Appendices

School-to-Work Linkages in Texas

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Appendix A. Variables Used in the Analyses

Variable	Description
Dependent Variables	
Earnings	Continuous: In regression analyses, earnings were transformed using the natural log.
Unemployment	Binary: In labor force but not employed.
Main Independent Variables	
Linkage Strength	Continuous: Standardized for the analyses. Measured whether an individual's college major was more (positive values) or less (negative values) connected to specific occupations in the labor market. Based on the Mutual Information Index (M), which is briefly summarized in Appendix B. See DiPrete, Bol, Eller, and van de Werfhorst (2017) and Bol, Ciocca Eller, van de Werfhorst, and DiPrete (2019) for additional details.
In Matched Occupation	Binary: Indicated whether an individual was working in the top-two most common occupations for their college major. Included in earnings analyses only.
Other Control Variables	
Age	Continuous: Ranged from 25-64. In regression analyses, age was modeled as a quadratic function. In graphs, results were presented at ages 30, 45, and 60.
Female	Binary: Male (ref.) and Female.
Race/Ethnicity	Categorical: White (ref.), Black, Hispanic, and Asian/Pacific Islander.
Foreign-Born	Binary: Born outside the U.S. and its outlying areas/territories.
Non-Native English-Speaker	Binary: Spoke a language other than English at home.
Married	Binary: Unmarried (ref.) and Married.
Number of Children	Continuous: Counted children living in the household. Top-coded at 9.
Disabled	Binary: Whether an individual had cognitive, ambulatory, independent living, self-care, vision, or hearing difficulties.
Employed Part-Time	Binary: In labor force but working 34 hours or less per week. This variable was included in the earnings analyses only. It was not included in the unemployment analyses because it was collinear with the outcome. (Workers who were employed part-time or full-time were still included in the unemployment analyses.)
Self-Employed	Binary: Not Self-Employed (ref.) and Self-Employed. This variable was included in the earnings analyses only. It was not included in the unemployment analyses because it was collinear with the outcome. (Workers who were self-employed or not self-employed were still included in the unemployment analyses.)
Currently Attending College	Binary: Not Currently Attending College (ref.) and Currently Attending College.
Metropolitan Area	Categorical: Metro (ref.), Metro/Non-Metro Mix, and Non-Metro. Based on county: counties in a central city or suburb were considered metro, while counties in a rural area were considered non-metro. Counties that were partly in central city/suburban areas and partly in rural areas were considered metro/non-metro mix.

Appendix B. Methodology

Data

The study used data from the 1% sample of the American Community Survey (ACS), 2013-2017. The sample was limited to individuals aged 25-64 who were living in Texas, whose highest credential was a bachelor's degree, and who identified as white, Black, Hispanic, or Asian or Pacific Islander (N = 135,261).[1,2]

Sample

In the analyses of earnings, the sample was limited to individuals who reported positive earnings in the previous year (N = 115,243).[3] Additional cases were dropped because they could not be matched to the linkage and match data (see the Generating Linkage Strength and In Matched Occupation section for an explanation). The final sample for the earnings analyses consisted of 114,792 individuals.

In the analyses of unemployment, the sample was limited to individuals who were in the labor force (N = 112,730).[4] Additional cases were dropped because they could not be matched to the linkage data (see the Generating Linkage Strength and In Matched Occupation section for an explanation). The final sample for the unemployment analyses consisted of 112,719 individuals.

Research Questions 1 and 2 used the earnings sample to predict linkage strength and in matched occupation. Research Question 3 predicted earnings, and the main independent variables of interest were linkage strength and whether an individual was working in a matched occupation. Research Question 4 predicted unemployment, and the main independent variable of interest was linkage strength. The unemployment analyses did not control for match, part-time employment, and self-employment.[5] A list of control variables is available in Appendix A.

Generating Linkage Strength and In Matched Occupation

The key variables in the study were linkage strength and whether an individual was working in a matched occupation. The general approach came from a study on school-to-work linkages (DiPrete, Bol, Eller, & van de Werfhorst, 2017). In that study, the authors developed a method to calculate "the strength of linkages between educational credentials, including fields of study, and occupational positions" (p. 1869).

