# Appendices for Online Publication

# A Additional Tables and Figures

Table A1: Employed Population by License Status and Type

| Q1 | Q2 | Q3 | Workers | |
|---|---|---|---|---|
| Has licensing or certification? | State issued? | Required for job? | Number | Share |
| No | No | No | 452,667 | 0.725 |
| Yes | No | No | 23,713 | 0.038 |
| Yes | Yes | No | 37,026 | 0.059 |
| Yes | No | Yes | 7,052 | 0.011 |
| Yes | Yes | Yes | 104,239 | 0.167 |

*Notes:* This table reports counts of unique employed workers according to their answers to questions 1–3 as described in Section 3. Workers are here counted as answering affirmatively if they ever answer affirmatively while in the sample. All other combinations of answers are ruled out by the CPS skip pattern.

Table A2: Variance Components of License Status and State–Occupation Licensing Rate

| Component | Individual License Status | Licensing Rate |
|---|---|---|
| State | 0.002 | 0.005 |
| Occupation | 0.321 | 0.905 |
| Residual | 0.677 | 0.089 |

*Notes:* This table reports the results of a variance decomposition of individual license status and the state–occupation licensed rate in the CPS sample. For both variables, state fixed effects explain negligible shares of total variance, whereas occupation fixed effects explain considerable shares of variance, particularly after collapsing to state–occupation means.

Table A3: Summary Statistics of Licensed and Unlicensed Workers

| | (1) | (2) | (3) |
|---|---|---|---|
| | Has state-issued occupational license | | |
| Variable | Yes | No | $p$-val. (1) − (2) |
| Age | 40.33 | 35.90 | 0.000 |
| Female | 0.52 | 0.47 | 0.000 |
| Married | 0.52 | 0.39 | 0.000 |
| Children at Home | 0.47 | 0.35 | 0.000 |
| *Education* | | | |
| Less than HS | 0.03 | 0.15 | 0.000 |
| HS Graduate | 0.21 | 0.30 | 0.000 |
| Some College | 0.32 | 0.29 | 0.000 |
| Bachelor's Degree | 0.24 | 0.19 | 0.000 |
| More than Bachelor's | 0.19 | 0.07 | 0.000 |
| *Race/Ethnicity* | | | |
| Non-Hispanic White | 0.77 | 0.74 | 0.000 |
| Black | 0.14 | 0.16 | 0.021 |
| Asian | 0.05 | 0.06 | 0.083 |
| Other | 0.03 | 0.04 | 0.003 |
| Hispanic | 0.87 | 0.79 | 0.000 |
| Citizen | 0.99 | 0.99 | 0.589 |
| Lives in MSA | 0.74 | 0.75 | 0.029 |
| Paid by Hour | 0.38 | 0.56 | 0.000 |
| Hourly Wage | 41.80 | 31.01 | 0.000 |
| Weekly Labor Income | 2,606.59 | 1,845.21 | 0.000 |
| Union | 0.14 | 0.07 | 0.000 |
| Usually Full-Time | 0.75 | 0.65 | 0.000 |
| Any Disability | 0.04 | 0.04 | 0.517 |
| Veteran | 0.06 | 0.04 | 0.000 |
| Number of Workers | 74,086 | 470,905 | |

*Notes:* This table reports summary statistics on the characteristics of unique workers by their licensing status according to the first survey month in the CPS. To be consistent across rows, only workers in the Merged Outgoing Rotation Group are included in the sample.

Table A4: Data Sources on State–Occupation Variation in Occupational Licensing Policies

| Occupation | | Policy by Count of States (plus D.C.) | | |
|---|---|---|---|---|
| Name | Code | Licensed | Unlicensed | Source |
| Construction managers | 0220 | 33 | 18 | NCSL |
| Gaming managers | 0330 | 30 | 21 | IJ |
| Claims adjusters | 0540 | 34 | 17 | Other |
| Conservation scientists and foresters | 1640 | 11 | 40 | Other |
| Librarians | 2430 | 12 | 39 | Other |
| Teacher assistants | 2540 | 5 | 46 | IJ |
| Dietitians and nutritionists | 3030 | 27 | 24 | Other |
| Nurse midwives | 3257 | 38 | 13 | IJ |
| Diagnostic related technologists | 3320 | 6 | 45 | NCSL |
| Opticians, dispensing | 3520 | 22 | 29 | IJ |
| Massage therapists | 3630 | 46 | 5 | NCSL |
| Dental assistants | 3640 | 9 | 42 | IJ |
| Pharmacy aides | 3647 | 45 | 6 | NCSL |
| Veterinary assistants | 3648 | 38 | 13 | NCSL |
| Phlebotomists | 3649 | 4 | 47 | Other |
| Fire inspectors | 3750 | 33 | 18 | NCSL |
| Animal control workers | 3900 | 7 | 44 | IJ |
| Private detectives and investigators | 3910 | 46 | 5 | NCSL |
| Security guards | 3930 | 40 | 11 | NCSL |
| Bartenders | 4040 | 13 | 38 | IJ |
| Landscaping supervisors | 4210 | 7 | 44 | IJ |
| Gaming supervisors | 4300 | 30 | 21 | IJ |
| Animal trainers | 4340 | 9 | 42 | IJ |
| Gaming services workers | 4400 | 28 | 23 | IJ |
| Funeral service workers | 4460 | 3 | 48 | IJ |
| Funeral directors | 4465 | 50 | 1 | Other |
| Misc. personal appearance workers | 4520 | 36 | 15 | IJ |
| Tour and travel guides | 4540 | 37 | 14 | IJ |
| Child care workers | 4600 | 43 | 8 | IJ |
| Travel agents | 4830 | 7 | 44 | IJ |
| Real estate brokers and agents | 4920 | 46 | 5 | NCSL |
| Bill collectors | 5100 | 31 | 20 | IJ |
| Gaming cage workers | 5130 | 28 | 23 | IJ |
| Weighers | 5630 | 25 | 26 | IJ |
| Animal breeders | 6020 | 28 | 23 | IJ |
| Fishers | 6100 | 43 | 8 | IJ |
| Logging workers | 6130 | 2 | 49 | IJ |
| Brick and stone masons | 6220 | 26 | 25 | IJ |
| Carpenters | 6230 | 25 | 26 | IJ |
| Cement masons | 6250 | 24 | 27 | IJ |
| Drywall installers | 6330 | 26 | 25 | IJ |
| Electricians | 6355 | 31 | 20 | NCSL |
| Glaziers | 6360 | 26 | 25 | IJ |
| Insulation workers | 6400 | 25 | 26 | IJ |
| Plumbers | 6440 | 37 | 14 | NCSL |
| Sheet metal workers | 6520 | 25 | 26 | IJ |
| Building inspectors | 6660 | 33 | 18 | NCSL |
| Security and fire alarm installers | 7130 | 36 | 15 | IJ |
| HVAC mechanics and installers | 7315 | 36 | 15 | NCSL |
| Locksmiths and safe repairers | 7540 | 14 | 37 | IJ |
| Mobile home installers | 7550 | 39 | 12 | IJ |
| Upholsterers | 8450 | 9 | 42 | IJ |
| Taxi drivers and chauffeurs | 9140 | 16 | 35 | IJ |
| Crane and tower operators | 9510 | 17 | 34 | IJ |
| Packers | 9640 | 6 | 45 | IJ |

*Notes:* This table lists the 55 occupations for which we collected policy data at the level of state–occupation cells. We report the occupation's name and CPS code, the number of states (plus D.C.) where this occupation appears to be licensed or unlicensed, and our data sources, which refer to the following documents: NCSL = National Conference of State Legislatures (2019), IJ = Carpenter et al. (2017). For "Other" and further discussion, see Appendix D.

Table A5: Comparing Two Measures of Licensing—Self-Reported Share Versus Policy

| | Dependent Variable: % Licensed in Cell | |
|---|---|---|
| | (1) | (2) |
| Policy Indicator | 0.066*** | 0.066*** |
| | (0.008) | (0.008) |
| Two-Way Fixed Effects | Y | Y |
| Demographic Controls | N | Y |
| Observations | 189,738 | 189,738 |
| Clusters | 2,470 | 2,470 |

*Notes:* This table reports estimates from Equation 10, but using the share of workers in a state–occupation cell who self-report they are licensed as the outcome, and a binary indicator that a cell, per sources in Table A4, has a licensing policy as the policy variable. Both columns include fixed effects for state and occupation, and in Column 2, we add demographic strata, industry, and month fixed effects. The regression is on individual worker data to allow for the inclusion of worker-level controls. Standard errors are clustered by cell. $^{***} = p < 0.01$.

Table A6: Which Occupations Contribute Most to Empirical Identification?

| Occupation | | Influence | | |
|---|---|---|---|---|
| Name | Code | Treat. Eff. Weight | Workers Per 10,000 | Ratio |
| *Panel A: Most Influential Occupations* | | | | |
| Electricians | 6355 | 0.0414 | 61.3 | 6.74 |
| Nursing, psychiatric, and home health aides | 3600 | 0.0282 | 146.2 | 1.93 |
| Patrol officers | 3850 | 0.0243 | 53.4 | 4.55 |
| Pipelayers, plumbers, etc. | 6440 | 0.0214 | 44.4 | 4.82 |
| Teacher assistants | 2540 | 0.0179 | 70.9 | 2.52 |
| Construction managers | 0220 | 0.0169 | 65.4 | 2.59 |
| Social workers | 2010 | 0.0151 | 58.1 | 2.60 |
| Personal and home care aides | 4610 | 0.0150 | 93.2 | 1.61 |
| Dental assistants | 3640 | 0.0143 | 22.1 | 6.48 |
| Automotive service technicians and mechanics | 7200 | 0.0137 | 67.1 | 2.04 |
| *Panel B: Most Overweighted Occupations* | | | | |
| Brokerage clerks | 5200 | 0.0014 | 0.3 | 42.63 |
| Emergency management directors | 0425 | 0.0030 | 0.7 | 40.66 |
| Aircraft assemblers | 7710 | 0.0013 | 0.5 | 27.16 |
| Fire inspectors | 3750 | 0.0046 | 1.7 | 26.94 |
| Opticians, dispensing | 3520 | 0.0098 | 3.7 | 26.10 |
| Explosives workers | 6830 | 0.0018 | 0.7 | 25.74 |
| Manufactured building and home installers | 7550 | 0.0013 | 0.5 | 24.91 |
| Funeral service workers | 4460 | 0.0017 | 0.7 | 24.85 |
| Ambulance drivers and attendants, excl. EMTs | 9110 | 0.0025 | 1.0 | 24.50 |
| Septic tank servicers and sewer pipe cleaners | 6750 | 0.0019 | 0.8 | 24.32 |

*Notes:* This table reports the top 10 most influential occupations according to two criteria. Panel A reports influential occupations according to the implicit weights on potentially heterogeneous treatment effects by occupation in the two-way fixed effect estimator, as derived by de Chaisemartin and D'Haultfoeuille (2019). Panel B reports overweighted occupations, as defined by the ratio of the implicit weight and the occupation's sample share of workers. This table is closely related to Table 1 in the main text, which lists occupations with high interstate variance in licensing; naturally, many of the listed occupations appear in both tables.

Table A7: Additional Reduced-Form Effects of Occupational Licensing

| | Licensed = 1 | % Licensed in Cell | |
|---|---|---|---|
| | (1) | (2) | (3) |
| *Panel A: Weekly Hours Per Worker* | | | |
| | 1.690*** | 1.856*** | 1.421*** |
| | (0.058) | (0.313) | (0.298) |
| Observations | 2,149,992 | 2,149,992 | 2,149,992 |
| Clusters | 21,890 | 21,890 | 21,890 |
| *Panel B: Employment Count (Poisson)* | | | |
| | | -0.268*** | |
| | | (0.061) | |
| Observations | | 22,098 | |

*Notes:* This table reports estimates from Equation 10 of effects of licensing on outcomes of interest that correspond to reduced-form moments of the model. The estimate in Column 1 refers to individual-worker licensing status, whereas those in Columns 2 and 3 refer to the state–occupation cell licensed share of workers. In Column 3, we include strata fixed effects for predetermined demographic observables. In Panel A, the dependent variable is the level of weekly hours per worker, and we include fixed effects for occupation, state, industry, and month. In Panel B, the dependent variable is the state-occupation employment count in a Poisson regression, and we include fixed effects for occupation and state. Standard errors are clustered at the level of the state–occupation cell. $^{***} = p < 0.01$.

Table A8: Reduced-Form Worker Effects of Occupational Licensing, Including Universally Licensed Occupations

| | Licensed = 1 | % Licensed in Cell | |
|---|---|---|---|
| | (1) | (2) | (3) |
| *Panel A: Years of Education* | | | |
| | 0.375*** | 0.449*** | 0.388*** |
| | (0.010) | (0.054) | (0.052) |
| Observations | 2,149,992 | 2,149,992 | 2,149,992 |
| Clusters | 21,890 | 21,890 | 21,890 |
| *Panel B: Years of Age* | | | |
| | 1.289*** | 1.737*** | 1.715*** |
| | (0.035) | (0.266) | (0.264) |
| Observations | 811,117 | 811,117 | 811,117 |
| Clusters | 19,266 | 19,266 | 19,266 |
| *Panel C: Log Hourly Wage* | | | |
| | 0.154*** | 0.200*** | 0.149*** |
| | (0.005) | (0.024) | (0.023) |
| Observations | 365,261 | 365,261 | 365,261 |
| Clusters | 20,273 | 20,273 | 20,273 |
| *Panel D: Log Weekly Hours Per Worker* | | | |
| | 0.045*** | 0.049*** | 0.036*** |
| | (0.002) | (0.010) | (0.010) |
| Observations | 2,149,992 | 2,149,992 | 2,149,992 |
| Clusters | 21,890 | 21,890 | 21,890 |
| *Panel E: Log Employment* | | | |
| | | -0.179*** | |
| | | (0.061) | |
| Observations | | 22,098 | |

*Notes:* This table reports estimates from Equation 10 of the effects of licensing on outcomes of interest that correspond to reduced-form moments of the model. The only difference is in sample: Here we include universally licensed occupations as defined by Gittleman et al. (2018). The estimate in Column 1 refers to individual-worker licensing status, whereas those in Columns 2 and 3 refer to the state–occupation cell licensed share of workers. In Columns 1 and 3, we include strata fixed effects for predetermined demographic observables. All specifications include fixed effects for occupation, state, industry, and month, except in Panel E, which has only state and occupation fixed effects. Standard errors are clustered at the level of the state–occupation cell. *** = $p < 0.01$.

