nonwhite and for most education levels, all of which would make its expected earnings ratio higher. In contrast, Utah has a very large unadjusted effect, second only to Louisiana, but that effect is almost entirely explained by composition. The explanation is gender differences in educational attainment, which are very substantial for both college graduation and postgraduate studies.[7] About two-thirds of the negative state effects of Kansas and Idaho reflect composition—again, primarily due to educational differences—but relatively little of Alabama's does.

For states with a large positive gross effect, the same kind of diverse patterns are seen. About two-thirds of DC's very high gross earnings ratio is due to race, ethnicity (high non-Hispanic black population), and other compositional effects. California has the second highest unadjusted state effect, but, like DC, after adjustment for all the covariates, its impact is just one-third of its original magnitude. For California, all the change is due to the racial and ethnic composition of the YRFT workforce. New York has an even larger adjustment, from 6.2 percentage points to zero; note that the second "bar" for NY is missing (i.e., equals zero). In contrast, Oregon and Maine have modest positive unadjusted effects—about 4.5 percentage points—and adjustment for covariates actually increases the estimated state impact. Maine has the largest positive adjusted state effect of all the states, 7.7 percentage points, with Oregon second at 5.7 percentage points. In Maine's case, the large adjusted

[7]Utah has the nation's lowest female-to-male ratio for both college and postgraduate education.

effect reflects primarily its overwhelmingly white, non-Hispanic population, which, all else constant, would tend to make its earnings ratio lower than average. Oregon, in contrast, is quite average with respect to all ratios of gender characteristics, so its relatively high earnings ratio is less affected by regression controls.

Robustness Tests

To test the robustness of these estimates, I estimated regression models with two additional covariates, one to control for differences in self-employment and the other for possible differences in hours worked among YRFT workers. A full discussion of these analyses is included in the Online Appendix. I find that self-employment does vary by gender and that is does affect earnings by gender differently. Self-employed YRFT male workers earn 6.9 percent ($t = 8.6$) less than otherwise similar males, while self-employed females earn 17.9 percent less ($t = 17.8$). But despite this, the maximum positive change in the estimated state effects is 0.004 and the largest negative change is −0.002. No conclusions are altered.

The work hours variable, which refers to the time of the interview rather than the previous year, has some problematic features that suggest treating these results cautiously. See the Online Appendix for a discussion of the issues. Average reported work hours in the survey week by gender for these YRFT workers are very similar; among those with positive current usual hours, men report an average of 44.2 hours and women 43.1 hours. An additional hour of work increases earnings by 1.08 percent ($t = 45.5$) for men and 1.09 percent ($t = 34.5$) for women.

Just as with self-employment, inclusion of current hours of work does almost nothing to the estimated state effects. Relative to the baseline model with covariates, the biggest positive change is 0.002 (several states) and the biggest negative change is −0.011 (Mississippi). The effects of the states with the largest positive and negative impacts are unchanged. With both self-employment and work hours controlled, the range of state effects on the gender ratio is from −0.095 (Louisiana) to 0.076 (Maine), just slightly smaller than the range from −0.115 to 0.076 when neither are included.

As a third robustness test, I use quantile regression (least absolute deviations) to examine the impact of state of residence at male and female median, rather than mean, earnings. Figure 3 in the Online Appendix summarizes the results of this exercise. The overall correlation coefficient between the two sets of estimates is 0.908; very few state estimates change by more than a minimal amount. Louisiana retains its distinction as having the most negative impact and is a very conspicuous outlier, while Oregon now edges out Maine for the most positive state impact. Mississippi has the largest difference between the two estimates: its composition-adjusted impact at the medians is much more positive than at the means.

Extensions: A Closer Look at Extremes

Thus far, the state effect simply summarizes the fact that a state's gender earnings ratio is higher or lower than expected, given the composition of its workers by race, ethnicity, educational attainment, and the other covariates and if the effect of these variables on earnings was uniform across states. It follows that the remaining effect must be related to differences across states in the value of traits or to other unmeasured factors that differentially affect productivity by gender and whose means differ and are correlated with state of residence.

As a preliminary effort to evaluate this, I focus more closely on states at the two extremes of the distribution of state gender earnings ratio effects. I look at earnings by gender cross-classified with more detailed information on education and occupation. Occupation is usually not considered an appropriate variable in earnings regressions because it is endogenous and often captures the correlated explanatory power of other explanatory variables such as education and marital/family status as well as possible discriminatory or socialization mechanisms. I use it here descriptively as a measure of the job actually done in order to see if gender earnings differences persist within relatively narrow occupations across these states.

