Anti-Globalization Sentiment: Exposure and Immobility
Supplemental Information

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Contents

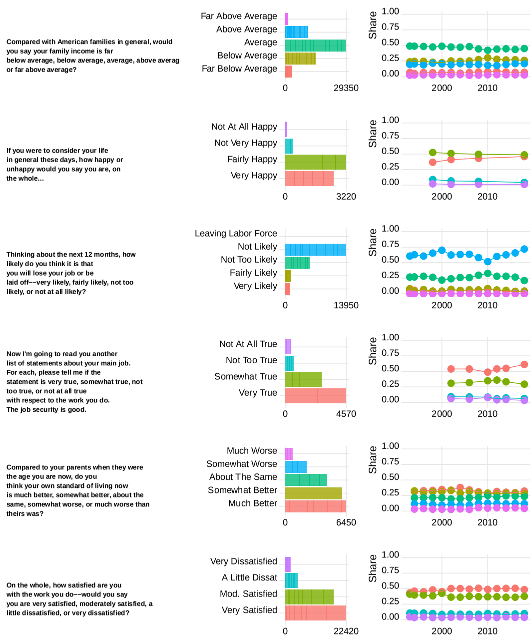
1 Data Description

Table SI.1 summarizes these data sources. The precise wording of the outcome questions of interest is summarized in Figure SI.1, which also includes the distributions and coverage for each.

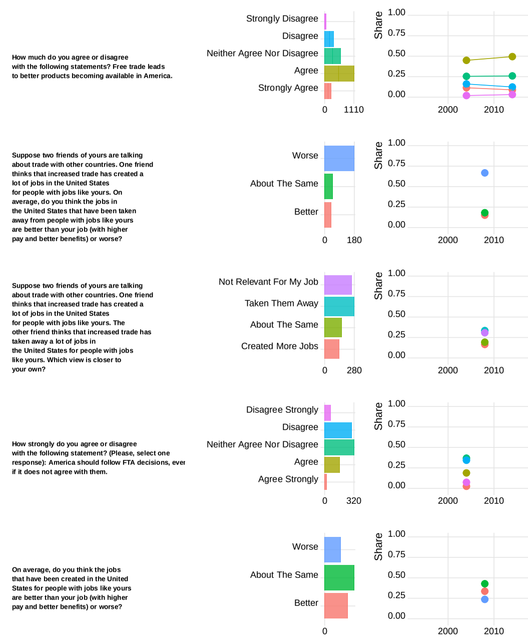
Table SI.1: Data Sources and Description

Variables	**Description**	**Source**
Opinion outcome measures (LHS)	Opinions on trade, immigration, and labor force position.	GSS
Individual covariates (RHS)	Gender, race, marital status, educational attainment, age, foreign born status, foreign born status of the respondent's parents, and number of children born	GSS
State covariates (RHS)	Male and female unemployment rate; share of labor force in manufacturing; proportions black, Hispanic, foreign born, and with a college education, and proportion employed in routine-intensive occupations	Census
Occupational Tasks (Risk)	Degree to which different occupations engage with different tasks and require different skills	O*NET
Occupations-by-Industry (Risk)	Proportion of occupations by industry	Census
Occupations-by-Location (Risk)	Proportion of occupations by state	Census J2J

Figure SI.1: Questions of Interest



(a) Questions pertaining to labor market insecurity.



(b) Questions pertaining to trade and globalization.

(c) Questions pertaining to immigration.

2 Constituent Subjective Questions

Our main analysis focused on indices that summed over multiple constitutive questions about job insecurity, financial dissatisfaction, and status concerns. Here, we present the marginal effects of the industry-level trade shock interacted with our logged occupational immobility measure for the *constitutive* questions. The top row of Figure SI.2 summarizes these results for questions pertaining to job insecurity, the middle row summarizes these results for questions pertaining to financial dissatisfaction, and the bottom row summarizes these results for questions pertaining to status. While not every constitute question is statistically significant, all exhibit the same positive marginal correlations in which the relationship between the trade shock and negative views is stronger among those experiencing greater occupational immobility.

3 Multilevel Model Robustness

Our main results use ordinary least squares regressions with year and state fixed effects. Here we confirm that our results are robust to an alternative specification in which individuals are nested within industries, states and years in a multilevel model. Specifically, we estimate a regression with the following structure:

$$\begin{aligned}
y_{inst} &= \gamma_n + \alpha_s + \delta_t + \beta_1 IE^i_{nt} + \beta_2 \sigma^i_{jns} + \beta_3 \sigma^i_{jns} \times IE^i_{nt} + \beta_4 \mathbf{X}_i + \beta_4 \mathbf{S}_{s,t_{pre}} \text{ where} \\
\gamma_n &\sim N(0, \sigma^2_\gamma) \text{ and} \\
\alpha_s &\sim N(0, \sigma^2_\alpha) \text{ and} \\
\delta_t &\sim N(0, \sigma^2_\delta)
\end{aligned}$$