Table A9: Reduced-Form Effects of Occupational Licensing, ACS Sample

| | (1) | (2) |
|---|---|---|
| *Panel A: Years of Age* | | |
| % Licensed | 0.642*** | 0.660*** |
| | (0.191) | (0.191) |
| Observations | 1,326,484 | 1,326,484 |
| Clusters | 19,187 | 19,187 |
| *Panel B: Log Hourly Wage* | | |
| % Licensed | 0.101*** | 0.075*** |
| | (0.016) | (0.015) |
| Observations | 4,032,135 | 4,032,135 |
| Clusters | 20,124 | 20,124 |
| *Panel C: Log Weekly Hours Per Worker* | | |
| % Licensed | 0.020** | 0.016** |
| | (0.008) | (0.008) |
| Observations | 4,032,135 | 4,032,135 |
| Clusters | 20,124 | 20,124 |
| *Panel D: Log Employment* | | |
| % Licensed | -0.247*** | |
| | (0.060) | |
| Observations | 20,230 | |

*Notes:* This table reports estimates from Equation 10 of the effects of licensing on outcomes of interest that correspond to reduced-form moments of the model. The data is the 5-year sample (2010–2015) of the American Community Survey. In Column 2, we include strata fixed effects for predetermined demographic observables. All specifications include fixed effects for occupation, state, industry, and month, except in Panel D, which has only state and occupation fixed effects. Standard errors are clustered at the level of the cell. $^{*} = p < 0.10$, $^{**} = p < 0.05$, $^{***} = p < 0.01$.

Table A10: Robustness Checks, Including Universally Licensed Occupations

| | (1) Likely Policy Diffs. | (2) Unions & Cert. | (3) Occ. & Demo. Mix | (4) State–Occ. Group FE | (5) Div.–Occ. FE |
|---|---|---|---|---|---|
| *Panel A: Years of Education* | | | | | |
| % Licensed | 0.500*** | 0.426*** | 0.378*** | 0.335*** | 0.276*** |
| | (0.069) | (0.052) | (0.052) | (0.049) | (0.049) |
| Observations | 2,149,992 | 2,149992 | 2,144,001 | 2,149,992 | 2,149,989 |
| Clusters | 21,890 | 21,890 | 21,015 | 21,890 | 21,887 |
| *Panel B: Years of Age* | | | | | |
| % Licensed | 1.715*** | 1.751*** | 1.752*** | 1.718*** | 1.256*** |
| | (0.264) | (0.269) | (0.267) | (0.250) | (0.266) |
| Observations | 811,117 | 811,117 | 809,150 | 811,117 | 811,090 |
| Clusters | 19,266 | 19,266 | 18,814 | 19,266 | 19,239 |
| *Panel C: Log Hourly Wage* | | | | | |
| % Licensed | 0.186*** | 0.108*** | 0.147*** | 0.135*** | 0.119*** |
| | (0.029) | (0.023) | (0.023) | (0.023) | (0.023) |
| Observations | 365,261 | 365,261 | 364,221 | 365,260 | 365,163 |
| Clusters | 20,273 | 20,273 | 19,668 | 20,272 | 20,175 |
| *Panel D: Log Weekly Hours Per Worker* | | | | | |
| % Licensed | 0.038*** | 0.036*** | 0.036*** | 0.033*** | 0.029*** |
| | (0.013) | (0.010) | (0.010) | (0.010) | (0.009) |
| Observations | 2,149,992 | 2,149,992 | 2,144,001 | 2,149,992 | 2,149,989 |
| Clusters | 21,890 | 21,890 | 21,015 | 21,890 | 21,887 |
| *Panel E: Log Employment* | | | | | |
| % Licensed | -0.109 | -0.197*** | -0.139** | -0.052 | -0.125** |
| | (0.084) | (0.063) | (0.057) | (0.054) | (0.051) |
| Observations | 21,890 | 22,098 | 21,026 | 22,098 | 22,008 |

*Notes:* This table reports estimates from variations on Equation 10 as explained in the main text. All estimates refer to the coefficient on the licensed share of workers in the state–occupation cell. All specifications include fixed effects for occupation, state, industry, and month, except in Panel E, which has only state and occupation fixed effects. Standard errors are clustered at the level of the state–occupation cell. $^{*} = p < 0.10$, $^{**} = p < 0.05$, $^{***} = p < 0.01$.

Table A11: Additional Robustness Checks

| | (1) State–Occ. Group FE | (2) State-Demog. & Occ-Demog. FE | (3) Flexible Licensed Share | (4) Emp. Growth, 2000–2010 |
|---|---|---|---|---|
| *Panel A: Years of Education* | | | | |
| % Licensed | 0.319*** | 0.312*** | 0.364*** | 0.418*** |
| | (0.054) | (0.053) | (0.055) | (0.065) |
| Observations | 1,865,209 | 1,865,172 | 1,865,209 | 1,619,807 |
| Clusters | 20,321 | 20,319 | 20,321 | 14,243 |
| *Panel B: Years of Age* | | | | |
| % Licensed | 1.070*** | 0.665*** | 0.964*** | 1.044*** |
| | (0.239) | (0.203) | (0.244) | (0.299) |
| Observations | 722,168 | 722,128 | 722,168 | 605,824 |
| Clusters | 17,842 | 17,830 | 17,842 | 12,845 |
| *Panel C: Log Hourly Wage* | | | | |
| % Licensed | 0.139*** | 0.133*** | 0.163*** | 0.121*** |
| | (0.024) | (0.023) | (0.023) | (0.028) |
| Observations | 317,141 | 316,764 | 317,142 | 275,150 |
| Clusters | 18,752 | 18,601 | 18,753 | 13,399 |
| *Panel D: Log Weekly Hours Per Worker* | | | | |
| % Licensed | 0.032*** | 0.027*** | 0.028*** | 0.054*** |
| | (0.011) | (0.010) | (0.010) | (0.012) |
| Observations | 1,865,209 | 1,865,172 | 1,865,209 | 1,619,807 |
| Clusters | 20,321 | 20,319 | 20,321 | 14,243 |
| *Panel E: Log Employment* | | | | |
| | -0.097 | | -0.297*** | -0.329*** |
| | (0.061) | | (0.058) | (0.073) |
| Observations | 20,524 | | 20,524 | 13,160 |

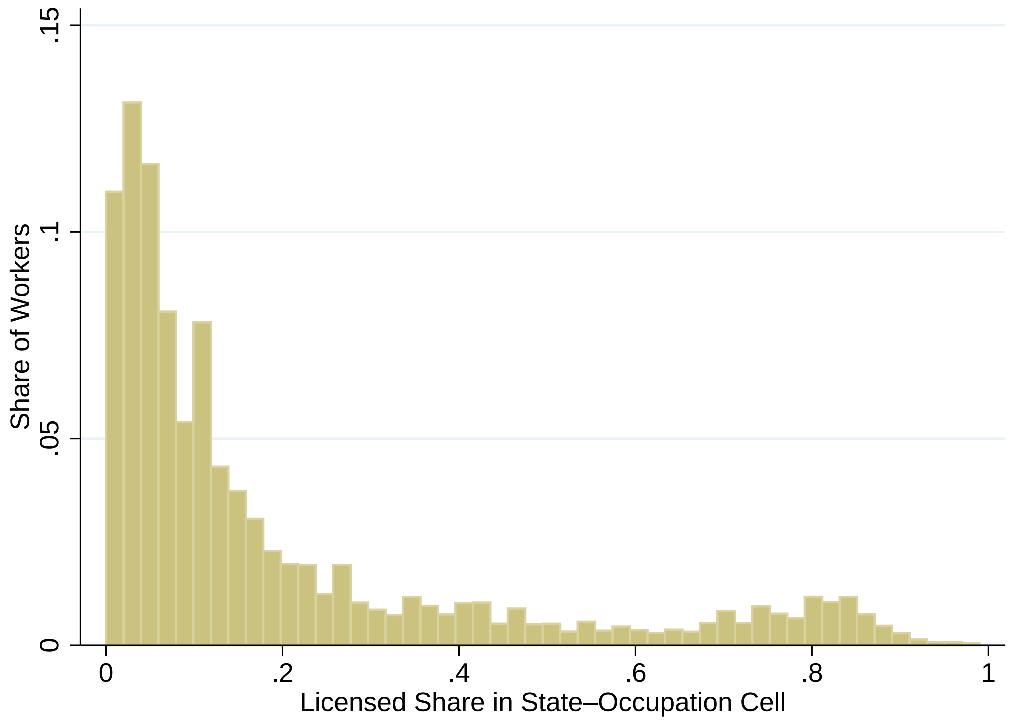
*Notes:* This table reports estimates from Equation 10. For discussion, see Appendix C. All estimates refer to the coefficient on the licensed share of workers in the state–occupation cell. All specifications include fixed effects for occupation, state, industry, and month, except in Panel E, which has only state and occupation fixed effects. Standard errors are clustered at the level of the cell. $^{***} = p < 0.01$.

Table A12: State–Occupation Licensed Shares and Local Political Determinants

| | Dependent Variable: % Licensed | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\%\text{Rep}_o \times \text{Slant}_s$ | -0.007 | | |
| | (0.012) | | |
| $\%\text{Dem}_o \times \text{Slant}_s$ | | 0.014 | |
| | | (0.012) | |
| $\%\text{Indep}_o \times \text{Polarization}_s$ | | | -0.004 |
| | | | (0.016) |
| Observations | 18,245 | 18,245 | 18,245 |

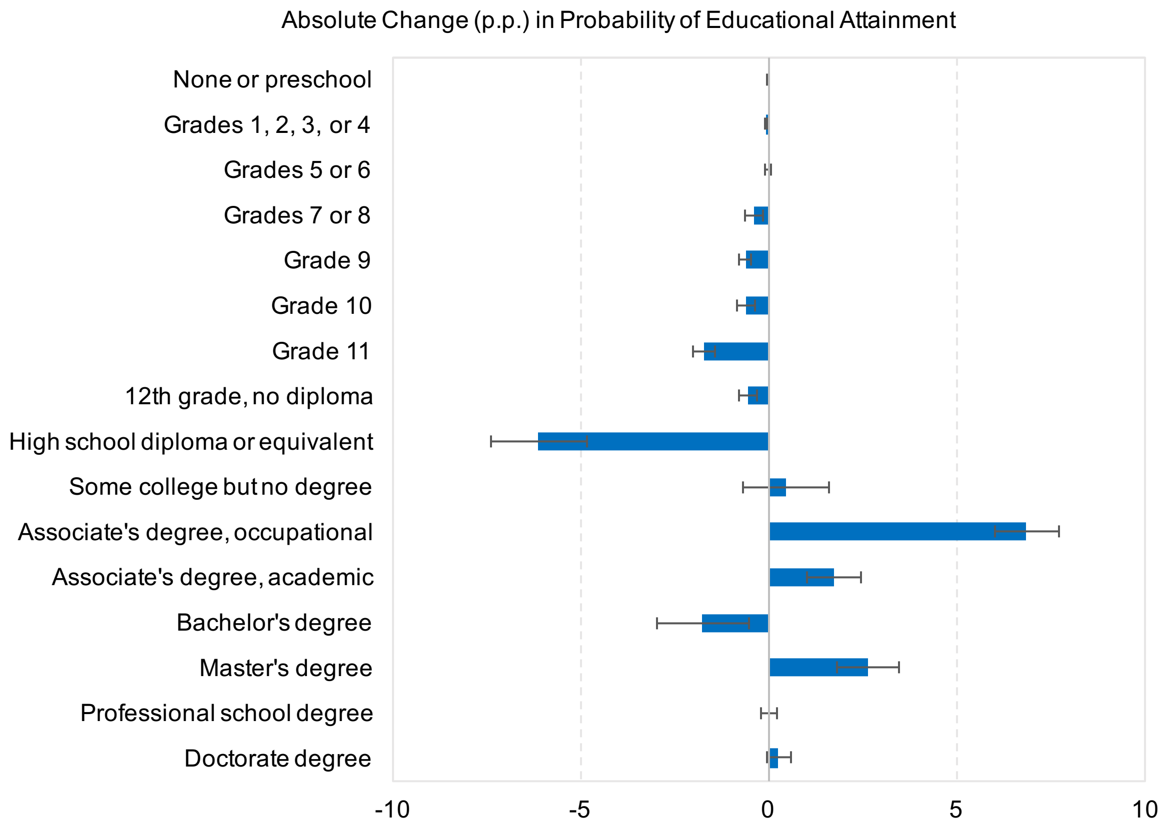
*Notes:* This table reports estimates from Equation 13, which tests for political determinants of licensing at the state–occupation level that reflect either local political economy or occupation-specific political position. For discussion, see Appendix C. Variables are defined in the main text. Both specifications include fixed effects for occupation and state. Standard errors are clustered at the level of the state–occupation cell. $^{*} = p < 0.10$, $^{*} = p < 0.05$, $^{***} = p < 0.01$.