The states I look at carefully in this way are, in descending order of negative adjusted effects, Louisiana, Wyoming, New Mexico, Alabama, and Oklahoma, and in descending order of positive adjusted effects, Maine, Massachusetts, Oregon, Minnesota, Indiana, and the District of Columbia.[8] In order to do this analysis, I switch from the CPS March supplement to the ACS for 2008–2009. The ACS was the data source for the Census Bureau reports on gender median earnings ratios. The 2008–2009 sample includes over 6 million observations, including nearly 2 million for YRFT workers age 18–65. The work experience and earnings information is identical to that on the CPS, except that interviewing is continuous over the calendar year and the work and earnings timeframe is the previous 12 months. The ACS sample includes more than 90,000 YRFT workers in the states with the largest negative effects on the gender earnings ratio and nearly 150,000 in the states with largest positive effects on the ratio. This facilitates analysis by relatively detailed occupational and educational cells. It is not feasible to do this more disaggregate analysis of earnings with the sample sizes by state available in the CPS within detailed education and occupation cells by gender.

The top section of Table 2 shows the earnings ratio by gender and education, using a more detailed educational classification for postsecondary schooling

[8]The negative state effects range from −0.116 to −0.040. The positive state effects range from 0.029 to 0.067.

TABLE 2

Gender Mean Earnings Ratios by Detailed Educational Attainment and Occupation, States with Large Positive and Negative Effects on Gender Earnings Ratio

	Neg. States	Pos. States	Difference
Education			
Not HS graduate	62.7%	72.3%	9.6%
HS graduate	65.1%	73.2%	8.1%
<1 year coll	66.1%	74.0%	8.0%
1+ year coll, no degree	63.9%	71.4%	7.6%
Assoc. degree	71.8%	77.3%	5.5%
4 year degree	63.3%	70.6%	7.3%
Master's degree	64.1%	67.5%	3.5%
Prof. degree	66.0%	68.7%	2.7%
PhD	72.4%	79.4%	7.0%
Occupation			
Managerial (high)	60.4%	68.5%	8.1%
Managerial (low)	72.1%	79.6%	7.6%
Business and finance	60.9%	67.6%	6.7%
Engineers & other sci.	77.2%	82.7%	5.5%
Counselors, clergy, etc.	81.8%	89.0%	7.2%
Attorneys & judicial	61.6%	78.9%	17.3%
Other legal	48.6%	77.8%	29.2%
Education	68.7%	77.0%	8.3%
Entertainment	66.0%	82.2%	16.3%
Medical (MD, DDS, DVM, OD, DC)	78.1%	61.6%	−16.5%
Other medical, incl. nursing	72.2%	83.9%	11.7%
Protective services	77.6%	84.8%	7.2%
Food services	80.3%	78.9%	−1.4%
Janitorial and other	64.7%	72.1%	7.4%
Misc. services	70.4%	76.1%	5.7%
Sales (high)	68.0%	71.2%	3.2%
Sales (low)	59.7%	66.4%	6.7%
Office/clerical (high)	67.8%	76.6%	8.9%
Office/clerical (low)	87.7%	90.6%	2.9%
Agriculture	93.7%	87.9%	-5.8%
Construction/extraction	82.0%	100.6%	18.6%
Repair services	85.3%	91.7%	6.4%
Production (mfg.)	61.5%	71.1%	9.6%
Transportation	67.3%	73.7%	6.4%
Military	87.4%	100.4%	13.0%
All	67.3%	73.5%	5.6%
Sample size	93,815	151,470	

SOURCE: Author tabulations from ACS 2008–2009. Sample is YRFT workers, age 18–65. Negative states are Alabama, Louisiana, New Mexico, Oklahoma, and Wyoming. Positive states are DC, Indiana, Maine, Massachusetts, Minnesota, and Oregon. Designations "high" and "low" for managerial, sales, and office/clerical refer to average earnings above and below the occupation median. See Online Appendix for details of occupational classification.

that separates those with less than four years of college into three groups and similarly separates those with post-BA education into three groups. The table shows that low gender earnings ratios exist across the education distribution in the states with the lowest gender earnings ratio. In these states, the ratio is, with two exceptions, in the 63–66 percent range; the two exceptions—workers with an Associate Degree and those with a PhD—are at about 72 percent. In the other group of states, the ratios are consistently 6 to 8 percentage points higher. No group of workers by detailed education has a higher gender earnings ratio in the states with the negative impacts than in the states with the positive impacts.

Differences in mean earnings by occupation are summarized in the bottom portion of Table 2. The ACS includes a very detailed occupational coding with over 470 separate classifications. To make the analysis tractable, I combined these into 25 reasonably, although certainly not perfectly, homogeneous categories that have sufficient numbers of YRFT workers of both genders. See the Online Appendix for details on the construction of the occupational classification.