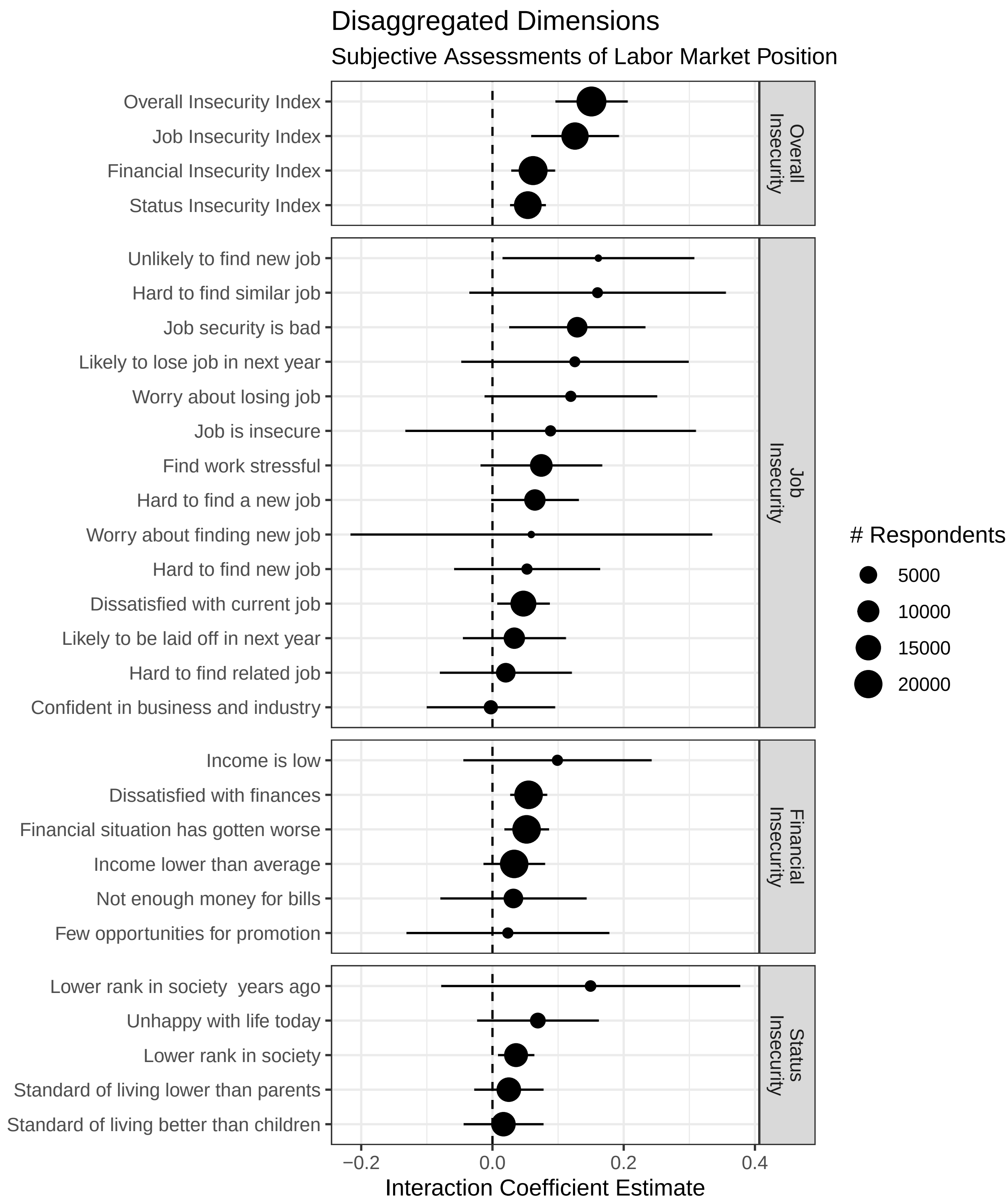
Figure SI.3 compares the main findings estimated using OLS (in dark gray circles) with the multilevel model (in white circles) which are substantively similar to our main results. However, we draw the reader's attention to the noisier estimates for the measures of protectionism when using the multilevel modeling setup.

4 Sensitivity Analysis

Our main results rely on the reader to accept that our choice of individual and local-level covariates, combined with our fixed effects specification, are sufficient to capture causally identified relationships between changes in import exposure and survey responses. As this claim is difficult to justify in this empirical context, we argue that the correlations we document are nevertheless revealing about an important period in American politics during which dramatic changes in Chinese productivity had equally far-reaching implications for U.S. labor markets. In the following section, we further defend the causal interpretation of our findings via sensitivity analysis.

Instead of accepting that our specification and covariates perfectly isolate the conditionally independent effect of import exposure across different levels of occupational immobility, sensitivity analysis instead answers the question of "how bad would confounding have to be to overturn our results?" Insofar as causal identification with observational data is never perfect, this type of analysis instead documents how fragile our findings are in the face of unknowable or unmeasureable confounding. We implement the method described in Cinelli and Hazlett (2020) in which we simulate an unobserved confounder that is correlated with both our treatment of interest (the industry-level trade shock) and the outcome of interest (one of the many survey responses that capture different dimensions of the anti-globalist bundle of views). These simulations allow us to estimate how strong the correlation between this unobserved confounder and treatment/outcome would have to be to render our findings statistically insignificant (or to cross the