Figure A1: Distribution of State–Occupation Licensed Shares



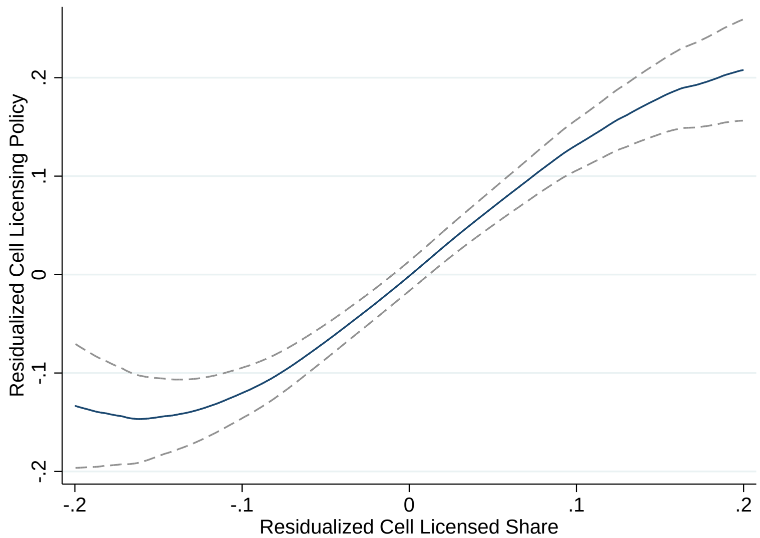

*Notes:* This figure shows the distribution of estimated shares of workers with a mandatory state-issued occupational license in each state–occupation cell, weighted by each cell's total employment count. Licensed shares are estimated by the empirical Bayes procedure described in Section 3 and Appendix E.

Figure A2: Effect of Licensing on Highest Level of Educational Attainment (All Levels)



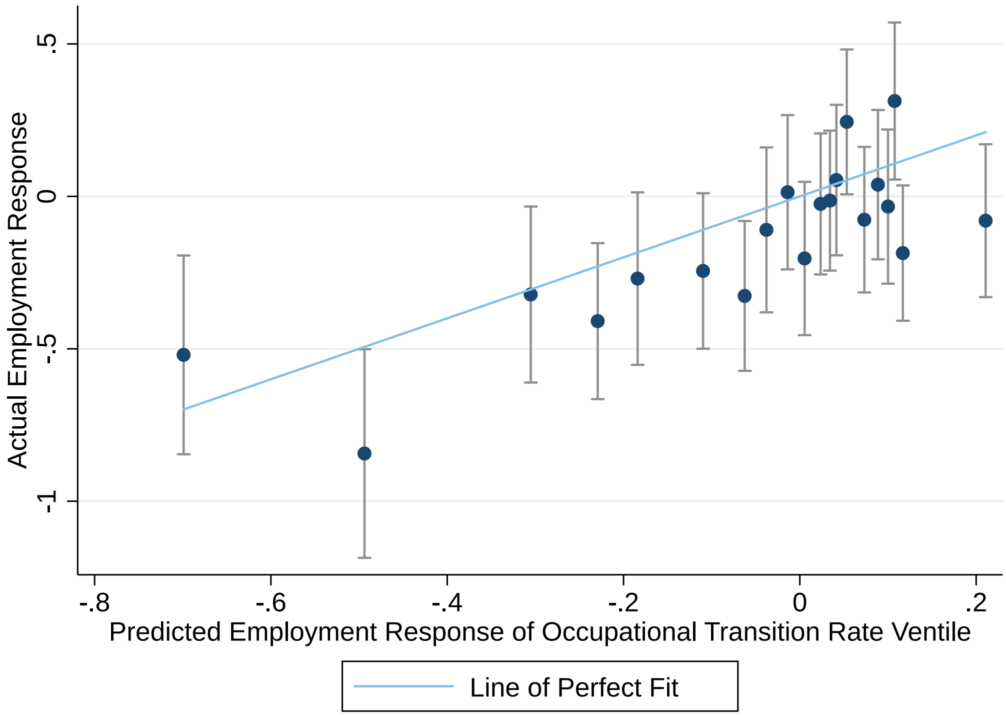

*Notes:* This figure presents estimates from Equation 10 of the effects of licensing on the shares of workers in a cell by their highest level of educational attainment, including details on attainment below a high school diploma. Standard errors are clustered at the state–occupation cell level. Bars reflect 95-percent confidence intervals with standard errors clustered by cell.

Figure A3: Another Comparison of the Self-Reported Licensed Share Versus Licensing Policy



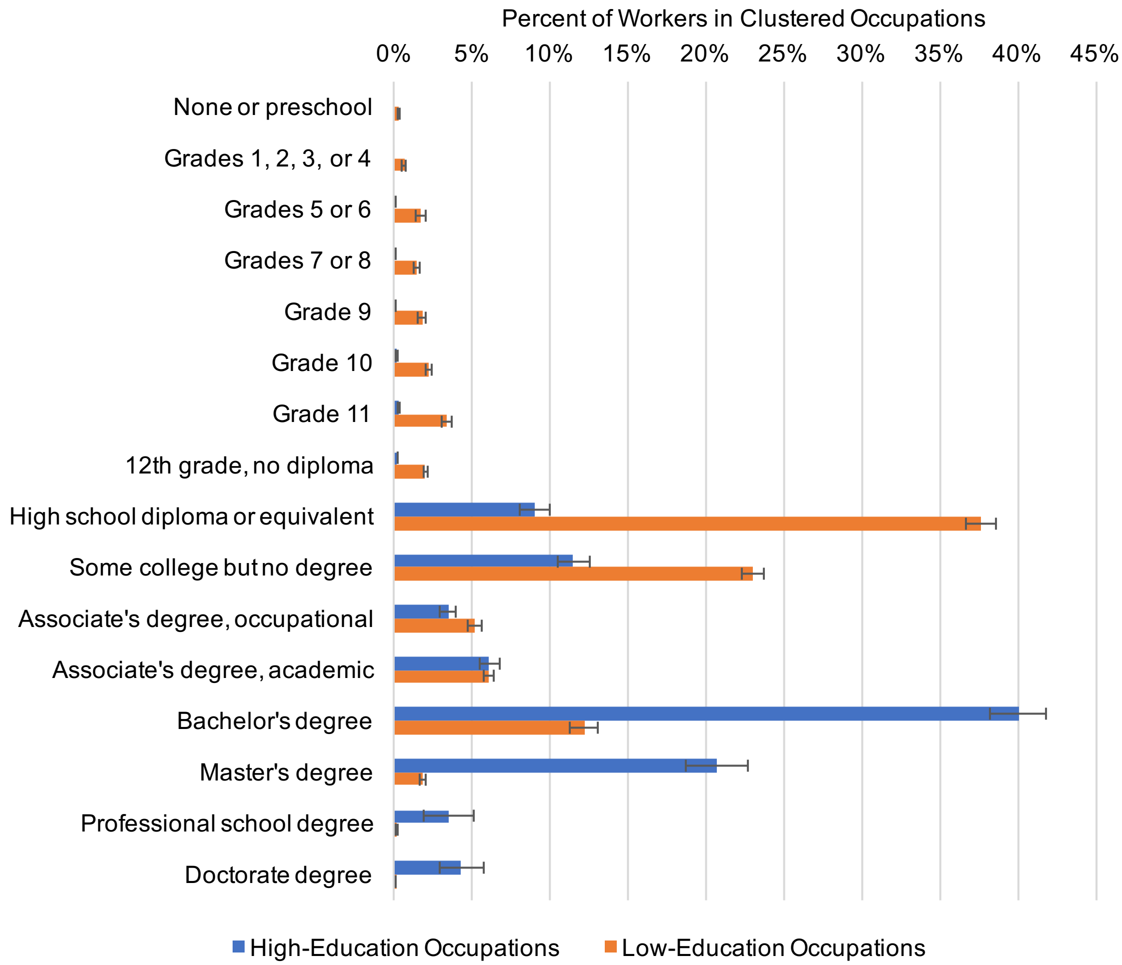

*Notes:* This figure presents a local first-degree polynomial fit of the partial relationship between the licensing policy at the level of the state–occupation cell and the cell-level share of workers who self-report that they are licensed, after partialling out state and occupation fixed effects. This relationship is estimated on the sample of workers in the 55 occupations for which we observe policy, as explained in Section 3 and Appendix Table A4.

Figure A4: Does the Model Explain the Heterogeneous Employment Effects of Licensing?



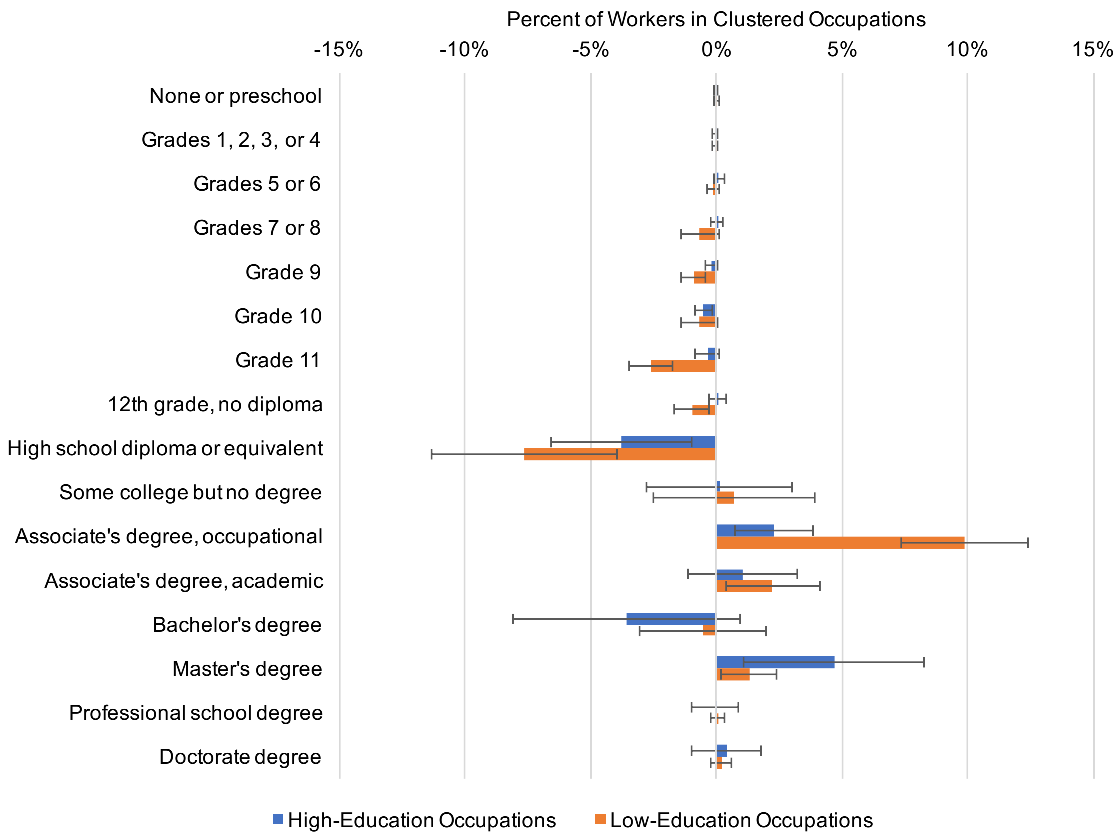

*Notes:* This figure plots actual and model-predicted employment responses to licensing for twenty groups of workers. Each point reflects a worker ventile of the distribution of predicted occupational transition rates, where the horizontal coordinate is the model-predicted response of ventile employment to licensing and the vertical coordinate is the actual employment response as estimated by a Poisson regression specification of Equation 10. The model-predicted estimates are also based on several calibrated values, as we discuss in Section 6. If actual employment responses coincide exactly with the model-predicted responses, they would fall on the light blue line. The model predicts that workers with high rates of occupational mobility should select out of employment in licensed occupations, a prediction that is strongly borne out in the data. Regressing actual on model-predicted employment responses yields a slope of 0.93 (SE = 0.17) and intercept of -0.09 (SE = 0.04), with an $R^2$ of 0.63. To assess the downward bias of the $R^2$ due estimation error in actual employment responses, we simulated this regression: For each vintile, we take 1,000 draws from a normal distribution whose mean is the vintile's model-predicted response and whose standard deviation is the estimated standard error on the vintile's actual response. Regressing these simulated responses on the model-predicted responses, we find an $R^2$ of 0.73. The nearness of our $R^2$ with the simulated upper-bound $R^2$ suggests our model rationalizes nearly all of the signal variance in actual employment responses by vintile.