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[1] The degree restriction was necessary because the ACS did not ask people with a sub-baccalaureate credential about their college major. Moreover, the college major question was worded in such a way that it asked respondents to report the major from their bachelor's degree. For example, an individual who held a bachelor's degree in sociology and a master's degree biology would report sociology as their college major. Due to concerns conflating level of education with college major (see DiPrete et al., 2017, for a discussion), the research team decided to limit the analyses to individuals with a bachelor's degree only.

[2] The study focused on white, Black, Hispanic, and Asian or Pacific Islander individuals and excluded individuals from other races and ethnicities because of sample size issues. A key focus was on racial and ethnic differences, and the standard errors from the other and mixed category used in earlier iterations were too large to make such comparisons meaningful.

[3] Individuals who reported negative or zero earnings were excluded.

[4] Individuals who were neither working nor looking for work were excluded.

[5] Match was based on occupation, and unemployed individuals might not have listed an occupation to calculate match. Part-time employment and self-employment also required an individual to be working, and unemployed individuals might not have listed their prior employment statuses.

In this study, linkage strength was a measure of how related a college major was to specific occupations in the labor market. Linkage was a structural measure that characterized majors as a whole rather than the majors certain individuals chose. If people from a given major, on average, tended to cluster in a small number of occupations, then the major would have high linkage strength (e.g., if the majority of nursing majors end up working as nurses). In contrast, a major would have low linkage strength if people from that major ended up working in a wide array of occupations (e.g., if most history majors did *not* become historians, but were employed in jobs ranging from business to law).

This study adopted the approach developed by DiPrete et al. (Methodologically-inclined readers should refer to DiPrete et al. for a detailed description of the linkage strength measure; a brief summary is provided below.) Their approach was based on multigroup segregation measures, specifically the Mutual Information Index (M). For this study, linkage strength was calculated as the following:

$$M(ed)_g = \sum_j p_{j|g} log\left(\frac{p_{j|g}}{p_j}\right) \tag{1}$$

where $p_{j|g}$ represented the conditional probability an individual who worked in occupation j held a bachelor's degree in college major g, while p_j represented the unconditional probability an individual worked in occupation j. This measure was calculated using adults between 25 and 64 years old whose highest credential was a bachelor's degree. Respondents also had to satisfy the following conditions:

- Were employed and reported an occupation,
- Were not in the armed forces,
- Were employed full-time,
- Were not self-employed, and
- Were not attending school.

These restrictions were aligned with DiPrete et al. Moreover, a small number of observations (N = 68) were excluded because, after these restrictions, there were too few cases to calculate a reliable linkage score.[6]

In the end, linkage strength scores were calculated for the 36 majors included in the analyses; please see Figure B1.1 for a list of the 36 majors. The raw scores ranged from 0.12-2.39. These values carried no meaning on their own except higher values corresponded to a stronger linkage between that major and specific jobs in the labor market, while lower values corresponded to weaker linkages between majors and specific jobs. To aid interpretation, linkage scores were standardized to have a mean of 0 and a standard deviation of 1. Please note in the body of the report, the term *points* was used to convey the same concept as *standard deviation*.

Figure B1.1 below presents a dot plot of each college major and its standardized linkage strength score. The plot shows variation in linkage strength across the 36 majors. Majors like liberal arts (-1.02 SD), social science (-1.00 SD), and history (-0.97 SD) appeared to have looser connections to specific jobs in the labor