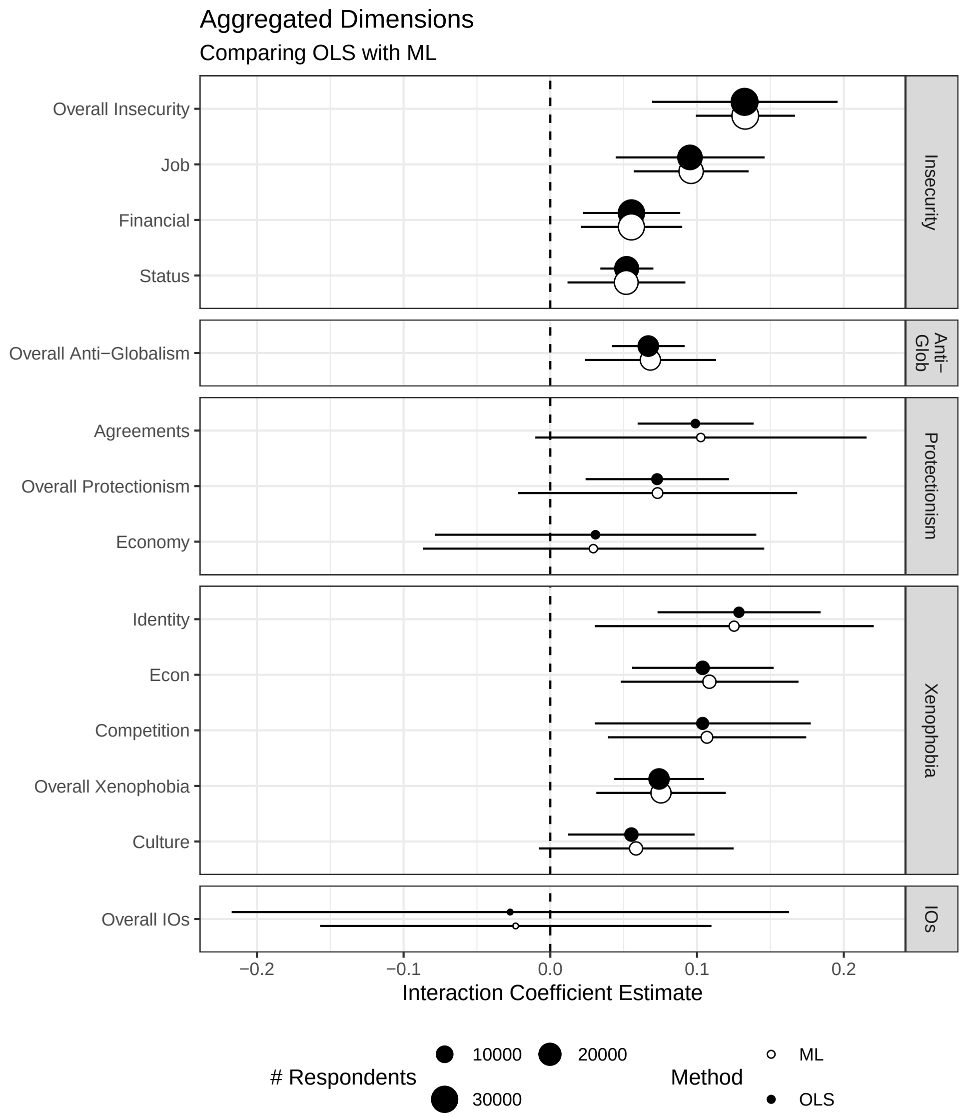
Figure SI.2: Subjective Risk, Constitutive Questions



Interaction coefficients (x-axis) expressing increase in marginal effect of import competition on self-reported dimensions of labor market insecurity (y-axis).

null, or to be statistically significant and of the opposite sign). We compare these thresholds to those that we observe in our data by looking at the most highly correlated controls for reference. While there is no

Figure SI.3: Multilevel Model Robustness



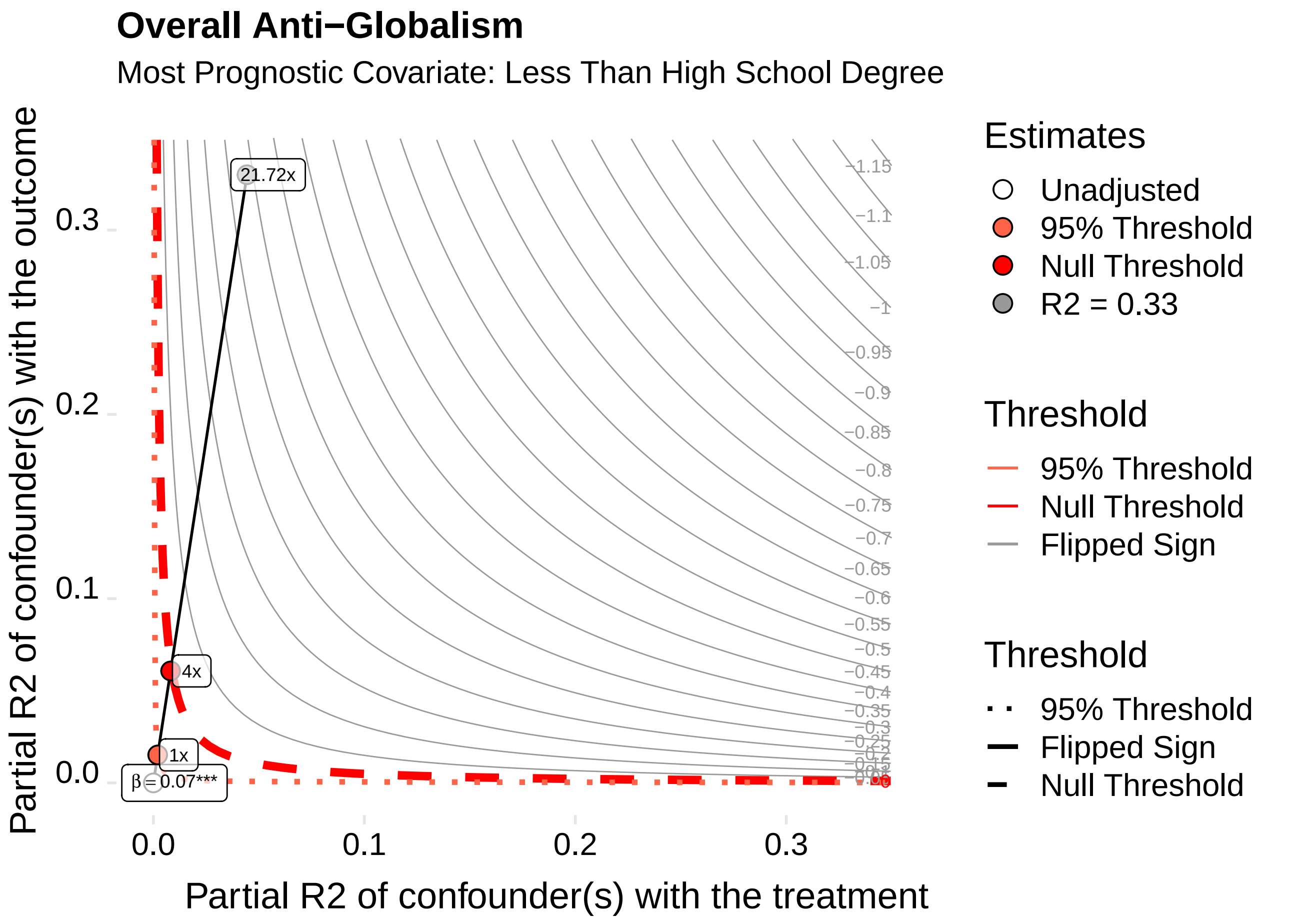
Interaction coefficients estimated with OLS (dark circles) versus a multilevel model (white circles).