Figure A5: Distribution of Educational Attainment, by Occupation Cluster



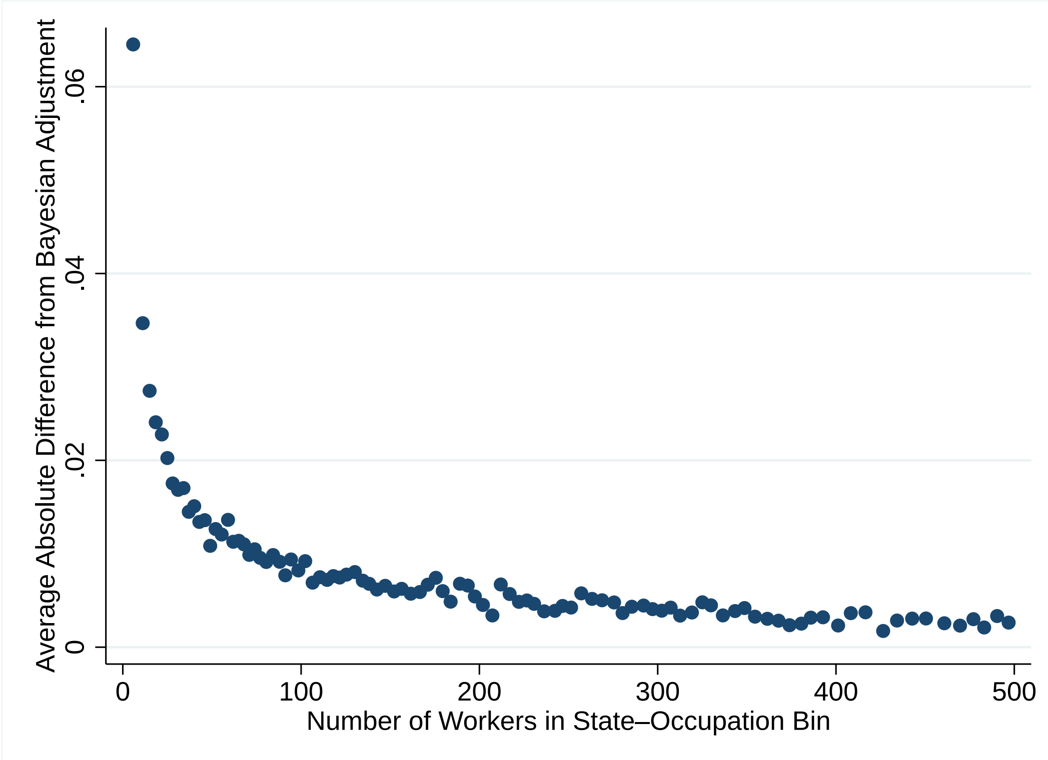

*Notes:* This figure reports the cluster means from the weighted $k$-means clustering ($k = 2$) of Census occupational categories by the distribution of educational attainment in them. In our application, the cluster means represent the shares of workers with each level of educational attainment conditional upon cluster assignment. Bars indicate 95-percent confidence intervals, clustered by cell, but do not account for uncertainty in $k$-means assignment.

Figure A6: Distribution of Educational Attainment, by Occupation Cluster



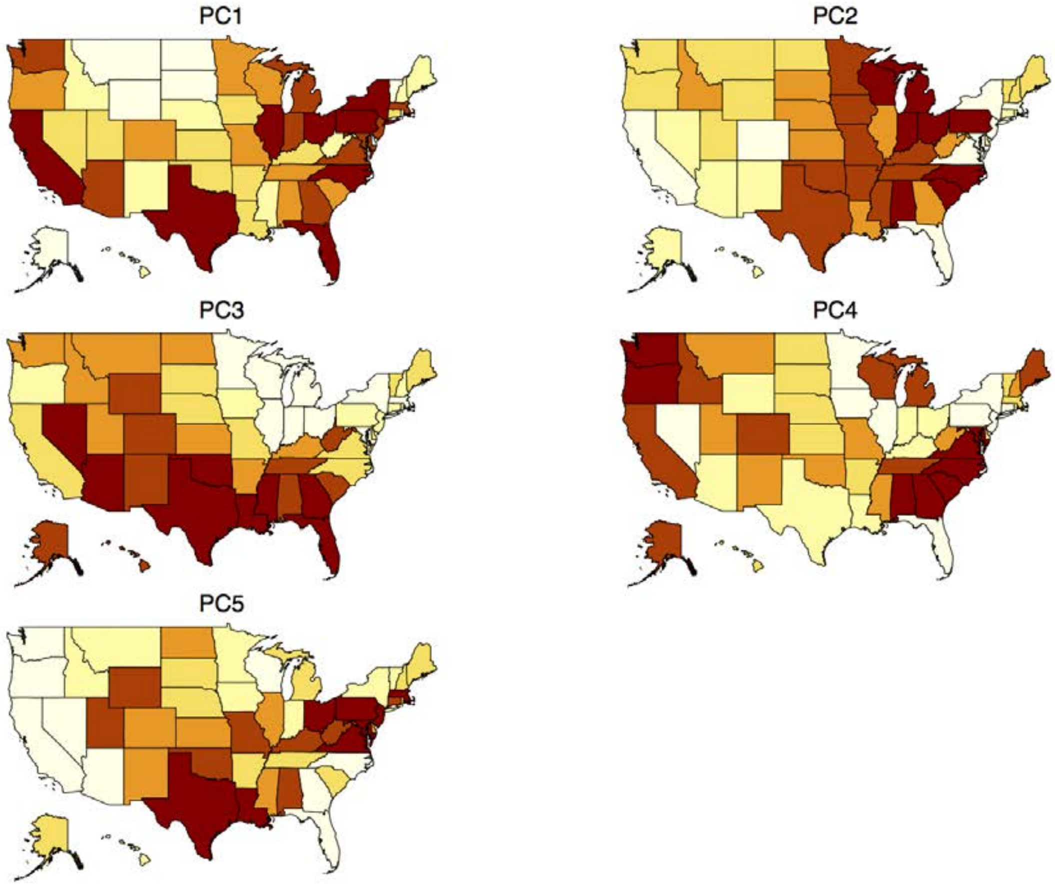

*Notes:* This figure presents estimates of the effects of occupational licensing on the cell shares of workers by detailed level of educational attainment, in which we split the effects based on whether the occupation is assigned to the low- or high-education cluster by a $k$-means procedure described in Appendix C.

Figure A7: Bayesian Adjustment Affects Only Very Small State–Occupation Cells




*Notes:* This figure presents a binned scatterplot of the average absolute difference between the cell licensed shares before and after the Bayesian adjustment described in Appendix E.

Figure A8: Principal Component Scores from Occupational Employment Shares




*Notes:* This figure depicts the principal component scores for state shares of employment by occupation, therefore extracting the low-dimensional patterns in states' employment mixes. In each of the five panels, states are ranked and colored according to their respective principal component score. The colors are in five equal-frequency bins.

# B Model Appendix

This appendix provides a detailed solution to the theoretical model of occupational licensing presented in Section 2. See the text for the structure of the main model. We restate here only the full optimization problem of worker $i$:

$$\max_{\{c_{ij}\},h_i,y_i,J_i} \left\{ \log\left[ \left( \sum_j q_j c_{ij}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}} - \frac{\psi}{1+\eta} h_i^{1+\eta} \right] - \rho(\tau_{J_i} + y_i) + a_{iJ_i} \right\}$$
$$\text{s.t.} \ \sum_j w_j c_{ij} \leq A_{J_i}(y_i) w_{J_i} h_i.$$

The worker's problem can be solved in four stages:

1. Given an income $I_i = A_j(y_i) w_{J_i} h_i$, choose the consumption allocation $\{c_{ij}\}$ that maximizes the value of the CES composite good.

2. Given an effective hourly wage $A_j(y_i) w_j$, choose the hours $h_{i:J_i=j}$ that maximize indirect utility in each occupation.

3. Given conditional consumption–labor sets $\{\{c_{ij}\}, h_i | J_i = j, y_i = y\}$ for each occupation, choose the years of schooling $y_{i:J_i=j}$ that maximize indirect utility in each occupation.

4. Given indirect utilities $\widetilde{V_{ij}}$ conditional upon entering each occupation $j$, choose $J_i = \arg\max_j \widetilde{V_{ij}}$.

## B.1 Consumption Decision

Begin with the CES utility maximization problem:

$$\max_{\{c_{ij}\}} \sum_j q_j c_{ij}^{\frac{\varepsilon-1}{\varepsilon}} \ \text{s.t.} \ \sum_j w_j c_{ij} \leq I_i,$$

where we hold $I_i$ fixed. Given a large number of industries, the first order conditions with respect to $c_{ij}$ are

$$q_j c_{ij}^{-1/\varepsilon} + \lambda w_j = 0 \quad \forall j,$$

where $\lambda$ is a Lagrange multiplier on the budget constraint. We omit the familiar CES derivations and proceed to the results. Individual consumptions are

$$c_{ij} = \frac{A_j(y_i) w_{J_i} (w_j/q_j)^{-\varepsilon}}{P^{1-\varepsilon}},$$

where the ideal price index is

$$P = \left( \sum_j q_j^{\varepsilon} w_j^{1-\varepsilon} \right)^{\frac{1}{1-\varepsilon}},$$

such that the value of the optimal CES composite good available to the worker who has years of education $y_i$ and works $h_i$ hours in industry $J_i$ has a consumption level

$$C_i^*(y_i, h_i, J_i) = \frac{I(y_i, h_i, J_i)}{P} = \frac{A_{J_i}(y_i) w_{J_i} h_i}{P}.$$

We normalize the wage of a reference occupation $w_0 = 1$ such that $\tau_0 = 1$.

## B.2 Labor Supply Decision

Let $V_j$ indicate the payoff-period utility apart from idiosyncratic occupation preferences and that is thus common across workers in occupation $j$. We can rewrite the optimization problem at this stage as

$$\max_{h_i} \left\{ C_i^*(h_i) - \frac{\psi}{1+\eta} h_i^{1+\eta} \right\} \text{ s.t. } C_i^*(h_i) \equiv C_i^*(h_i | y_i, J_i) \leq \frac{A_{J_i}(y_i) w_{J_i} h_i}{P}.$$

This yields the first-order condition with respect to $h_i$

$$\frac{A_{J_i}(y_i) w_{J_i}}{P} - \psi h_i^{\eta} = 0,$$

and thereby the constant elasticity intensive-margin labor supply function

$$h_i^*(w_{J_i}) = \left( \frac{A_{J_i}(y_i) w_{J_i}}{\psi P} \right)^{\frac{1}{\eta}}.$$

We can now express $V_j$ as a function of the wage $w_{J_i}$, which the worker takes as given, and the schooling choice $y_i$, which we endogenize in the next subsection of this appendix:

$$\begin{aligned} V_j(y_j) &= \frac{A_{J_i}(y_i) w_{J_i}}{P} \left( \frac{A_{J_i}(y_i) w_{J_i}}{\psi P} \right)^{\frac{1}{\eta}} - \frac{\psi}{1+\eta} \left( \frac{A_{J_i}(y_i) w_{J_i}}{\psi P} \right)^{\frac{1+\eta}{\eta}} \\ &= \frac{\eta}{1+\eta} \left( \frac{A_{J_i}(y_i) w_{J_i}}{\psi P} \right)^{\frac{1+\eta}{\eta}}. \end{aligned}$$

### B.3 Schooling

After observing $\{\tau_j\}$, workers set their level of schooling to maximize their present-value utility conditional upon entering each occupation. The solution to the schooling decision problem is

$$y_i^* = \arg\max_{y_i} \{\log V_j(y_i) - \rho y_i\},$$

which yields the first-order condition

$$\frac{1+\eta}{\eta} \cdot \frac{A'_{J_i}(y_i^*)}{A_{J_i}(y_i^*)} - \rho = 0.$$

We can therefore define $v_j$ as the common indirect utility of the worker in occupation $j$, which is

$$v_j = e^{-\rho(y_i^* + \tau_j)} V_j(y_i^*) = \frac{\eta e^{-\rho(y_i^* + \tau_j)}}{1+\eta} \left( \frac{A_{J_i}(y_i^*) w_{J_i}}{\psi P} \right)^{\frac{1+\eta}{\eta}}.$$

### B.4 Occupation Decision and Utility

The conditional indirect utility of a worker in occupation $j$ is the product of common conditional indirect utility $v_j$ and his or her idiosyncratic occupation preference term $a_{ij}$:

$$v_{ij} = a_{ij} v_j.$$

As $v_{ij}$ is increasing in the i.i.d. Fréchet random variable $a_{ij}$, $v_{ij}$ is itself distributed i.i.d. Fréchet. The worker's problem at this stage is to pick the occupation $j$ that maximizes $V_{ij}$:

$$J_i^* = \arg\max_j v_{ij}.$$

By max-stability of $v_{ij}$, $v_{iJ_i}^*$ is distributed i.i.d. Fréchet:

$$v_{iJ_i}^* = a_{iJ_i} \left( \sum_j \left( \frac{\eta e^{-\rho(y_{i:J_i=j}^* + \tau_j)}}{1+\eta} \right)^{\sigma} \left( \frac{A_j(y_{i:J_i=j}^*) w_j}{\psi P} \right)^{\frac{\sigma(1+\eta)}{\eta}} \right)^{\frac{1}{\sigma}},$$

where $a_{ij}$ is i.i.d. Fréchet with dispersion parameter $\sigma$. Notice that the second term is independent of the choice $J_i$. The choice probability of occupation $j$ is

$$s_j = P\left( J_i^* = \arg\max_j v_{ij} \right) = P\left( (a_{ij} - a_{ij'}) \geq \log\left( \frac{v_j}{v_{j'}} \right) \forall j \right) = \frac{v_j^{\sigma}}{\sum_{j'} v_{j'}^{\sigma}}.$$

The expected utility of workers in occupation $j$ is

$$\overline{u_j} = \mathbb{E}[V^*_{iJ_i}|J_i = j] = \mathbb{E}\left[a_{iJ_i}\left(\sum_j \left(\frac{\eta e^{-\rho(y^*_{i:J_i=j}+\tau_j)}}{1+\eta}\right)^{\sigma}\left(\frac{A_j(y^*_{i:J_i=j})w_j}{\psi P}\right)^{\frac{\sigma(1+\eta)}{\eta}}\right)^{\frac{1}{\sigma}}\middle|J_i = j\right]$$

$$= \Gamma\left(1-\frac{1}{\sigma}\right)\left(\sum_j \left(\frac{\eta e^{-\rho(y^*_{i:J_i=j}+\tau_j)}}{1+\eta}\right)^{\sigma}\left(\frac{A_j(y^*_{i:J_i=j})w_j}{\psi P}\right)^{\frac{\sigma(1+\eta)}{\eta}}\right)^{\frac{1}{\sigma}}$$

$$\propto \left(\sum_j e^{-\rho\sigma(y^*_{i:J_i=j}+\tau_j)}\left(A_j(y^*_{i:J_i=j})w_j\right)^{\frac{\sigma(1+\eta)}{\eta}}\right)^{\frac{1}{\sigma}}.$$

Expected utility in occupation $j$ is the same in all occupations and therefore equal to expected utility of all workers ($\overline{u_j} = \overline{u}$ for all $j$).