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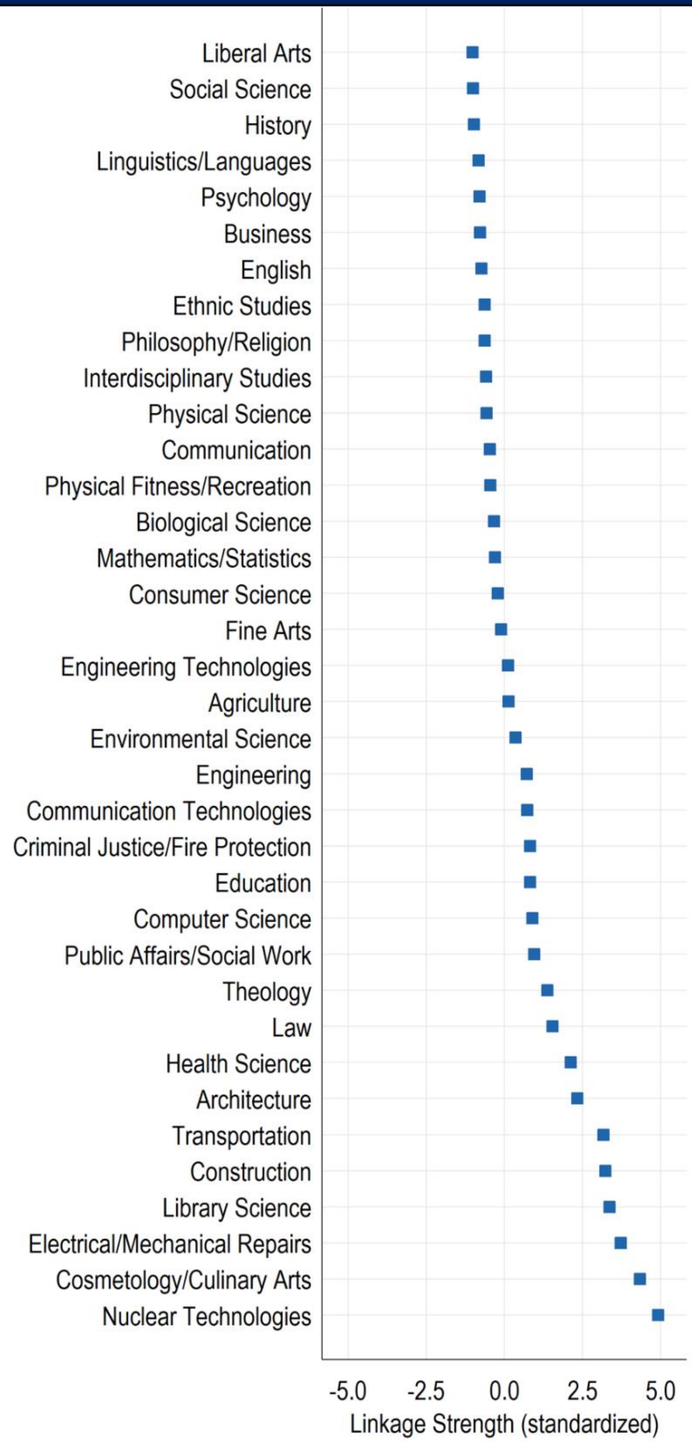
[6] College majors with fewer than 100 cases were excluded from linkage score calculations. The 68 cases dropped corresponded to the military technologies major.

market than majors like electrical/mechanical repairs (3.72 SD), cosmetology/culinary arts (4.33 SD), and nuclear technologies (4.93 SD).

Figure B1.1. Standardized Linkage Strength Scores for Each College Major



In addition to standardized linkage strength, the other key variable in the study was whether an individual was working in a matched occupation. While the connections between majors and jobs might be useful to understand and predict labor market outcomes, the rewards (or penalties) of linkage strength might be reserved to those working in occupations tied to their major. For example, although library science had a relatively high linkage score (3.37 SD), the benefits flowing from that major having tight connections to specific jobs in the labor market might apply only to individuals who ended up working in libraries. Libraries might regulate access to library jobs, prefer job applicants with library science backgrounds, and find ways to provide their employees with long-term job stability.