standard threshold, a reassuring result is one in which *none* of the observables are sufficiently strongly correlated with either treatment or outcome (or both) to overturn the results.

We rely on contour plots (visualized in Figure SI.4) in which the x-axes chart the partial R^2 with treatment, the y-axes chart the partial R^2 with the outcome, and the contour lines capture what would be required to reduce significance below the 95% level of confidence (dotted red line), flip the sign of the coefficient (dashed red line), or produce increasingly large estimates of the opposite sign. The white point in the bottom-left reflect the estimated coefficient assuming no unobserved confounder exists. We then map the most prognostic observable control into this space, visualizing how much more correlated an unobserved confounder would have to be with both the outcome and the treatment to reduce our point estimate for the interaction of trade exposure and occupational risk to less than 95% confidence (dashed red line), to zero (solid red line), and finally to the maximum threshold of a partial R^2 of 0.33 with either the outcome or the treatment.

An alternative approach to visualization is to calculate extreme values of the association between an

Figure SI.4: Contours of adjusted coefficient estimates

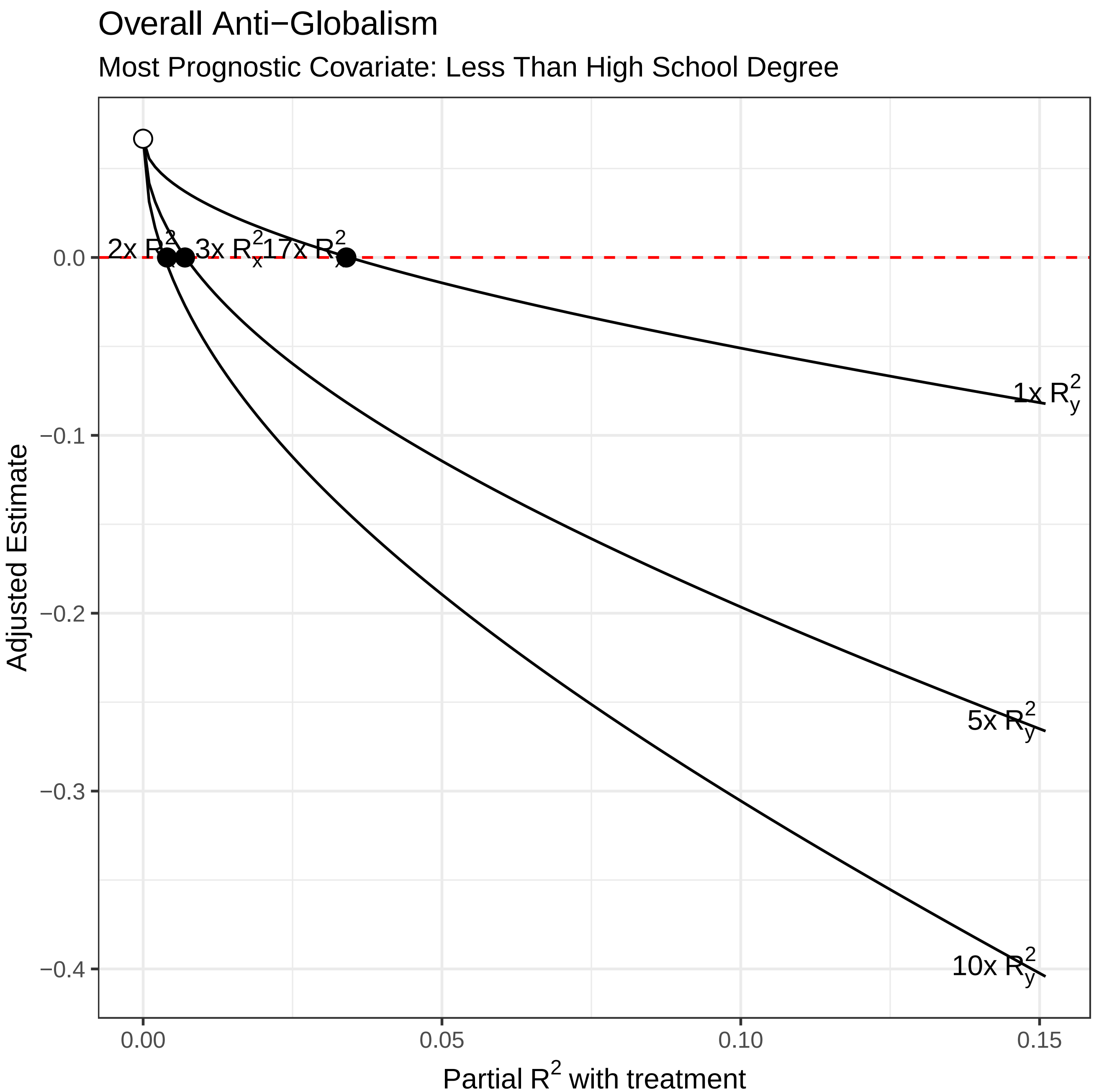


Contour plot displaying how strongly predictive of an unobserved confounder would have to be of anti-globalist views (y-axis) and import exposure (x-axis) to overturn the observed coefficient estimate. The most prognostic observed covariate (whether the respondent has some college education but no degree) is indicated with a line extending from the origin, which points indicating how much more prognostic the unobserved confounder would have to be to reduce the statistical significance below the 95% level of confidence (dotted red line, 2x as prognostic) and to cross the null (dashed red line, 6x as prognostic). Such an unobserved measure would need to be 26.4 times as prognostic of anti-globalist views as the most prognostic observed variable.