Not shown in the table is the difference in the occupational distribution in the two groups of states, but it is interesting and easily summarized. (See Table 3 in the Online Appendix for details.) First, the overall occupational structure of the two sets of states is quite similar. The Duncan Index, which measures the similarity between two distributions, is 0.096. This figure, which means that about 10 percent of workers would need to change occupations in order to make the two occupational distributions identical, is very low, especially for the level of disaggregation used.[9] Second, traditional occupational differences by gender exist in both groups of states and are more pronounced in the states with the low gender earnings ratio. Men are more likely to be in management, science/engineering, and in blue-collar employment such as production, construction, and transportation. Women are more heavily represented in education, in other medical services (primarily nursing), and in office/clerical occupations. Occupations where the difference in the gender difference is greatest between the two sets of states are construction/extraction, education, and office/clerical, all of which have a larger gender difference in the states with a negative earnings ratio effect.[10] The overall index of occupational dissimilarity by gender is 0.413 in the states with the positive earnings ratio effect and 0.499 in the states with the negative earnings ratio effect. In contrast, the corresponding Duncan Index is 0.423 in the other 40 states.

The pattern of earnings differences within occupation parallels much of what was seen in the distribution of earnings by educational attainment. In

[9]The Duncan Index is $D = \Sigma \text{abs}(X_j - Z_j)/2$, where X_j and Z_j are the percent of all YRFT workers in occupation j in the two sets of states. $D = 0$ when the distributions are identical and equals 100 when the distributions are completely nonoverlapping. The Duncan Index is typically increasing in the number of occupational categories.

[10]For construction work, men outnumber women by more in the states with the negative impact, while women outnumber men by more in office and clerical work in those states.

22 of the 25 occupations shown, the gender earnings ratio is lower in the states with the negative impact on the gender ratio than in the other set of states. The biggest effects are in other legal (29.2 percentage points), attorneys and judges (17.3 pps), construction and extraction (18.6 pps), entertainment (16.3 pps), and auxiliary medical services (11.7 pps). The only occupations with the reverse relationship are medical (−16.5 pps), agriculture (−5.8 pps), and food services (−1.4 pps). Except for medical, which includes physicians, pharmacists, dentists, chiropractors, opticians, and veterinarians, these are all blue-collar occupations and except for food services, they are all very small. Agriculture accounts for well under 1 percent of employment in these states, while medical accounts for about 1 percent and food services about 3 percent.

Using the occupational distribution and mean earnings by occupation, I use a standardization procedure to compute predicted earnings by gender if these states retained their current occupational distribution by gender, but had the mean occupational earnings of men and women in the positive ratio states. I then calculate the corresponding predicted gender mean earnings ratio for these states. This exercise quantifies the importance of within-occupation earnings differences relative to differences in the occupational structure. The predicted ratio in the negative earnings states is $R'_n = \Sigma a_{jfn} E_{jfp} / \Sigma a_{jmn} E_{jmp}$, where a_{jn} is occupation j's share of total YRFT employment by gender (f or m) in the states with the negative earnings ratio impact and E_{jp} (for f or m) is mean earnings in occupation j by gender in the states with the positive earnings ratio impact.

The actual gender mean earnings ratio in the states with the negative effects is 67.3 percent, compared to 73.5 percent in the states with the positive effects. Using the mean occupational earnings by gender in the positive ratio states, both male and female earnings in the negative states would increase, but earnings would increase by 22 percent for women and 9 percent for men. This is consistent with the lower earnings ratio for women in the states with a negative impact on the ratio seen in Table 2. As a consequence, the resulting mean earnings ratio increases to 74.4 percent, which is not only 7.1 percentage points higher than the actual ratio, but also nearly 1 percentage point higher even than the actual observed gender earnings ratio in the positive states. This implies that the occupational distribution in the states with a negative impact on the gender earnings ratio is actually relatively more favorable to women's earnings than the distribution in the positive states and that it is the within-occupation gender earnings differences that are the cause of the lower earnings ratio. The big drivers of this calculation are education, other medical (including nursing), and office and clerical, all of which employ a relatively large proportion of the female YRFT workforce and that have a gender earnings ratio in the positive states that is 8.3, 11.7, and 6.6 percentage points higher, respectively.

The message from Table 2 is quite consistent: the states with large negative regression-adjusted effects on the gender earnings ratio have consistently low earnings ratios across multiple dimensions, including quite detailed distributions of both education and occupation. There is no single smoking gun; the lower earnings ratio persists in almost all categories.