Following the example of Bol, Ciocca Eller, van de Werfhorst, and DiPrete (2019), this study generated a binary variable that indicated whether an individual was employed in a matched occupation. First, within each college major, occupations were sorted by their actual frequency (called $ActualFreq$), the number of individuals in the dataset working in a given occupation. For example, among library science majors, the most common occupation was librarian (N = 4,331), while the least common occupation was clergy (N = 10). Second, within each major, a counterfactual frequency (called $CounterfactualFreq$) that assumed majors and occupations were unrelated was calculated:

$$CounterfactualFreq = TotOcc\left(\frac{TotMaj}{Tot}\right) \qquad (2)$$

where $TotOcc$ represented the number of people who worked in a given occupation (an individual's current job or profession, e.g., financial analyst, civil engineer, psychologist)[7], $TotMaj$ represented the number of people who majored in a given field, and Tot represented the total number of people in the dataset. The formula determined the number of individuals with a given occupation and major if occupations and majors were statistically independent (i.e., if the occupation distribution was proportional to the major distribution). Next, the following ratio was calculated:

$$Ratio = \frac{ActualFreq}{CounterfactualFreq} \qquad (3)$$

The ratio of the actual frequency to the counterfactual frequency showed, for each college major, how common (or uncommon) an occupation was in reality compared to a hypothetical world in which people were randomly assigned to occupations. Higher values meant the occupation was more common than the counterfactual of random assignment, while lower values meant the occupation was less common than the counterfactual of random assignment.

In the final step, within each college major, occupations were ranked according to their ratio values. In line with Bol et al. (2019), the two occupations with the highest ratio values were considered the matched occupations for a given major. For library science, the matched occupations were librarian and library assistants. Please note in the body of the report, the term *common* was used to represent the two occupations with the highest ratio values, recognizing the term did not completely capture the complexity of how match was calculated.

[7] Four-digit ACS occupation codes were used. Please visit the following webpage for details: https://usa.ipums.org/usa/volii/occ_acs.shtml.

It is important to remember linkage strength is a characteristic of a society: it measures the flow from college majors to specific occupations in the labor market. In contrast, match is a characteristic of individuals: it measures whether an individual has entered an occupation common among people with their given college major. Despite these distinctions, linkage and match both involve an element of personal decision-making: individuals *decide* to major in a field with strong connections to occupations and individuals *decide* to work in an occupation common among people with their college major.

Analytic Strategy

Research Question #1: Which groups of people were more likely to enter strongly linked majors?

To address this research question, ordinary least squares regression models that predicted linkage strength and controlled for background characteristics (see Appendix A for a list) were estimated. All models incorporated survey weights and included year fixed-effects. The sample was limited to individuals who could be matched to the linkage and match data (see the Generating Linkage Strength and In Matched Occupation section for an explanation).[8]

Research Question #2: Which groups of people were more likely to work in a matched occupation?

To address this research question, binary logistic regression models that predicted working in a matched occupation and controlled for background characteristics (see Appendix A for a list) were estimated. All models incorporated survey weights and included year fixed-effects. The sample was limited to individuals who could be matched to the linkage and match data (see the Generating Linkage Strength and In Matched Occupation section for an explanation).

Research Question #3: What was the role of linkage strength and match in wages? How did linkage strength and match jointly affect wages? How did this vary by age, gender, race/ethnicity, nativity, and language?

Ordinary least squares (OLS) regression models were used to examine how linkage strength and match predicted wages. The outcome measured the natural log of wages; this transformation was used to normalize wages. The first model controlled for linkage strength and background characteristics (see Appendix A for a list). The second model added in a control for match and a linkage strength-by-match interaction term. The interaction term was added because, as shown in Bol et al. (2019), the role of linkage strength might depend on whether an individual was working in an occupation aligned with their educational background. All models incorporated survey weights and included year fixed-effects. The sample was limited to individuals who reported earnings in the previous year and who could be matched to the linkage and match data (see the Generating Linkage Strength and In Matched Occupation section for an explanation). To test whether the role of linkage strength and match varied by age, gender, race/ethnicity, nativity, and language, interaction terms between linkage strength, match, linkage strength-by-match, and these demographic variables were added to the models (e.g., a three-way interaction term like linkage-by-match-by-nativity). Post-estimation analyses included testing differences

[8] In a robustness check, the sample was limited to individuals who could be matched to the linkage data only. Results were substantively similar and are available from the authors upon request.

in the role of linkage by match *within* groups (e.g., among U.S.-born workers, whether linkage was more positively associated with wages for workers in matched occupations or workers not in matched occupations) and testing differences in the role of linkage by match *across* groups (e.g., whether linkage was more positively associated with wages for U.S.-born workers in matched occupations or foreign-born workers in matched occupations). For details on model specification, please contact the authors.