unobserved confounder and the outcome, and to calculate how the adjusted coefficient estimate (y-axis in Figure SI.5) would change as we increase the association between the confounder and the import exposure treatment (x-axis). As illustrated in Figure SI.5, an unobserved confounder as prognostic of the outcome as respondents with some college education, would need to be 31 times as prognostic of import exposure as this measure in order to cross the null and flip the sign of the estimate. Conversely, a confounder 10 times as prognostic of the outcome would only need to be 4 times as prognostic of the treatment in order to achieve the same result of undermining the sign of our estimate.

A final approach to visualization is presented in Figure SI.6. Here, we calculate how many multiples of the observed association between a handful of different predictors (points) and either the treatment (x-axis) or outcome (y-axis) an unobserved confounder would need to be to overturn the sign of the estimated coefficient. As illustrated, the three most prognostic observed measures are different categories of educational attainment, including those with some college but no degree, those with a high school degree, and those with less than a high school degree. An unobserved confounder would need to be 4 times as prognostic of the treatment and 7 times as prognostic of the outcome as those with only some

Figure SI.5: Sensitivity to extreme confounders associated with 1x, 5x, and 10x times the partial R_y^2

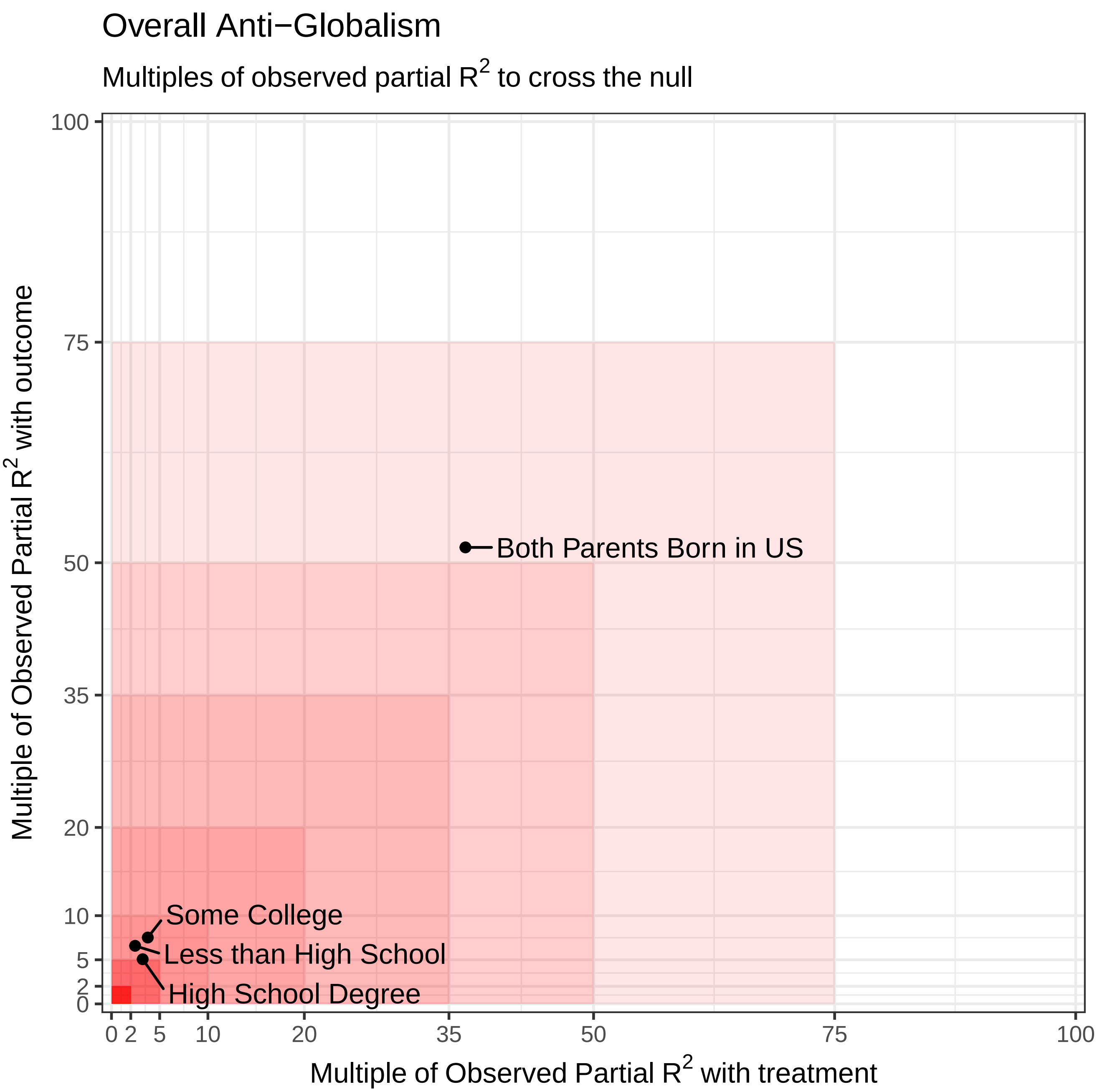


Sensitivity to extremes. Lines capture how the coefficient estimate of interest would be adjusted (y-axis) were there an unobserved confounder equally prognostic of the outcome as the most prognostic observed covariate, 5 times as prognostic, or 10 times as prognostic, for varying degrees of association between the same unobserved measure and the treatment (x-axis).

college education in order to overturn the sign of the observed estimate.