## B.5 Willingness to Pay

We assume that willingness to pay is a function of the licensing cost and the expectation of workers' idiosyncratic occupation preference term conditional upon entering the occupation:

$$\log q_j = \kappa_{0j} + \kappa_1 \log(1-\ell_j) + \kappa_2 \log \mathbb{E}[a_{iJ_i}|J_i = j].$$

For an occupation $j$ that is sufficiently small, changes in $\tau_j$ have a negligible effect on expected utility $\overline{u}$. Also recall that

$$\frac{\partial \log \overline{u}}{\partial \tau_j} = \frac{\partial \log v_j}{\partial \tau_j} + \frac{\partial \log \mathbb{E}[a_{iJ_i}|J_i = j]}{\partial \tau_j}.$$

By the choice probability equation above, we also have

$$\frac{\partial \log s_j}{\partial \tau_j} = \sigma \frac{\partial \log v_j}{\partial \tau_j}.$$

Then combining these statements, we have

$$\frac{\partial \log \mathbb{E}[a_{iJ_i}|J_i = j]}{\partial \tau_j} = -\frac{\partial \log v_j}{\partial \tau_j} = -\frac{1}{\sigma}\frac{\partial \log s_j}{\partial \tau_j},$$

and so

$$\frac{d \log q_j}{\partial \tau_j} = \kappa_1 - \kappa_2 \frac{\partial \log \mathbb{E}[a_{iJ_i}|J_i = j']}{\partial \tau_j}$$

$$= \kappa_1 - \frac{\kappa_2}{\sigma}\frac{\partial \log s_{j'}}{\partial \tau_j}$$

$$= \kappa_1 - \frac{\kappa_2}{\sigma}\frac{\partial \log s_j}{\partial \tau_j} \equiv \alpha,$$

as employment shares have a constant semi-elasticity in years of training.

## B.6 Equilibrium Conditions

Consumption demand:

$$\frac{\partial \log C_j}{\partial \tau_j} = \varepsilon \left( \frac{\partial \log q_j}{\partial \tau_j} - \frac{\partial \log w_j}{\partial \tau_j} \right)$$

Willingness to pay:

$$\frac{\partial \log q_j}{\partial \tau_j} = \alpha$$

Intensive-margin labor supply:

$$\frac{\partial \log h_{i:J_i=j}}{\partial \tau_j} = \frac{1}{\eta} \frac{\partial \log w_j}{\partial \tau_j}$$

Schooling:

$$\frac{\partial \log y_{i:J_i=j}}{\partial \tau_j} = 0$$

Extensive-margin labor supply:

$$\frac{\partial \log s_j}{\partial \tau_j} = \sigma \left( \frac{1+\eta}{\eta} \frac{\partial \log w_j}{\partial \tau_j} - \rho \right)$$

Labor market clearing:

$$\frac{\partial \log C_j}{\partial \tau_j} = \frac{\partial \log H_j}{\partial \tau_j} = \frac{\partial \log s_j}{\partial \tau_j} + \frac{\partial \log h_{i:J_i=j}}{\partial \tau_j}$$

## B.7 Model Solution

The model can be solved by using the four labor market equilibrium conditions and the WTP equation. Let

$$\boldsymbol{x}' = \left[ \tfrac{\partial \log s_j}{\partial \tau_j} \quad \tfrac{\partial \log h_{i:J_i=j}}{\partial \tau_j} \quad \tfrac{\partial \log w_j}{\partial \tau_j} \quad \tfrac{\partial \log H_j}{\partial \tau_j} \quad \tfrac{\partial \log q_j}{\partial \tau_j} \right].$$

The above results form a system of linear equations of the form $\boldsymbol{A}\boldsymbol{x} = \boldsymbol{C}\boldsymbol{x} + \boldsymbol{b}$, where $\boldsymbol{A}$ and $\boldsymbol{C}$ are 5-by-5 matrices and $\boldsymbol{x}'$ is a vector of length 5. If $\boldsymbol{A}$ and $\boldsymbol{C}$ are both of full rank and $\boldsymbol{b} \neq \boldsymbol{0}$, the system admits a unique solution $\boldsymbol{x} = (\boldsymbol{A} - \boldsymbol{C})^{-1}\boldsymbol{b}$. We confirm first that $\boldsymbol{b} \neq \boldsymbol{0}$:

$$\boldsymbol{b} = \begin{bmatrix} -\rho\sigma \\ 0 \\ \alpha \\ 0 \\ \alpha \end{bmatrix}.$$

Thus, for $\boldsymbol{b} \neq \boldsymbol{0}$, we require that either $\rho\sigma \neq 0$ or $\alpha \neq 0$. The former condition will hold in all cases of interest. Since $\boldsymbol{A} = \boldsymbol{I}$, we also have

$$\boldsymbol{A} - \boldsymbol{C} = \begin{bmatrix} 1 & 0 & -\sigma(1+\eta)/\eta & 0 & 0 \\ 0 & 1 & -1/\eta & 0 & 0 \\ 0 & 0 & 1 & 1/\varepsilon & 0 \\ -1 & -1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

The determinant of this matrix is

$$|\boldsymbol{A} - \boldsymbol{C}| = -\frac{1 + \sigma(1+\eta) + \eta\varepsilon}{\eta\varepsilon}.$$

$\boldsymbol{A} - \boldsymbol{C}$ is of full rank if and only if $|\boldsymbol{A} - \boldsymbol{C}| \neq 0$, thus if $1 + \sigma(1+\eta) + \eta\varepsilon \neq 0$ and $|\eta\varepsilon| < \infty$. The economic content of this parameter restriction is to establish that, if a market-clearing wage exists, it is unique: It rules out the case in which the total labor supply elasticity—that is, the sum of the extensive and intensive margins—is exactly equal to the labor demand elasticity. This holds in any case of interest, as we assume $\sigma > 0$, $\eta > 0$, and $\varepsilon > 1$. With these restrictions, we have a unique solution to the model:

$$\begin{bmatrix} \frac{\partial \log s_j}{\partial \tau_j} \\ \frac{\partial \log h_{i:J_i=j}}{\partial \tau_j} \\ \frac{\partial \log w_j}{\partial \tau_j} \\ \frac{\partial \log H_j}{\partial \tau_j} \\ \frac{\partial \log q_j}{\partial \tau_j} \end{bmatrix} = \begin{bmatrix} 1 & 0 & -\frac{\sigma(1+\eta)}{\eta} & 0 & 0 \\ 0 & 1 & -1/\eta & 0 & 0 \\ 0 & 0 & 1 & 1/\varepsilon & 0 \\ -1 & -1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} -\rho\sigma \\ 0 \\ \alpha \\ 0 \\ \alpha \end{bmatrix}$$

$$= \frac{1}{1 + \sigma(1+\eta) + \eta\varepsilon} \begin{bmatrix} \alpha\varepsilon\sigma(1+\eta) - \rho\sigma(1+\eta\varepsilon) \\ \alpha\eta\varepsilon + \rho\sigma\eta \\ \alpha\varepsilon + \rho\sigma \\ (1+\sigma)(1+\eta)\alpha\varepsilon - \rho\sigma\eta(\varepsilon - 1) \\ \alpha(1 + \sigma(1+\eta) + \eta\varepsilon) \end{bmatrix}.$$

## B.8 Social Welfare

The logarithm of expected utility is

$$\log \overline{u} \propto \frac{1}{\sigma}\left[\sum_j e^{-\rho(y_j^*+\tau_j)}\left(\frac{A_j(y_j^*)w_j}{P}\right)^{\frac{\sigma(1+\eta)}{\eta}}\right].$$

Then we can use a first-order approximation for the partial derivative with respect to $\tau_{j'}$:

$$\frac{\partial \log \overline{u}}{\partial \tau_{j'}} = \sum_j s_j \frac{\partial}{\partial \tau_{j'}}\left[\frac{1+\eta}{\eta}\big(\log A_j(y_j^*) + \log w_j - \log P\big) - \rho(y_j^* + \tau_j)\right].$$

By the envelope theorem,

$$\frac{\partial}{\partial \tau_{j'}}\left[\frac{1+\eta}{\eta}\log A_j(y_j^*) - \rho y_j^*\right] = 0 \quad \forall j,$$

and thus

$$\frac{\partial \log \overline{u}}{\partial \tau_{j'}} = \sum_j s_j \left[\frac{1+\eta}{\eta}\left(\frac{\partial \log w_j}{\partial \tau_{j'}} - \frac{\partial \log P}{\partial \tau_{j'}}\right) - \rho \frac{\partial \tau_j}{\partial \tau_{j'}}\right].$$

Splitting the sum into occupation $j'$ whose $\tau_{j'}$ changes and all others, we have that

$$\frac{\partial \tau_{j'}}{\partial \tau_{j'}} = 1 \text{ and } \frac{\partial \tau_j}{\partial \tau_{j'}} = 0 \quad \forall j' \neq j,$$

and so, simplifying further, we obtain

$$\frac{\partial \log \overline{u}}{\partial \tau_{j'}} = \frac{1+\eta}{\eta}\left[s_{j'}\frac{\partial \log w_{j'}}{\partial \tau_{j'}} + \sum_{j:j\neq j'} s_j \frac{\partial \log w_j}{\partial \tau_{j'}}\right] - \rho s_{j'} - \frac{1+\eta}{\eta}\frac{\partial \log P}{\partial \tau_{j'}}.$$

Inverting Equation 9, and doing this for both $j'$ and $j : j \neq j'$, we obtain

$$\frac{\partial \log w_{j'}}{\partial \tau_{j'}} = \frac{\eta}{1+\eta}\left(\frac{1}{\sigma}\frac{\partial \log s_{j'}}{\partial \tau_{j'}} + \rho\right)$$
$$\frac{\partial \log w_j}{\partial \tau_{j'}} = \frac{\eta}{\sigma(1+\eta)}\frac{\partial \log s_j}{\partial \tau_{j'}} \quad \forall j : j \neq j'$$

and substitutions yield

$$\frac{\partial \log \overline{u}}{\partial \tau_{j'}} = \frac{s_{j'}}{\sigma}\frac{\partial \log s_{j'}}{\partial \tau_{j'}} + \frac{1}{\sigma}\sum_{j:j\neq j'} s_j \frac{\partial \log s_j}{\partial \tau_{j'}} - \frac{1+\eta}{\eta}\frac{\partial \log P}{\partial \tau_{j'}}.$$

Independence of preferences across occupations gives us that displaced workers from occupation $j'$ are apportioned to occupations $j \neq j'$ according to the shares of $j$ in total employment:

$$\frac{\partial \log s_j}{\partial \tau_{j'}} = -\frac{s_j}{1-s_{j'}} \frac{\partial \log s_{j'}}{\partial \tau_{j'}}.$$

Under our assumption of a utilitarian social welfare function, $\mathcal{W} = \sum_i u_i = \sum N\bar{u}$. By these substitutions, we obtain

$$\frac{\partial \log \mathcal{W}}{\partial \tau_{j'}} = \frac{s_{j'}}{\sigma} \frac{\partial \log s_{j'}}{\partial \tau_{j'}} - \frac{1}{\sigma} \sum_{j:j\neq j'} \frac{s_j^2}{1-s_{j'}} \frac{\partial \log s_{j'}}{\partial \tau_{j'}} - \frac{1+\eta}{\eta} \frac{\partial \log P}{\partial \tau_{j'}},$$

which rewrites to

$$\frac{\partial \log \mathcal{W}}{\partial \tau_{j'}} = \frac{1}{\sigma} \frac{\partial \log s_{j'}}{\partial \tau_{j'}} \left( s_{j'} - \frac{\sum_{j\neq j'} s_j^2}{1-s_{j'}} \right) - \frac{1+\eta}{\eta} \frac{\partial \log P}{\partial \tau_{j'}},$$

which has a rich economic interpretation. We have characterized the welfare effect of licensing occupation $j$ on employment in occupation $j$ even in a model with nonnegligible spillovers across occupations, and it reflects changes in employment in the licensed occupation and in the price level. Second, the normalized Herfindahl index of employment shares summarizes the extent of these cross-occupation spillovers. This is, to the best of our knowledge, a novel theoretical connection between the normalized Herfindahl index and the relevance of spillovers to welfare.