Research Question #4: What was the role of linkage strength in unemployment? How did this vary by age, gender, race/ethnicity, nativity, and language?

Binary logistic regression models were used to examine how linkage strength predicted unemployment. The model estimated controlled for linkage strength and background characteristics (see Appendix A for a list). Please note the model did not control for match; this decision was in line with Bol et al. (2019). The match variable was based on an individual's occupation and most unemployed individuals did not list an occupation. All models incorporated survey weights and included year fixed-effects. The sample was limited to individuals who were in the labor force and who could be matched to the linkage data (see the Generating Linkage Strength and In Matched Occupation section for an explanation). To test whether the role of linkage strength varied by age, gender, race/ethnicity, nativity, and language, interaction terms between linkage strength and these demographic variables were added to the models. Post-estimation analyses included testing differences in the role of linkage *across* groups (e.g., whether linkage was more negatively associated with unemployment for U.S.-born workers or foreign-born workers). For details on model specification, please contact the authors.

Appendix C. Regression Models for Research Question 1

Table C1. Ordinary Least Squares Regression Models Predicting Linkage Strength in Texas

Variable	Coef.	Sig.
Age	-0.01	***
Age^2	0.00	***
Female	0.12	***
Race/Ethnicity (ref. = White)		
Black	0.04	*
Hispanic	0.00	
Asian	0.17	***
Foreign-Born	0.11	***
Non-Native English-Speaker	0.08	***
Married	0.06	***
Number of Children	0.03	***
Disabled	0.06	**
Employed Part-Time	-0.02	+
Self-Employed	-0.18	***
Currently Attending College	0.07	***
Metropolitan Area (ref. = Metro)		
Metro/Non-Metro Mix	0.15	***
Non-Metro	0.13	***
Intercept	0.04	
R^2	0.02	
N	114,792	

Source: American Community Survey 1% Sample, 2013-2017.
Note: Sample was limited to bachelor's degree holders who reported earnings and for whom linkage strength could be calculated. The model included control variables (see Appendices A and B for details) as well as year fixed-effects. Estimates incorporated survey weights.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Appendix D. Regression Models for Research Question 2

Table D1. Odds Ratios from Binary Logistic Regression Models Predicting Match in Texas

Variable	Coef.	Sig.
Age	0.95	***
Age^2	1.00	***
Female	2.69	***
Race/Ethnicity (ref. = White)		
Black	0.80	***
Hispanic	1.00	
Asian	1.34	***
Foreign-Born	0.84	***
Non-Native English-Speaker	1.07	+
Married	1.20	***
Number of Children	1.07	***
Disabled	0.87	**
Employed Part-Time	0.57	***
Self-Employed	0.50	***
Currently Attending College	1.11	*
Metropolitan Area (ref. = Metro)		
Metro/Non-Metro Mix	1.36	***
Non-Metro	1.47	***
Intercept	0.27	***
Goodness-of-Fit	14.32	
N	114,792	

Source: American Community Survey 1% Sample, 2013-2017.
Note: Sample was limited to bachelor's degree holders in the labor force for whom linkage strength could be calculated. The model included control variables (see Appendices A and B for details) as well as year fixed-effects. Estimates incorporated survey weights.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Appendix E. Regression Models for Research Question 3

Table E1. Ordinary Least Squares Regression Models Predicting the Relationship between Log Wages, Linkage Strength, and Match in Texas

Variable	Model 1		Model 2	
	Coef.	Sig.	Coef.	Sig.
Linkage Strength (standardized)	0.04	***	0.02	***
In Matching Occupation			0.08	***
Linkage x Match			0.03	***
R^2	0.34		0.34	
N	114,792		114,792	

Source: American Community Survey 1% Sample, 2013-2017.
Note: Sample was limited to bachelor's degree holders who reported earnings and for whom linkage strength could be calculated. All models include control variables (see Appendices A and B for details) as well as year fixed-effects. Estimates incorporated survey weights.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Table E2. Ordinary Least Squares Regression Models Predicting the Relationship between Log Wages, Linkage Strength, and Match by Age in Texas