With these demonstrations of sensitivity analysis used to clarify how this approach works, we now turn to summarizing the sensitivity of every estimate in our main analyses, by only plotting the multiples required of the most prognostic covariate for each outcome (Figure SI.7). As above, we shade regions of greater sensitivity in red. We also label each point by the outcome and – in parentheses – the most prognostic control we observed in that model. Points are further sized by the magnitude of the unad-

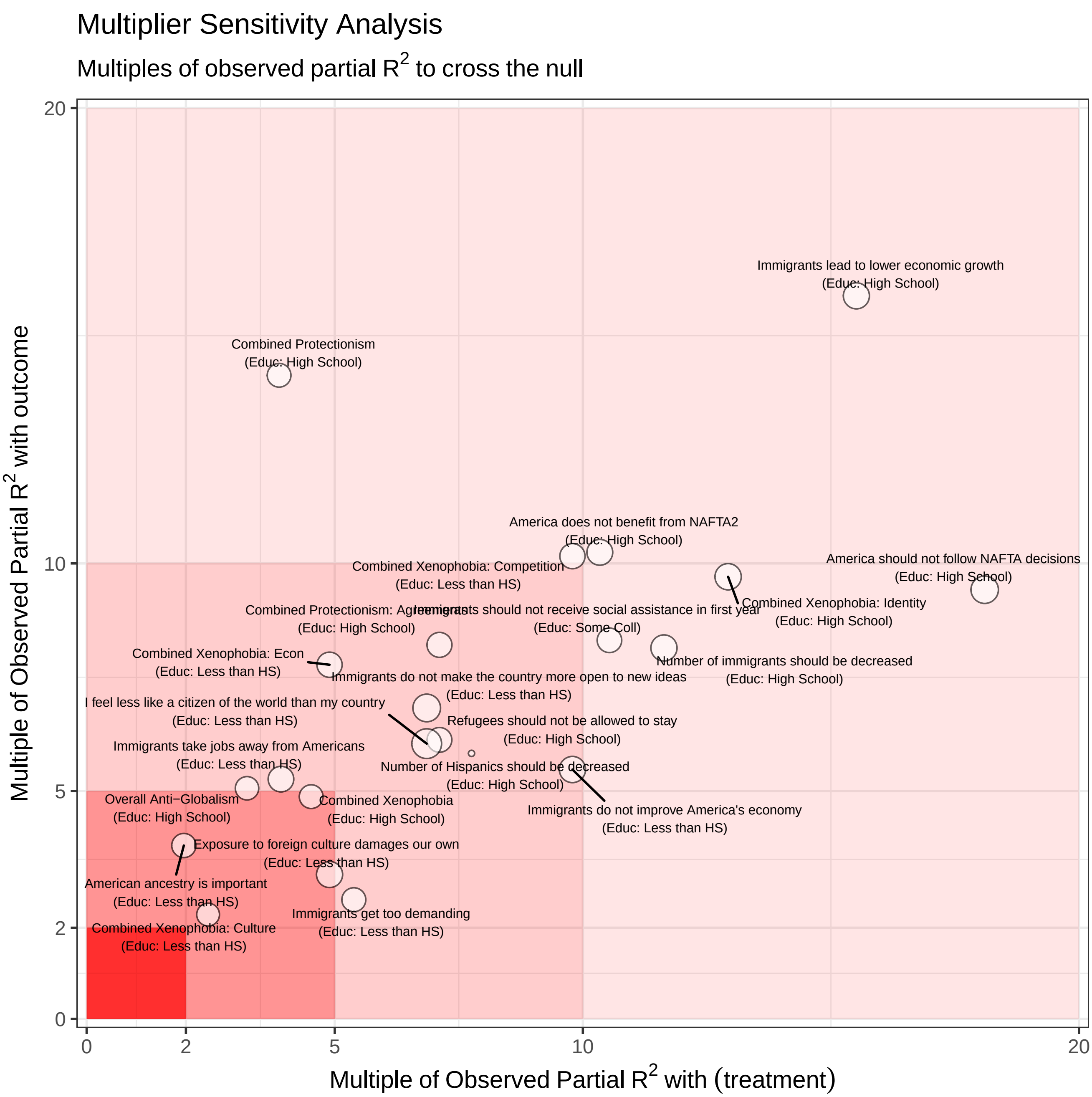
Figure SI.6: Multiples of observed associations required to overturn interaction estimate



Multiples of observed associations required to overturn sign of estimated coefficient. X-axis summarizes the multiples of the partial R^2 with treatment and the y-axis summarizes the multiples of the partial R^2 with the outcome.

justed coefficient estimate, capturing the interaction effect of import exposure and job immobility. As illustrated, among the statistically significant estimates, none are more sensitive than the overall anti-globalist measure summarized in the preceding plots. While we underscore that these diagnoses don't mean that our results are fully insulated against misspecification, we do argue that they give us confidence in our conclusions, at least as far as the sign of the interaction terms goes.

Figure SI.7: Multiples of observed associations required to overturn sign of estimated coefficient. X-axis summarizes the multiples of the partial R^2 with treatment and the y-axis summarizes the multiples of the partial R^2 with the outcome. Outcomes are given in text, with treatments below in parentheses. Points are sized by the magnitude of the unadjusted coefficient.



5 Migration Patterns

An alternative threat to our claim that the industry-level trade shock causes changes in opinions hinges on our assumption of immobility. Specifically, there may be selection effects in which those who continue to work in import-competing industries are inherently more anti-globalist for reasons other than the effect of import competition.