In the limit $H_j = \sum_j s_j^2 \to 0$ in which the effective number of occupations approaches infinity, spillovers become negligible, and we obtain a particularly stark welfare result:

$$\frac{\partial \log \mathcal{W}}{\partial \tau_j} = \frac{s_j}{\sigma} \frac{\partial \log s_j}{\partial \tau_j} - \frac{1+\eta}{\eta} \frac{\partial \log P}{\partial \tau_j},$$

In the paper, we perform several manipulations on this result. First, we define occupational surplus as the difference in social welfare, holding all other $\{\tau_j\}$ constant, between the equilibrium with $\tau_j = 0$ (no licensing) and the equilibrium $\tau_j \to \infty$ (occupation banned).

$$\mathcal{W}_j = \mathcal{W}(0, \{\tau_{j'}\}) - \lim_{\tau_j \to \infty} \mathcal{W}(\tau_j, \{\tau_{j'}\})).$$

Then the above rewrites to

$$\frac{\partial \log \mathcal{W}_j}{\partial \tau_j} = \frac{1}{\sigma} \frac{\partial \log s_j}{\partial \tau_j} - \frac{1+\eta}{\eta s_j} \frac{\partial \log P}{\partial \tau_j}.$$

Furthermore, we can obtain the partial derivative of $P$ with respect to $\tau_{j'}$:

$$
\begin{aligned}
\frac{\partial \log P}{\partial \tau_{j'}} &= \frac{1}{1-\varepsilon} \cdot \frac{\partial}{\partial \tau_{j'}} \log \sum_j q_j^{\varepsilon} w_j^{1-\varepsilon} \\
&\approx \frac{1}{1-\varepsilon} \sum_j s_j \frac{\partial}{\partial \tau_{j'}} \left[\varepsilon \log q_j + (1-\varepsilon) \log w_j\right] \\
&= \frac{1}{1-\varepsilon} \sum_j s_j \left[\varepsilon \left(\frac{\partial \log q_j}{\partial \tau_{j'}} - \frac{\partial \log w_j}{\partial \tau_{j'}}\right) + \frac{\partial \log w_j}{\partial \tau_{j'}}\right].
\end{aligned}
$$

From Equation 8, we have

$$
\varepsilon \left(\frac{\partial \log q_j}{\partial \tau_{j'}} - \frac{\partial \log w_j}{\partial \tau_{j'}}\right) = \frac{\partial \log s_j}{\partial \tau_{j'}} + \frac{\partial \log h_{i:J_i=j}}{\partial \tau_{j'}},
$$

and so by substitution,

$$
\begin{aligned}
\frac{\partial \log P}{\partial \tau_j} &= \frac{1}{1-\varepsilon} \sum_j s_j \left(\frac{\partial \log s_j}{\partial \tau_{j'}} + \frac{\partial \log h_{i:J_i=j}}{\partial \tau_{j'}} + \frac{\partial \log w_j}{\partial \tau_{j'}}\right) \\
&= \frac{1}{1-\varepsilon} \sum_j s_j \frac{\partial \log w_j H_j}{\partial \tau_{j'}}.
\end{aligned}
$$

A similar argument as above applies to the off-diagonal terms, yielding the approximation

$$
\frac{\partial \log P}{\partial \tau_j} = \frac{s_j}{1-\varepsilon} \frac{\partial \log w_j H_j}{\partial \tau_{j'}},
$$

which in turn implies

$$
\frac{\partial \log \mathcal{W}_j}{\partial \tau_j} = \frac{1}{\sigma} \frac{\partial \log s_j}{\partial \tau_j} + \frac{1+\eta}{\eta(\varepsilon-1)} \frac{\partial \log w_j H_j}{\partial \tau_{j'}}.
$$

We have now mapped the social welfare effect of licensing into two reduced-form comparative statics that are, in principle, estimable from only labor market data—the effects of licensing on the own-occupation employment share and wage bill—and three structural parameters. These structural parameters all have known sign ($\sigma > 0$, $\eta > 0$, $\varepsilon - 1 > 0$), and thus we can view the welfare effect as a weighted sum of these two reduced-form responses.

A second manipulation of the welfare result is to define changes in worker and consumer surplus as respectively

$$
\begin{aligned}
\frac{\partial \log \mathcal{W}^L}{\partial \tau_j} &= \frac{s_j}{\sigma} \frac{\partial \log s_j}{\partial \tau_j} \\
\frac{\partial \log \mathcal{W}^C}{\partial \tau_j} &= -\frac{1+\eta}{\eta} \frac{\partial \log P}{\partial \tau_j}.
\end{aligned}
$$

We introduce this terminology to think intuitively about the incidence of licensing: Workers bear the costs of licensing insofar as licensing reduces the present value of nominal income in an occupation (and thus spurs workers to exit the occupation on the margin), whereas consumers bear the costs of licensing insofar as licensing raises the price level, reducing the real income of all workers, including those not in the licensed occupation. Using Proposition 1, we express licensing's effects on worker and consumer surplus in terms of structural parameters:

$$\frac{\partial \log \mathcal{W}^L}{\partial \tau_j} = s_j \cdot \frac{(1+\eta)\alpha\varepsilon - \rho(1+\eta\varepsilon)}{1+\sigma(1+\eta)+\eta\varepsilon}$$
$$\frac{\partial \log \mathcal{W}^C}{\partial \tau_j} = \frac{s_j}{1+\sigma(1+\eta)+\eta\varepsilon}\left[\frac{(1+\sigma)(1+\eta)^2\alpha\varepsilon}{\eta(\varepsilon-1)} - \rho\sigma(1+\eta)\right].$$

Taken together, and rescaled into occupational surplus, we obtain

$$\frac{\partial \log \mathcal{W}_j}{\partial \tau_j} = \frac{1+\eta}{\eta}\frac{\alpha\varepsilon}{\varepsilon-1} - \rho.$$

## B.9 Incidence

We can also use the model to analyze incidence. First, we may write the share of licensing costs that are offset for workers by increases in wages fully in terms of primitives:

$$\frac{1}{\rho}\frac{\partial \log w_j}{\partial \tau_j} = \frac{\alpha\varepsilon\eta/\rho + \sigma\eta}{1+\sigma(1+\eta)+\eta\varepsilon}.$$

Next, we can write the effect of licensing on the WTP-adjusted price in terms of primitives:

$$\frac{1}{1-\varepsilon}\frac{\partial \log(q_j^{\varepsilon} w_j^{1-\varepsilon})}{\partial \tau_j} = \frac{\rho\sigma\eta(\varepsilon-1) - (1+\sigma)(1+\eta)\alpha\varepsilon}{(\varepsilon-1)(1+\sigma(1+\eta)+\eta\varepsilon)},$$

and then we can calculate the share of the price increase offset by increases in WTP in terms of primitives:

$$\frac{\varepsilon}{\varepsilon-1}\frac{\partial \log q_j/\partial\tau_j}{\partial \log w_j/\partial\tau_j} = \frac{\alpha\varepsilon}{\alpha\varepsilon+\rho\sigma}\frac{1+\sigma(1+\eta)+\eta\varepsilon}{\eta(\varepsilon-1)}.$$

Additional incidence results are provided below as proofs to propositions.

## B.10 Proofs of Propositions

### Proposition 1

Section B.7 presents a detailed derivation.

**Proposition 2**

Take the partial derivative with respect to $\alpha$:

$$\frac{\partial}{\partial\alpha}\begin{bmatrix}\frac{\partial\log s_j}{\partial\tau_j}\\ \frac{\partial\log h_{i:J_i=j}}{\partial\tau_j}\\ \frac{\partial\log w_j}{\partial\tau_j}\\ \frac{\partial\log H_j}{\partial\tau_j}\\ \frac{\partial\log q_j}{\partial\tau_j}\end{bmatrix} = \frac{1}{1+\sigma(1+\eta)+\eta\varepsilon}\cdot\frac{\partial}{\partial\alpha}\begin{bmatrix}\alpha\varepsilon\sigma(1+\eta)-\rho\sigma(1+\eta\varepsilon)\\ \alpha\eta\varepsilon+\rho\sigma\eta\\ \alpha\varepsilon+\rho\sigma\\ (1+\sigma)(1+\eta)\alpha\varepsilon-\rho\sigma\eta(\varepsilon-1)\\ \alpha(1+\sigma(1+\eta)+\eta\varepsilon)\end{bmatrix}$$

$$= \frac{1}{1+\sigma(1+\eta)+\eta\varepsilon}\cdot\begin{bmatrix}\sigma\varepsilon(1+\eta)\\ \eta\varepsilon\\ \varepsilon\\ (1+\sigma)(1+\eta)\varepsilon\\ 1+\sigma(1+\eta)+\eta\varepsilon\end{bmatrix}.$$

One immediately sees the claimed sign on all cross-partials.

**Proposition 3**

Section B.8 presents a detailed derivation.

**Proposition 4**

Proposition 3 proves that the social welfare effect of licensing, in terms of the percentage change in occupational surplus, is

$$\frac{\partial\log\mathcal{W}_j}{\partial\tau_j} = \frac{1}{\sigma}\frac{\partial\log s_j}{\partial\tau_j} + \frac{1+\eta}{\eta(\varepsilon-1)}\frac{\partial\log w_jH_j}{\partial\tau_j},$$

and substituting in comparative statics from Proposition 1, we obtain

$$\frac{\partial\log\mathcal{W}_j}{\partial\tau_j} = \frac{(1+\eta)\alpha\varepsilon-\rho(1+\eta\varepsilon)+\frac{(1+\sigma)(1+\eta)^2\alpha\varepsilon}{\eta(\varepsilon-1)}-\rho\sigma(1+\eta)}{1+\sigma(1+\eta)+\eta\varepsilon},$$

and since we wish to test that $\partial\log\mathcal{W}_j/\partial\tau_j < 0$, we multiply by the common factor $1+\sigma(1+\eta)+\eta\varepsilon$ and obtain the test

$$(1+\eta)\alpha\varepsilon-\rho(1+\eta\varepsilon)+\frac{(1+\sigma)(1+\eta)^2\alpha\varepsilon}{\eta(\varepsilon-1)}-\rho\sigma(1+\eta) < 0,$$

which simplifies to

$$\rho > \frac{1+\eta}{\eta}\frac{\alpha\varepsilon}{\varepsilon-1}.$$

**Proposition 5**

*Incidence ($\gamma^L$).* We divide our formula for the worker welfare effect by the social welfare effect:

$$\gamma^L = \frac{\Delta\mathcal{W}^L}{\Delta\mathcal{W}} = \frac{\frac{(1+\eta)\alpha\varepsilon-\rho(1+\eta\varepsilon)}{1+\sigma(1+\eta)+\eta\varepsilon}}{\frac{1+\eta}{\eta}\frac{\alpha\varepsilon}{\varepsilon-1}-\rho}$$
$$= \frac{(1+\eta)\alpha\varepsilon-\rho(1+\eta\varepsilon)}{(1+\eta)\alpha\varepsilon-\rho\eta(\varepsilon-1)}\cdot\frac{\eta(\varepsilon-1)}{1+\sigma(1+\eta)+\eta\varepsilon}.$$

*Conditions for $\Delta\mathcal{W}^L < 0 < \Delta\mathcal{W}^C$.* First, using the worker welfare formula, we obtain

$$\Delta\mathcal{W}^L < 0 \iff (1+\eta)\alpha\varepsilon-\rho(1+\eta\varepsilon) < 0$$
$$\iff \alpha < \frac{\rho(1+\eta\varepsilon)}{(1+\eta)\varepsilon}.$$

Next, using the consumer welfare formula, we obtain

$$\Delta\mathcal{W}^C > 0 \iff \frac{(1+\sigma)(1+\eta)^2\alpha\varepsilon}{\eta(\varepsilon-1)} - \rho\sigma(1+\eta) > 0$$
$$\iff \alpha > \frac{\rho\sigma\eta(\varepsilon-1)}{(1+\sigma)(1+\eta)\varepsilon}.$$

Thus,

$$\Delta\mathcal{W}^L < 0 < \Delta\mathcal{W}^C \iff \alpha \in \left(\frac{\rho\sigma\eta(\varepsilon-1)}{(1+\sigma)(1+\eta)\varepsilon}, \frac{\rho(1+\eta\varepsilon)}{(1+\eta)\varepsilon}\right).$$

## B.11 Constructive Proof of Identification

We show constructively that the vector of reduced-form empirical moments $\hat{\boldsymbol{\beta}} = [\widehat{a_i}, \widehat{w_j}, \widehat{h_{i:J_i=j}}, \widehat{s_j}]$ just-identify the vector of structural parameters $\boldsymbol{\theta} = [\rho, \eta, \alpha, \overline{\tau}]$ with the calibration of $\sigma$ and $\varepsilon$. The structural parameters may be recovered by

$$\eta = \widehat{w_j}/\widehat{h_i}$$
$$\overline{\tau} = \widehat{a_i}$$
$$\alpha = \widehat{w_j} + \frac{1}{\varepsilon}(\widehat{s_j} + \widehat{h_i})$$
$$\rho = \widehat{w_j} - \frac{\widehat{w_j}\widehat{s_j}}{\sigma(\widehat{w_j}+\widehat{h_j})}.$$

These results follow quite immediately from algebraic manipulations of the four main equations in our model solution.

## B.12 Generalization to Heterogeneous Agents

We outline how our results generalize to models where agents differ in their characteristics according to their type $k = 1, \ldots, K$. We also provide a simple model with $K$ types and show how our approach accommodates selection by type into licensed occupations.

*Sufficient Statistics.* Our sufficient-statistics results are robust to heterogeneity in discount rate $\rho_k$, effective labor supply function $A_{jk}(y)$, and WTP effect $\alpha_{jk}$. This can be seen by repeating the sufficient-statistic derivations above for each type: Type-specific employment and wage bill effects remain sufficient statistics for type welfare. Under a utilitarian social welfare function, social welfare is a population-weighted average over these type-specific employment and wage bill effects, recovering the average effect on employment and the wage bill as sufficient statistics for social welfare:

$$\begin{aligned}\frac{\partial \log \mathcal{W}_j}{\partial \tau_j} &= \mathrm{E}\left[\frac{1}{\sigma}\frac{\partial \log s_{j,k}}{\partial \tau_j} + \frac{1+\eta}{\eta(\varepsilon-1)}\frac{\partial \log wH_{j,k}}{\partial \tau_j}\right] \\ &= \frac{1}{\sigma}\mathrm{E}\left[\frac{\partial \log s_{j,k}}{\partial \tau_j}\right] + \frac{1+\eta}{\eta(\varepsilon-1)}\mathrm{E}\left[\frac{\partial \log wH_{j,k}}{\partial \tau_j}\right] \\ &= \frac{1}{\sigma}\frac{\partial \log s_j}{\partial \tau_j} + \frac{1+\eta}{\eta(\varepsilon-1)}\frac{\partial \log w_j H_j}{\partial \tau_j},\end{aligned}$$

where $\mathrm{E}[\cdot]$ takes population averages, $s_{j,k}$ is the employment share of type $k$ in occupation $j$ and $wH_{j,k}$ is the nominal consumption of type $k$ on labor services from occupation $j$, as provided by workers of any type.