Variable	Coef.	Sig.
Linkage Strength (standardized)	0.10	
In Matching Occupation	0.31	*
Linkage x Match	0.07	
Age	0.08	***
Age x Linkage	0.00	
Age x Match	-0.01	+
Age x Linkage x Match	0.00	
Age^2	0.00	***
Age^2 x Linkage	0.00	
Age^2 x Match	0.00	+
Age^2 x Linkage x Match	0.00	
R^2	0.34	
N	114,792	

Source: American Community Survey 1% Sample, 2013-2017.
Note: Sample was limited to bachelor's degree holders who reported earnings and for whom linkage strength could be calculated. The model included control variables (see Appendices A and B for details) as well as year fixed-effects. Estimates incorporated survey weights.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Table E3. Ordinary Least Squares Regression Models Predicting the Relationship between Log Wages, Linkage Strength, and Match by Gender in Texas

Variable	Coef.	Sig.
Linkage Strength (standardized)	0.03	***
In Matching Occupation	0.07	***
Linkage x Match	-0.03	*
Female	-0.37	***
Female x Linkage	-0.03	***
Female x Match	0.01	
Female x Linkage x Match	0.09	***
R^2	0.34	
N	114,792	

Source: American Community Survey 1% Sample, 2013-2017.
Note: Sample was limited to bachelor's degree holders who reported earnings and for whom linkage strength could be calculated. The model included control variables (see Appendices A and B for details) as well as year fixed-effects. Estimates incorporated survey weights.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Table E4. Ordinary Least Squares Regression Models Predicting the Relationship between Log Wages, Linkage Strength, and Match by Race/Ethnicity in Texas

Variable	Coef.	Sig.
Linkage Strength (standardized)	0.02	**
In Matching Occupation	0.04	***
Linkage x Match	0.00	
Race/Ethnicity (ref. = White)		
Black	-0.27	***
Hispanic	-0.22	***
Asian	-0.03	+
Black x Linkage	0.02	
Hispanic x Linkage	-0.01	
Asian x Linkage	0.08	***
Black x Match	0.14	***
Hispanic x Match	0.09	***
Asian x Match	0.19	***
Black x Linkage x Match	0.06	*
Hispanic x Linkage x Match	0.08	***
Asian x Linkage x Match	-0.01	
R^2	0.35	
N	114,792	

Source: American Community Survey 1% Sample, 2013-2017.
Note: Sample was limited to bachelor's degree holders who reported earnings and for whom linkage strength could be calculated. The model included control variables (see Appendices A and B for details) as well as year fixed-effects. Estimates incorporated survey weights.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Table E5. Ordinary Least Squares Regression Models Predicting the Relationship between Log Wages, Linkage Strength, and Match by Nativity in Texas

Variable	Coef.	Sig.
Linkage Strength (standardized)	0.02	***
In Matching Occupation	0.06	***
Linkage x Match	0.01	+
Foreign-Born	-0.14	***
Foreign-Born x Linkage	0.02	+
Foreign-Born x Match	0.16	***
Foreign-Born x Linkage x Match	0.03	
R^2	0.34	
N	114,792	

Source: American Community Survey 1% Sample, 2013-2017.
Note: Sample was limited to bachelor's degree holders who reported earnings and for whom linkage strength could be calculated. The model included control variables (see Appendices A and B for details) as well as year fixed-effects. Estimates incorporated survey weights.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Table E6. Ordinary Least Squares Regression Models Predicting the Relationship between Log Wages, Linkage Strength, and Match by Language in Texas

Variable	Coef.	Sig.
Linkage Strength (standardized)	0.02	***
In Matching Occupation	0.06	***
Linkage x Match	0.00	
Non-Native English-Speaker	-0.14	***
Non-Native English-Speaker x Linkage	0.01	
Non-Native English-Speaker x Match	0.10	***
Non-Native English-Speaker x Linkage x Match	0.06	***
R^2	0.34	
N	114,792	