As described in the manuscript, consider a group of workers of varying ages, education, and attitudes toward free trade who work in the same industry in 1993. Over the ensuing decades,this industry struggles under increasing import competition. The younger, better educated, and more globalist workers exit to find work elsewhere, leaving behind an older, less educated, and anti-globalist core of immobile workers. A regression of opinions on import exposure would find a positive correlation between import competition and anti-globalist attitudes, but interpreting the changes in individual attitudes to be caused by import competition would be incorrect. Instead of an individual's position on free trade changing over time, the coefficient would capture a shifting composition of workers driven by selection.

We investigate the plausibility of this concern using county-to-county migration data from the IRS between 2004 and 2011 to test whether the county of origin and destination for movers is correlated with local measures of import exposure.

We regress population flows on the cross-sectional import exposure measure, controlling for a battery of pre-treatment county characteristics measured in the 1990s, including racial composition, the share employed in manufacturing, the share with a college degree, the share foreign born, and the shares employed in heavily routine task-oriented occupations and those working in occupations most vulnerable to outsourcing. We use a mixed effects model with year and county random effects for net population flows of the following form:

$$flow_{it} = \alpha + \beta_1 ipw_i + \beta_2 \mathbf{X}_{i,t0} + \gamma_t + \lambda_i + \epsilon_{it} \tag{SI.1}$$

where $flow_{it}$ is the net flow of individuals in county i in year t, ipw_i is the change in county i's import exposure between the 1990s and the 2000s, $\mathbf{X}_{i,t0}$ is a vector of county-level controls measured prior to 2001, and γ_t and λ_i are year and county random effects, respectively.

The above specification measures net flows of people between 2004 and 2011 as a function of county characteristics prior to 2001 and the change in county import exposure between the 1990s and the 2000s. But this specification doesn't capture the directedness of these flows. To test the latter, we construct a directed dyadic dataset where each county is linked to every other county by the population it loses to the destination county in a given year. We reconstruct our controls as the squared difference between the origin county and the destination county along a variety of demographic and economic dimensions, all measured prior to 2001. To capture the difference in trade exposure, we construct two different measures of import exposure and related covariates. The first is the difference in import exposure (and covariates) between the destination and origin counties, and takes on negative values when the origin county is more exposed than the destination. The second is simply a squared version of the difference. We control for random effects by year, origin county, and destination county and log the heavily skewed outcome variable, which we rescale in terms of migrations per 100,000 population in the origin county.[1] These results are summarized in Table SI.2.

Import competition does not determine geographic migration, be it measured as net outflows (column 1), or directed flows from an origin county to a destination county (columns 2 and 3). Instead, people appear to move to new counties as a function of how similar the county is to their origin county, particularly in terms of labor market characteristics. Note that, in this context, the *difference* between the origin and destination county's import exposure (column 3) is negative and significant, representing a 10% reduction in migration for each standard deviation increase in the squared difference. This does not imply that people move from highly exposed counties to less exposed counties though (which would be reflected by a significant coefficient in column 2). Rather, the squared difference in import exposure proxies for labor market differences due to the way the measure is constructed as the weighted change in imports.

[1] We also implement the multiway decomposition method introduced in Aronow, Samii, and Assenova (2015), which we apply to a similar regression that includes fixed effects for origin county and year along with destination state. The substantive results are the same although the statistical significance declines dramatically.

Table SI.2: Migration Patterns

	Outflows by Origin	Outflows by Origin and Destination	
	Orig County (1)	Dest-Orig (2)	(Dest-Orig)^2 (3)
IPW	0.010	-0.005	-0.101^{***}
	(0.018)	(0.005)	(0.002)
% Black	0.024	-0.029^{**}	-0.021^{***}
	(0.036)	(0.011)	(0.002)
% White	0.097^{*}	-0.054^{***}	-0.013^{***}
	(0.044)	(0.016)	(0.002)
% Empl MF	-0.0003	0.055^{***}	-0.031^{***}
	(0.019)	(0.005)	(0.002)
LFPR	-0.090^{***}	0.031^{**}	-0.142^{***}
	(0.018)	(0.010)	(0.006)
Observations	20,261	543,241	543,241

Notes: Mixed effects regressions of net outflows from origin county by origin import exposure and characteristics presented in column 1. Net outflows from origin county to destination county by difference between origin and destination import penetration presented in column 2. Net outflows from origin county to destination county by the squared difference in import penetration presented in column 3.

6 Industry-vs-Geography

6.1 Immobility Dimensions

Our main results use the combined immobility measure that links the industry-specific measure ($\sigma_{jn}^{\mathcal{N}}$) and the location-specific measure ($\sigma_{js}^{\mathcal{S}}$) via a simple average. We re-estimate our main specifications by these disaggregated components, revealing that the majority of the findings are driven by the location-specific immobility (Figure SI.8), and not the industry-specific immobility (Figure SI.9).

Why might geography matter so much more than industry when it comes to capturing the components of job immobility? One easy explanation is supported by the job-to-job transitions data, which reveals that geographic relocations are far more constrained within the state of origin than industry relocations. To support this conclusion, we plot the distributions of within-state and within-industry job transitions in Figure SI.10. Under the assumption that these transitions reflect the true costs of job transitions, we conclude that moving in geographic space is more costly than moving in industrial space. As such, it should perhaps not be surprising that the majority of our findings are driven by the geographic component of our job immobility measure.

6.2 Individual Versus Local Trade Shocks

Our main results use an industry-level measure of import competition, assigned to the individual respondent. Unlike the ADH measure (Autor, Dorn, and Hanson 2013) which relies on county-level measures of employment by industry to calculate county or commuting zone-level measures of exposure to changes in Chinese imports, ours directly maps these changes to the respondents in our survey via their measured industry of employment. This choice is motivated by our focus on individual-level measures of labor market position and occupational risk.