Summary and Conclusions

This article documents the existence of nonneutral state effects on earnings by gender for YRFT workers that influence the gender earnings ratio even after controlling for the skill and demographic composition of male and female workers in that state. Unadjusted earnings ratios range from more than 12 percentage points below the national average in Louisiana to 7.5 percentage points above the average in the District of Columbia. Controlling for education, race, ethnicity, and marital status moderates some, but not all, of the apparent differences. Louisiana's effect on the gender earnings ratio is almost unchanged, while DC's large positive effect and Utah's large negative are both sharply reduced. Maine emerges as the state with the largest net positive effect on the gender earnings ratio, with Oregon and Massachusetts not far behind. Louisiana has by far the lowest gender earnings ratio, given the characteristics of its YRFT workforce. These results are robust to the inclusion of measures of self-employment and hours worked and to estimates using quantile regression at the sample medians.

Looking in more detail at states at the two ends of the distribution reveals that the lower gender earnings ratio exists at a finer level of detail. For virtually every education level and occupation, the gender earnings ratio is lower in the states with a negative impact than in the states with a positive impact.

At this point, it is clear what is *not* a sufficient explanation for the observed gender impact by state—differences in observed worker composition—but not what the source of the observed impact *is*. I have not in this article explored policies at the state level that may be related to the differences in the gender earnings gap and that is an obvious step for additional research. Looking at finer-grained geographical areas such as large urban areas from the same perspective might also be instructive.

REFERENCES

Blau, Francine D., Marianne A. Ferber, and Anne E. Winkler. 2014. *The Economics of Women, Men, and Work*, 7th ed. Saddle River, NJ: Pearson.

Blau, Francine D., and Lawrence M. Kahn. 1997. "Swimming Upstream: Trends in the Gender Wage Differential in the 1980s." *Journal of Labor Economics* 15 (1, Part 1):1–42.

Corcoran, Mary, and Greg J. Duncan. 1979. "Work History, Labor Force Attachment, and Earnings Differences Between the Races and Sexes." *Journal of Human Resources* 14(1):3–20.

Fuller, Sylvia. 2008. "Job Mobility and Wage Trajectories for Men and Women in the United States." *American Sociological Review* 73(1):158–83.

Getz, David M. 2010. *Men's and Women's Earnings for States and Metropolitan Statistical Areas: 2009* (Vol. ACSBR/09–3). Washington, DC: U.S. Bureau of the Census.

Goldin, Claudia. 1992. *Understanding the Gender Gap: An Economic History of American Women*. London: Oxford University Press.

Hegewisch, Ariane, and Claudia Williams. 2013. *The Gender Wage Gap: 2012*. Washington, DC: Institute for Women's Policy Research.

Hoffman, Saul D., and Susan L. Averett. 2010. *Women and the Economy: Family, Work and Pay*, 2nd ed. Boston, MA: Pearson.

Lang, Kevin. 2007. *Poverty and Discrimination*. Princeton, NJ: Princeton University Press.

O'Neill, June. 1985. "The Trend in the Male-Female Wage Gap in the United States." *Journal of Labor Economics* 3(1, Part 2):S91–S116.

Ryu, Kirak. 2010. "State Policies and Gender Earnings Inequality: Multilevel Analysis of 50 U.S. States Based on U.S. Census 2000 Data." *Sociological Quarterly* 51(2):226–54.

Semega, Jessica. 2009. *Men's and Women's Earnings by State: 2008 American Community Survey*. American Community Survey Reports (Vol. ACSBR/08–3). Washington, DC: U.S. Bureau of the Census.

U.S. Census Bureau. "Historical Income Tables: People." Available at ⟨http://www.census.gov/hhes/www/income/data/historical/people/index.html⟩, accessed August 22, 2012.

Waldfogel, Jane. 1998. "Understanding the 'Family Gap' in Pay for Women with Children." *Journal of Economic Perspectives* 12(1):137–56.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix Figure 1: Distribution of Gender Median Earnings Ratios by State, Year-Round Full-Time U.S. Workers, 2008, American Community Survey
Appendix Figure 2: Gender Mean Earnings Ratio by U.S. State, Year-Round Full-Time Workers, 2007–2008
Appendix Figure 3: State Mean and Median Earnings Gender Ratio Effects, YRFT Workers, 2008–2009
Appendix Table 1: Demographic Characteristics and Annual Earnings, Year-Round Full-Time Workers, Age 18–65 by Sex, 2008–2009
Appendix Table 2: Determinants of Annual Earnings by Gender, With and Without State Effects, YRFT Workers, Age 18–65
Appendix Table 3: Occupational Distribution by Gender, States with Large Positive and Negative Effect on Gender Earnings Ratio