Generalizing our results to heterogeneity in $\sigma_k$, $\eta_k$, and $\varepsilon_k$ requires only slightly more work. As we use these parameters to scale our sufficient statistics, the social welfare effect is now

$$\begin{aligned}\frac{\partial \log \mathcal{W}_j}{\partial \tau_j} &= \mathrm{E}\left[\frac{1}{\sigma_k}\frac{\partial \log s_{j,k}}{\partial \tau_j} + \frac{1+\eta_k}{\eta_k(\varepsilon_k-1)}\frac{\partial \log wH_{j,k}}{\partial \tau_j}\right] \\ &= \mathrm{E}\left[\frac{1}{\sigma_k}\right]\mathrm{E}\left[\frac{\partial \log s_{j,k}}{\partial \tau_j}\right] + \mathrm{E}\left[\frac{1+\eta_k}{\eta_k(\varepsilon_k-1)}\right]\mathrm{E}\left[\frac{\partial \log wH_{j,k}}{\partial \tau_j}\right] \\ &\quad + \mathrm{Cov}\left(\frac{1}{\sigma_k}, \frac{\partial \log s_{j,k}}{\partial \tau_j}\right) + \mathrm{Cov}\left(\frac{1+\eta_k}{\eta_k(\varepsilon_k-1)}, \frac{\partial \log wH_{j,k}}{\partial \tau_j}\right).\end{aligned}$$

As this derivation shows, the welfare effects of licensing depend upon the covariance of the type-specific employment and wage bill effects of licensing with the type-specific parameters, rather than only population-average employment and wage bill effects as well as population-average parameters. Intuitively, if we observe that licensing reduces occupational employment more for types with stronger occupational preferences, or reduces the wage bill more for types with less elastic consumption preferences, then we would conclude the welfare costs of licensing are higher than in a case with the same population-average effects in employment and the wage bill but no heterogeneity in types. Due to the limited evidence on even population estimates of $\sigma$ and $\varepsilon$, we calibrate these parameters in the paper, and we are unaware of any credible evidence on the distribution $\sigma_k$, $\eta_k$, or $\varepsilon_k$ that would allow us to take a stance on the sign of either covariance term. We think there is considerable value to a sharper welfare analysis at the cost of ignoring the consequences of such heterogeneity.

*Incidence Analysis and Interpretation of Reduced-Form Results.* Although our social welfare results are relatively robust to heterogeneity, credible analysis of incidence requires more care. The threat is that, if workers differ by type on outcomes of interest, then we may confound selection effects of licensing with changes in the equilibrium. We make this point by introducing heterogeneity in the discount rate $\rho_k$ by type $k = 1, \ldots, K$. Heterogeneous discount rates introduce a problematic source of selection because high-discount rate types invest less in education, implying these workers have relatively low absolute advantage, and licensing is more costly to high-discount rate types, so licensing will select positively on absolute advantage. The change in the average cell wage induced by licensing therefore reflects a selection effect as well as an equilibrium effect.

To develop this point formally, recall that the share of type-$k$ workers in occupation $j$ is

$$s_{jk} = e^{-\rho_k \sigma(\tau_j + y^*_{jk})} [A_{jk}(y^*_{jk}) w_j]^{\frac{\sigma(1+\eta)}{\eta}} \Big/ \Phi_k,$$

where

$$\Phi_k = \sum_j e^{-\rho_k \sigma(\tau_j + y^*_{jk})} [A_{jk}(y^*_{jk}) w_j]^{\frac{\sigma(1+\eta)}{\eta}}.$$

We assume $K$ is large, so that any individual type $k$ is a negligible share of employment. Let $\rho_k = (1 + \lambda_k)\rho$ with $E\lambda_k = 0$ and $\rho > 0$. We can write the share of workers in occupation $j$ who are type $k$ as

$$\widetilde{s_{jk}} = \frac{s_{jk} N_k}{\sum_k s_{jk} N_k}.$$

In equilibrium, these type shares are log-proportional to discount rates multiplied by total investment in training and schooling:

$$\log \widetilde{s_{jk}} \propto \lambda_k (\tau_j + y^*_{jk}).$$

Applying the envelope theorem, the partial derivative of $k$'s share of employment in $j$ is

$$\frac{\partial \log \widetilde{s_{jk}}}{\partial \tau_j} = \rho \sigma \lambda_k,$$

implying that types with above-average discount rates select out of licensed occupations and types with below-average discount rates select into licensed occupations.

To show that this selection on type affects the average occupational wage $\overline{w_j}$, we step through the decomposition:

$$\overline{w_j} = \sum_{k=1}^{K} \widetilde{s_{jk}} w_{jk}$$
$$\log \overline{w_j} \approx \sum_{k=1}^{K} \widetilde{s_{jk}} \log w_{jk}$$
$$\frac{\partial \log \overline{w_j}}{\partial \tau_j} = \sum_{k=1}^{K} \widetilde{s_{jk}} \frac{\partial \log w_{jk}}{\partial \tau_j} + \sum_{k=1}^{K} \frac{\partial \widetilde{s_{jk}}}{\partial \tau_j} \log w_{jk}.$$

Applying the envelope theorem, and the assumption that worker types differ only in discount rates, we obtain that the change in type-specific log wages is constant over types:

$$\frac{\partial \log w_{jk}}{\partial \tau_j} \equiv \frac{\partial \log w_j}{\partial \tau_j} \, \forall k.$$

Next, we also use our selection result:

$$\frac{\partial \widetilde{s_{jk}}}{\partial \tau_j} = \widetilde{s_{jk}} \frac{\partial \log \widetilde{s_{jk}}}{\partial \tau_j} = \rho\sigma\lambda_k \widetilde{s_{jk}}.$$

Finally, we summarize the cross-sectional relationship between types' discount rates and types' effective labor supplies by

$$\log w_{jk} = \chi_j \lambda_k,$$

where $\chi_j$ is decreasing in the concavity $A_j''(y) < 0$ of the occupation-specific effective labor supply schedule, as when the schedule is highly concave, between-type differences in discount rates achieve smaller between-type differences in effective labor supplies and thus smaller between-type differences in observed wages. Combining these results, we have the selection-inclusive effect of licensing on the average wage:

$$\frac{\partial \log \overline{w_j}}{\partial \tau_j} = \frac{\partial \log w_j}{\partial \tau_j} + \rho\sigma\chi_j \mathrm{Var}_j(\lambda_k),$$

where $\mathrm{Var}_j(\lambda_k) = \sum_{k=1}^{K} \widetilde{s_{jk}} \lambda_k^2$. This result shows that in a model of discount-rate heterogeneity, estimates of the effect of licensing on average wages will overstate the true equilibrium effect due to selection. Furthermore, selection effects will be particularly important when occupations contain workers of a variety of types and these types differ substantially in their average wages.

This selection concern clearly also applies to the interpretation of our average wage effects. We explore it in Section 4 by seeing how our results change with detailed controls for observable predictors of wages as well as a bounding exercise from Oster (2019) and Finkelstein et al. (2018) to assess the plausibility that our results are consistent with $\partial \log w_j / \partial \tau_j = 0$ because of selection. We conclude that the intensity of selection on individual-level unobservables into licensed occupations would indeed need to be very large, relative to both the intensity of selection on observables or on household-level observables. To the extent our results nevertheless overstate the within-type wage gains from licensing, our results understate the extent of incidence on workers.

# C Further Results

## C.1 Supplementary Robustness Checks

Appendix Table A11 reports the results of several supplementary robustness checks beyond those in Table 3. Column 1 includes an alternative (coarser) set of state by occupation group fixed effects, this time using Census major occupational groups rather than Census detailed occupational groups.[29] Column 2 includes fixed effects for all two-way interactions of states with demographic characteristics and occupations with demographic characteristics: For some examples, this adds a fixed effect for women in Massachusetts, nonwhites in the teacher assistant occupation, and so on. These fixed effects will sweep out heterogeneous effects of demographic characteristics by occupation and by state, although not by cell. Our results are unchanged, supporting our interpretation of our results as causal effects of licensing and not as a consequence of sorting on worker characteristics. In Column 3, we include a more flexible specification of our two-way fixed effect strategy:

$$y_i = \alpha_o^0 + \alpha_o^1 \cdot \%\text{Licensed}_s + \alpha_s^0 + \alpha_s^1 \cdot \%\text{Licensed}_o + \beta \cdot \%\text{Licensed}_{i(o,s)} + X_i'\theta + \varepsilon_i,$$

where $\%\text{Licensed}_s$ and $\%\text{Licensed}_o$ are, respectively, state and occupation licensed shares. This specification allows for some occupations to be more or less responsive to variation in states' overall propensity to license, and similarly for some states to be more or less responsive to variation in occupations' overall propensity to be licensed. Our results are unchanged, suggesting that the variation in licensing after removing two-way fixed effects is quite idiosyncratic in nature.

In Column 4, we control for cell-level employment growth from 2000 to 2010. We estimate cell employment by centered five-year samples—that is, pooling 1998–2002 for 2000 and 2008–2012 for 2010. The licensed share continues to be estimated in our main sample. State-occupation cells with high or low licensed shares in our main sample did not have differential employment growth from 2000 to 2010. Consequently, although the number of cells shrinks by about 30 percent, our results are unchanged.

## C.2 Educational Attainment

Occupational licensing regulations commonly specify a minimum required educational credential (Gittleman et al., 2018). Here we seek to recover the relevant credential for each occupation when it is licensed, and splitting occupations by these credentials, estimate distinct effects of licensing on the distribution of educational attainment. We view these results as providing our most credible

[29] For more information, see Appendix B of the CPS March Supplement documentation.

evidence that licensing policy has a causal effect on educational attainment: That is, we claim that, absent licensing requirements, workers would not obtain such educational credentials.

Motivated by the results in Figure 2, we posit that licensing schemes divide into two types: one that requires associate's degrees or similar, and another requiring more than a bachelor's degree. We argue the former is consistent with licensed occupations with a relatively low average level of education and the latter with licensed occupations with a relatively high average level of education. We implement this division by $k$-means clustering: we compute the share of workers with each detailed level of education by occupation using sample weights and then use the $k$-means algorithm to divide occupations for $k = 2$. We find that these clusters split occupations into intuitively low- and high-education groups: See Appendix Figure A5.[30] In addition, our results are robust to alternative approaches, such as splitting occupations at the median by average years of education.

Appendix Figure A6 displays the results. Consistent with our hypothesis, occupational licensing has sharply heterogeneous effects on the education distribution in low- and high-education occupations. In low-education occupations, we see a large (7.7 p.p.) decline in the share of workers whose highest level of education is a high school diploma and a large (9.9 p.p.) increase in the share of workers with vocational associate's degrees. By contrast, in high-education occupations, the effects are concentrated in a large (3.6 p.p.) decline in the share of workers with bachelor's degrees and a concomitant (4.7 p.p.) increase in the share of workers with master's degrees. We can easily reject equality of coefficients for the effects of licensing in low- versus high-education occupations, for most individual education levels and jointly across all education levels. These results establish a notably direct link between the specific educational requirements likely required when an occupation is licensed and the actual changes in the distribution of educational attainment within that occupation.

### C.3 Robustness to Political Confounds

Do local political determinants of regulation including, but extending beyond, occupational licensing confound our identification strategy? For example, it may be that occupations whose workers tend to vote for Republicans (Democrats) also tend to be more heavily licensed in states that generally vote Republican (Democrat). To evaluate this and related hypotheses, we use data on the political ideology of workers by occupation from the 1972–2016 Cumulative Datafile of the U.S. General Social Survey (GSS) as well as the ideology of politicians in state legislatures from Shor and McCarty (2011).

The GSS asks participants for their occupation as well as their political party affiliation. Occupations are classified as in the CPS. The GSS asks about party affiliation with the question: "Generally speaking, do you usually think of yourself as a Republican, Democrat, Independent, or what?" We coded individuals who responded they were a "strong" or "not strong" Republican or

[30] 60.1 percent of workers are in occupations assigned to the low-education cluster. The clusters align naturally with low-education occupations as those in which the modal level of education attainment is a high school degree and high-education occupations as those in which the modal level is a bachelor's degree.

Democrat as their respective parties. Remaining respondents identified as either independents or members of another party and were coded as a third category. The pooled sample includes 62,644 responses and 534 unique occupations. To reduce sampling variance in the Republican and Democratic shares of workers in each occupation, we estimated a mixed-effects logistic regression model, with occupation random effects nested within random effects for 23 Census detailed occupation groups. The following analysis uses the model-based predicted Republican share of the two-party vote by occupation. For state-level variation, we use ideal-point estimates from Shor and McCarty (2011) of the average ideology of each U.S. state legislature in 2014, taking the simple average of the upper and lower legislative bodies in each state, as well as the distance between the median Republican and median Democratic legislator. For ease of interpretation, we then standardized these state-politics variables to be mean zero and unit standard deviation.

We estimate variations on the following specification, which interacts a GSS occupation-level variable with a Shor and McCarty (2011) state-level variable:

$$\%\text{License}_{os} = \alpha_o + \alpha_s + \beta \cdot (\text{OccupationPolitics}_o \times \text{StatePolitics}_s) + e_{os}. \tag{13}$$

We keep the state–occupation licensed share as the dependent variable, cluster at the state–occupation cell level, and include state and occupation fixed effects. To the extent a coefficient is significant, this may raise concerns that the state–occupation licensed share is correlated with other regulations and policies that vary among states and occupations.

Appendix Table A12, however, finds no evidence of associations of occupation- and state-level political variable interactions with the licensed share. We try plausible specifications that might reveal local political determinants of licensing. In Column 1, we interact the occupation Republican share with the average left-right slant of the state legislature. Column 2 uses instead the occupation Democratic share in the interaction. These two results suggest that Republican- and Democratic-leaning legislatures do not respectively differentially treat Republican- and Democratic-leaning occupations with licensing. Column 3 uses the share of workers who are either Republicans or Democrats and interacts this with the distance between party medians. The insignificant result suggests that polarized state legislatures do not differentially treat occupations that are relatively more or less politically independent with licensing.