Source: American Community Survey 1% Sample, 2013-2017.
Note: Sample was limited to bachelor's degree holders who reported earnings and for whom linkage strength could be calculated. The model included control variables (see Appendices A and B for details) as well as year fixed-effects. Estimates incorporated survey weights.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Appendix F. Regression Models for Research Question 4

Table F1. Odds Ratios from Binary Logistic Regression Models Predicting the Relationship between Unemployment and Linkage Strength in Texas

Variable	Coef.	Sig.
Linkage Strength (standardized)	0.86	***
Goodness-of-Fit	1.90	
N	112,719	

Source: American Community Survey 1% Sample, 2013-2017.
Note: Sample was limited to bachelor's degree holders in the labor force for whom linkage strength could be calculated. The model included control variables (see Appendices A and B for details) as well as year fixed-effects. Estimates incorporated survey weights.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Table F2. Odds Ratios from Binary Logistic Regression Models Predicting the Relationship between Unemployment and Linkage Strength by Age in Texas

Variable	Coef.	Sig.
Linkage Strength (standardized)	1.33	
Age	0.99	
Age x Linkage	0.98	
Age^2	1.00	
Age^2 x Linkage	1.00	
Goodness-of-Fit	1.96	
N	112,719	

Source: American Community Survey 1% Sample, 2013-2017.
Note: Sample was limited to bachelor's degree holders in the labor force for whom linkage strength could be calculated. The model included control variables (see Appendices A and B for details) as well as year fixed-effects. Estimates incorporated survey weights.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Table F3. Odds Ratios from Binary Logistic Regression Models Predicting the Relationship between Unemployment and Linkage Strength by Gender in Texas

Variable	Coef.	Sig.
Linkage Strength (standardized)	0.89	**
Female	0.98	
Female x Linkage	0.95	
Goodness-of-Fit	1.89	
N	112,719	

Source: American Community Survey 1% Sample, 2013-2017.
Note: Sample was limited to bachelor's degree holders in the labor force for whom linkage strength could be calculated. The model included control variables (see Appendices A and B for details) as well as year fixed-effects. Estimates incorporated survey weights.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Table F4. Odds Ratios from Binary Logistic Regression Models Predicting the Relationship between Unemployment and Linkage Strength by Race/Ethnicity in Texas

Variable	Coef.	Sig.
Linkage Strength (standardized)	0.88	***
Race/Ethnicity (ref. = White)		
Black	1.48	***
Hispanic	1.08	
Asian	1.01	
Black x Linkage	0.99	
Hispanic x Linkage	0.99	
Asian x Linkage	0.89	
Goodness-of-Fit	2.00	
N	112,719	

Source: American Community Survey 1% Sample, 2013-2017.
Note: Sample was limited to bachelor's degree holders in the labor force for whom linkage strength could be calculated. The model included control variables (see Appendices A and B for details) as well as year fixed-effects. Estimates incorporated survey weights.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Table F5. Odds Ratios from Binary Logistic Regression Models Predicting the Relationship between Unemployment and Linkage Strength by Nativity in Texas

Variable	Coef.	Sig.
Linkage Strength (standardized)	0.86	***
Foreign-Born	1.34	***
Foreign-Born x Linkage	1.01	
Goodness-of-Fit	1.98	
N	112,719	

Source: American Community Survey 1% Sample, 2013-2017.
Note: Sample was limited to bachelor's degree holders in the labor force for whom linkage strength could be calculated. The model included control variables (see Appendices A and B for details) as well as year fixed-effects. Estimates incorporated survey weights.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Table F6. Odds Ratios from Binary Logistic Regression Models Predicting the Relationship between Unemployment and Linkage Strength by Language in Texas

Variable	Coef.	Sig.
Linkage Strength (standardized)	0.87	***
Non-Native English-Speaker	1.26	**
Non-Native English-Speaker x Linkage	0.99	
Goodness-of-Fit	2.01	
N	112,719	

Source: American Community Survey 1% Sample, 2013-2017.
Note: Sample was limited to bachelor's degree holders in the labor force for whom linkage strength could be calculated. The model included control variables (see Appendices A and B for details) as well as year fixed-effects. Estimates incorporated survey weights.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

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