Though this exercise does not rule out all possible local political explanations, it does suggest that patterns of licensing across U.S. states and occupations are relatively idiosyncratic and not easily explained by local politics.

# D Licensing Policy Data

This appendix provides additional details on the construction of state–occupation licensing policy data we introduce in Section 3. Appendix Table A4 lists the 55 occupations for which we were able to code policy variation. For some occupations, data collection involved more than simply recording policy information from the National Conference of State Legislatures (NCSL) and the

Institute for Justice (IJ). Here, organized by occupation, we discuss choices that this undertaking required, as well as the sources beyond the NCSL and IJ that we consulted.

*0540 (claims adjusters, appraisers, examiners, and investigators).* We used information available on the website of Western International Staffing Inc., an insurance staffing agency that appears to specialize in temporary-help claims examiners and adjusters that insurers hire after natural disasters.[31]

*1640 (conservation scientists and foresters).* We cross-checked information on the Society of American Foresters website,[32] CareerOneStop.com, and the websites of state forester certification or licensing boards.

*2430 (librarians).* We cross-checked data on CareerOneStop.com with tables published by the American Library Association – Allied Professional Association (ALA-APA),[33] which describes itself as a nonprofit organization to advance "mutual professional interests of librarians and other library workers" and which is specialized in librarian licensing and certification efforts. As school library media specialists (i.e., school librarians) are licensed to be at least teachers in all 50 U.S. states, we use variation in public librarian licensing regulations only.

*3030 (dietitians and nutritionists).* We used a policy information table published by the Academy of Nutrition and Dietetics, which describes itself as the "world's largest organization of food and nutrition professionals."[34] We code a state–occupation cell as "licensed" if state-credentialed workers enjoy practice exclusivity, not only title protection.

*3649 (phlebotomists).* We recorded information on "mandatory certification" (i.e., licensing) from PhlebotomyExaminer.com, which we found had uniquely detailed information on the state-specific training, certification, and licensing regimes for phlebotomists.[35]

*4520 (miscellaneous personal appearance workers).* We used information from the U.S. Bureau of Labor Statistics Occupational Employment Statistics program on occupations in the 5-digit SOC code 39-5090 (also "miscellaneous personal appearance workers"). These were "makeup artists, theatrical and performance" "manicurists and pedicurists," "skin care specialists," and "shampooers." We used data from the Institute for Justice on the latter three occupations (the first is of negligible size), and took the simple average of whether each occupation was licensed in a state.

*4465 (morticians, undertakers, and funeral directors).* We consulted the paper of Pizzola and Tabarrok (2017).

*Various construction occupations.* To accommodate variation in licensing for commercial versus residential construction work in the same occupation, we code a state–occupation cell's value as 0 if the state licenses neither type of work in the occupation, 0.5 if the state licenses either commercial or residential work but not both, and 1 if the state licenses both commercial and residential work in the occupation. This applies for the following occupations: 6220 (brickmasons, blockmasons, and

[31] https://perma.cc/4F2X-TQ89.
[32] https://perma.cc/7CVJ-3ELS.
[33] https://perma.cc/Z8HT-59SG.
[34] https://perma.cc/Q2EQ-8646.
[35] https://perma.cc/9X37-PPKA.

stonemasons), 6230 (carpenters), 6250 (cement masons, concrete finishers, and terrazzo workers), 6330 (drywall installers, ceiling tile installers, and tapers), 6360 (glaziers), 6400 (insulation workers), and 6520 (sheet metal workers).

# E Econometric Extensions

This appendix provides further details on some econometric techniques used in this paper which are potentially somewhat novel or unfamiliar to some readers. In Sections E.1 and E.2, we introduce the beta–binomial model we use to reduce sampling variance in the licensed share. In Section E.3, we develop two controls we use in Section 6 of the main text as robustness checks. In Section E.4, we explain how we correct for the upward bias in estimating total variation distance.

## E.1 Estimating Cell-Level Standard Errors

In this subsection, we present both Bayesian and frequentist approaches to obtaining a formula for the mean and the standard error of the leave-out state–occupation licensed share. Throughout this subsection, we define for notational convenience

$$L_{os} = \sum_{i \in W_{os}} L_i,$$

where $L_i = 1$ if worker $i$ is licensed and equals zero otherwise, $s$ indexes states, $o$ indexes occupations, and worker $i$ is in $W_{os}$ if he or she is in state $s$ and occupation $o$. $L_o$ is defined analogously.

*Frequentist Approach.* The leave-out licensed share of worker is

$$\%L_i = \frac{L_{os} - L_i}{N_{os} - 1},$$

and using the formula for the variance of a Bernoulli random variable, we obtain the variance

$$\sigma^2_{u_i} = \frac{\%L_i(1 - \%L_i)}{N_{os} - 1}.$$

Two considerations weigh against a frequentist approach in our measurement error correction. First, we do not exploit information from licensed shares of workers in other states but the same occupation to reduce error. Second, the estimated cell-level measurement error is zero when all or no workers are licensed in the cell.

*Empirical Bayes Approach.* Following common practice in Bayesian statistics (Bolstad and Curran, 2016, Ch. 8), we propose to model the distribution of licensed and unlicensed workers across state–occupation cells as

$$p_o \sim \text{Beta}(\alpha_o, \beta_o)$$
$$L_{os} \sim \text{Binom}(N_{os}, p_o).$$

The first step is to calibrate $\alpha_o$ and $\beta_0$, the occupation-specific parameters of the prior distribution of the licensed share across state–occupation cells. We use the beta distribution because, as the conjugate distribution to the binomial, conditioning on the binomial count data of licensed and unlicensed workers will yield a posterior that is also a beta distribution, a result we provide below.

We estimate the parameters of the beta distribution by method of moments:

$$\widehat{\alpha_o} = \frac{\mu_{1o}^2 - \mu_{1o}^3 - \mu_{1o}\mu_{2o}}{\mu_{2o}}$$
$$\widehat{\beta_o} = -\frac{\mu_{1o}^2 - \mu_{1o}^3 - \mu_{1o}\mu_{2o}}{\mu_{1o}^2 - \mu_{1o}^3 - 2\mu_{1o}\mu_{2o}},$$

where $\mu_{1o} = L_o/N_o$ and $\mu_{2o} = \frac{1}{N_{os}^2}\left(L_{os}^2 - L_o^2\right)$. This procedure fails for 4 of 483 occupations. For these occupations, we assume the uninformative prior $\alpha_o = \beta_o = 1/2$ for the state–occupation licensed share.[36]

We now use Bayes' theorem to update the beta prior with the count data. Our assumption that counts of licensed and unlicensed workers in a state–occupation cell are drawn from a cell-specific binomial distribution implies

$$p(L_{os}|N_{os}, \theta_{os}) = \binom{N_{os}}{L_{os}} \theta_{os}^{L_{os}} \theta_{os}^{N_{os}-L_{os}}.$$

With a constant $k$, our prior is

$$p(\theta_{os}) = k\theta_{os}^{\widehat{\alpha_o}-1}(1-\theta_{os})^{\widehat{\beta_o}-1}.$$

By Bayes' theorem,

$$p(\theta_{os}|(L_{os}, N_{os})) = k'\theta_{os}^{\widehat{\alpha_o}-1+L_{os}}(1-\theta_{os})^{\widehat{\beta_o}-1+N_{os}-L_{os}}.$$

The posterior distribution for the state–occupation licensed share is therefore

$$\theta_{os}|(L_{os}, N_{os}) = \text{Beta}(\alpha_o - 1 + L_{os}, \widehat{\beta_o} - 1 + N_{os} - L_{os}).$$

The posterior mean is

$$\frac{\alpha_o + L_{os}}{\alpha_o + \beta_o + N_{os} - L_{os}},$$

[36] We also tried an MLE approach by estimating a beta-binomial regression of $L_{os}$ on a constant, given observations $N_{os}$, using the canonical logit link function. For 164 of 483 occupations, this procedure yields negative estimates of $\alpha_o$ or $\beta_o$, particularly when there are relatively few licensed or total workers in an occupation. We opted to use the method-of-moments procedure in light of the poor performance of the MLE procedure in small samples.

and the posterior variance is

$$\frac{(\alpha_o + L_{os})(\beta_o + N_{os} - L_{os})}{(\alpha_o + \beta_o + N_{os})^2(\alpha_o + \beta_o + 1 + N_{os})}.$$

The leave-out results in the text follow immediately. As the mean of the prior distribution is $\widehat{\alpha_o}/(\widehat{\alpha_o} + \widehat{\beta}_o)$, and the licensed share is $L_{os}/N_{os}$, the empirical Bayes estimate of the licensed share is a convex combination of the prior mean and the licensed share, with the relative weight on the licensed share increasing in the number of observations in the state–occupation cell. Notably, as the sample $N_{os}$ becomes large, the weights in the posterior shift away from the prior and toward the data.

### E.2 Applying the Correction

We document the consequences of the empirical Bayes adjustment of cell licensed shares. As the number of observations in a cell increases, the implied weight on the prior declines to zero. In Figure A7, we see that the adjustment is generally small, and only of consequence for cells with very few workers. For cells with more than 10 workers, the average absolute difference between the raw leave-out-mean and the empirical Bayes estimate is about 0.03. We have truncated Figure A7 at 500 workers to make the small cells visible.

### E.3 Additional Controls Used in Robustness Checks

Here we explain the occupation-mix and demographic-mix controls we use in our robustness checks in Section 6 of the main text, specifically in Table 3.

*Occupation-Mix Control.* To explain our procedure, let $M$ be a matrix of employment shares whose columns are occupations and rows are states. Find the first $k$ principal components of the submatrix $M_{-o^*,-s^*}$, which deletes column $o^*$ and row $s^*$. Then, by this rotation, predict the principal component scores for all occupations but $o^*$ in the holdout state $s$, and augment the matrix of principal component scores with these predicted scores. Using this augmented matrix, estimate the regression

$$s_{o^*s} = \sum_k \beta^k p_{ks} + e_s, \tag{14}$$

where $s_{o^*s}$ is the share of workers from state $s$ in occupation $o^*$ and $p_{ks}$ is the value of the $k$th principal component in $s$. For the holdout observation $(o^*, s^*)$, predict $\widehat{s_{o^*s^*}}$ by Equation 14. Repeat for all $(o, s)$ and use the log predicted value as a control. The resultant data capture the predictable variation in occupational employment shares across states from employment in other occupations in that state and correlations across occupations' employments in other states. For example, if some states with relatively many (few) farmers also tend to have relatively many (few) loggers, we would expect other states to respect this rural-urban pattern and would want to rule out the possibility that such patterns are used to identify causal effects of licensing. Our method is a "leave-out" strategy for predicting relative employment from such correlations.

We set $k = 5$, and Figure A8 depicts the results. Each panel of the figure assigns states to equal-frequency bins according to each of their principal component scores. We see strong regional and thematic patterns. PC1 is strongly correlated with population density, PC2 is East versus West, PC3 is North versus South, PC4 is high in the Pacific Coast and Deep South but low elsewhere, and PC5 is high in the Mid-Atlantic and Southwest but low elsewhere. Our control explains 18 percent of the "within" variation in log employment after state and occupation fixed effects. As reported in Section 6, we find broadly the same effects of licensing as in our baseline specification. This confirms that estimated employment effects are not confounded by correlations with broad features of the state occupational mix.

*Demographic-Mix Control.* We predict state–occupation employment levels using a Bartik-like technique that combines the national occupational employment shares of a demographic group $d \in \{1, \dots, K\}$ and the state shares of population of these demographic groups. For standard reasons, this predicted employment is formed via a "leave-self-out" method.

Let $L_{osd}$ be the employment count in occupation $o$ and state $s$ for workers of demographic type $d$. Let $L_{sd} = \sum_o L_{osd}$, $L_{od} = \sum_s L_{osd}$, $L_d = \sum_o L_{od}$ and $L_s = \sum_d L_{sd}$. Then our control is

$$\widehat{L_{os}} = \sum_d L_{sd} \left( \frac{L_{od} - L_{osd}}{L_d - L_{sd}} \right).$$

This control explains about 11 percent of the residual variation in employment after removing state and occupation fixed effects. Together with the occupation-mix control, about 25 percent of the residual variation in employment is explained.

## E.4 Bias Correction in Estimating Total Variation Distance

With $k = 1, \dots, K$ denoting a level of educational attainment, we define a treatment effect $\beta_k$ as the percentage point change in the share of workers with education $k$ that is the causal effect of licensing. Total variation distance is defined as

$$\text{TVD} = \sum_k |\beta_k|.$$

Computing $\widehat{\text{TVD}}$ from estimates $\widehat{\beta_k}$ will be biased upward, with the bias increasing in the standard error $\sigma_k$ and decreasing in the absolute value $|\beta_k|$. This is immediate from the case of $\beta_k = 0$ for all $k$ but $\widehat{\beta_k}$ estimated with any error: Estimated total variation distance is positive when true total variation distance is zero. Using the truncated normal distribution and unbiased estimators $\widehat{\beta_k}$ and

$\widehat{\sigma_k}$, the analytical expression for this bias is

$$\mathbb{E}[\widehat{\text{TVD}} - \text{TVD}] = \sum_k \frac{\phi(|\widehat{\beta_k}|/\widehat{\sigma_k})}{\Phi(|\widehat{\beta_k}|/\widehat{\sigma_k})}\widehat{\sigma_k}.$$

In our application, we estimate $\widehat{\text{TVD}} = 0.1194$ and $\mathbb{E}[\widehat{\text{TVD}} - \text{TVD}] = 0.0122$, therefore $\mathbb{E}[\text{TVD}] = 0.1072$. Our bias-corrected estimate is therefore that 10.72 percent of workers obtained a different level of educational attainment because of licensing than they would have attained absent licensing requirements. Our uncorrected estimate is biased upward by a factor of 1.11, implying that our estimate of total variation distance is only slightly inflated by the effect of sampling variance.

## References for Appendices

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