However, there is a growing appreciation for the importance of the effect of *local* measures of trade's negative labor market consequences on political outcomes. Researchers have increasingly focused on the effect of "exposure" to import competition that is associated living in areas that have lost jobs or closed factories in response to this increasing competition. The logic is that an individual needn't be directly affected by import competition to nevertheless perceive – and indeed suffer indirectly – from its negative consequences Alkon (2017).

Figure SI.8: Main results estimated interacted with $\sigma_{js}^{\mathcal{S}}$.

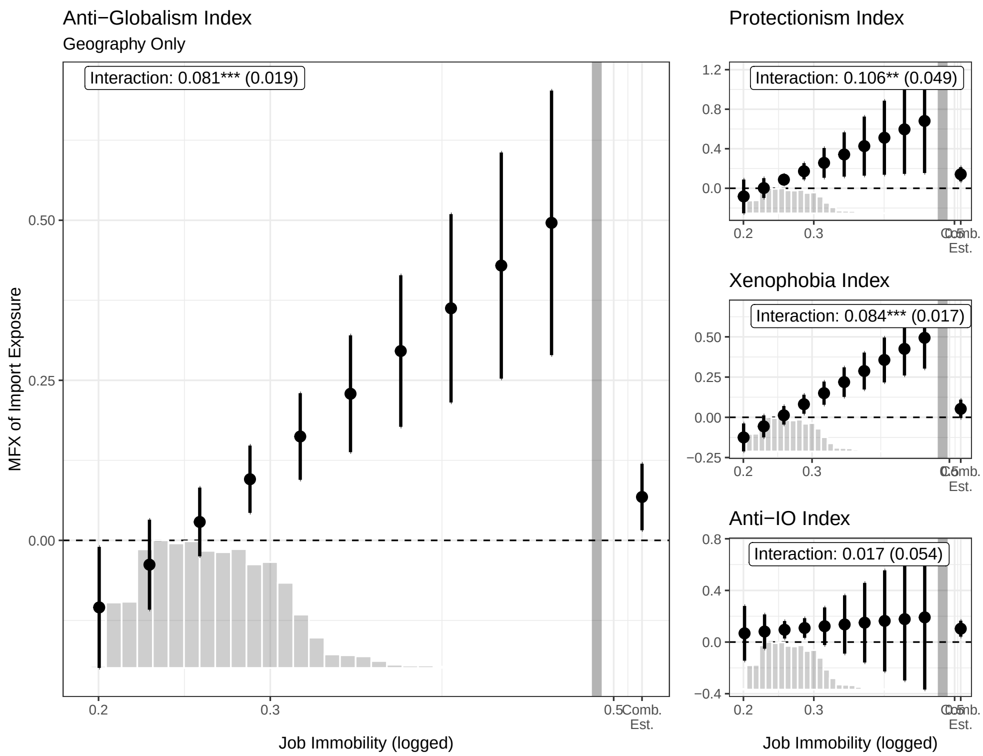


Figure SI.9: Main results estimated interacted with $\sigma_{jn}^{\mathcal{N}}$.

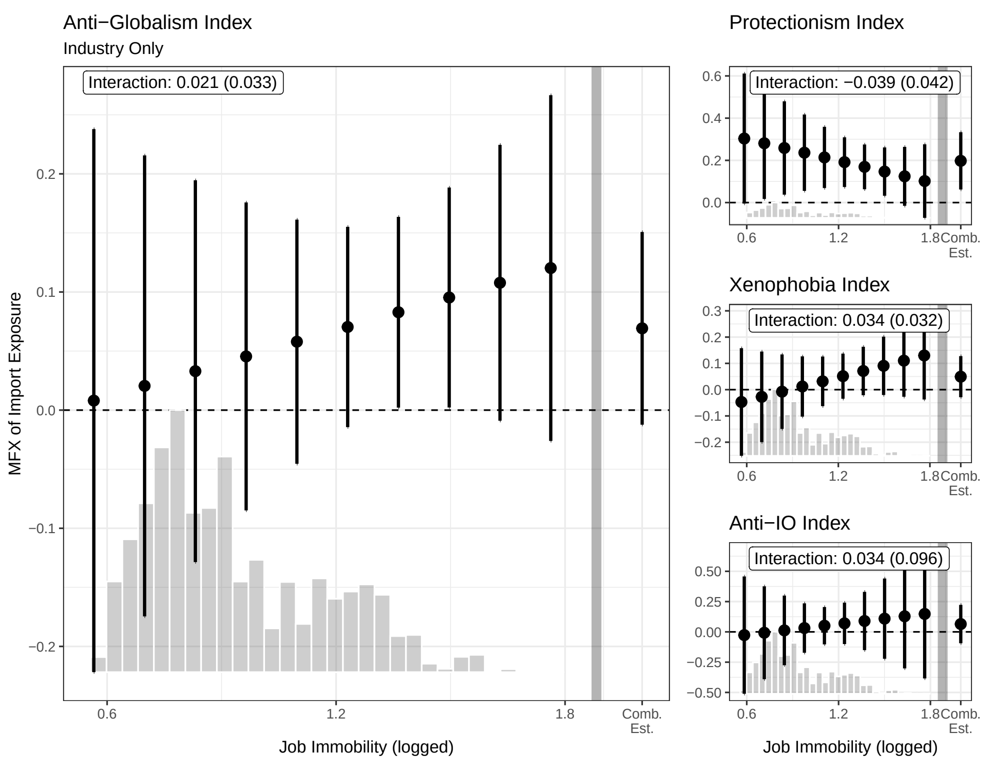
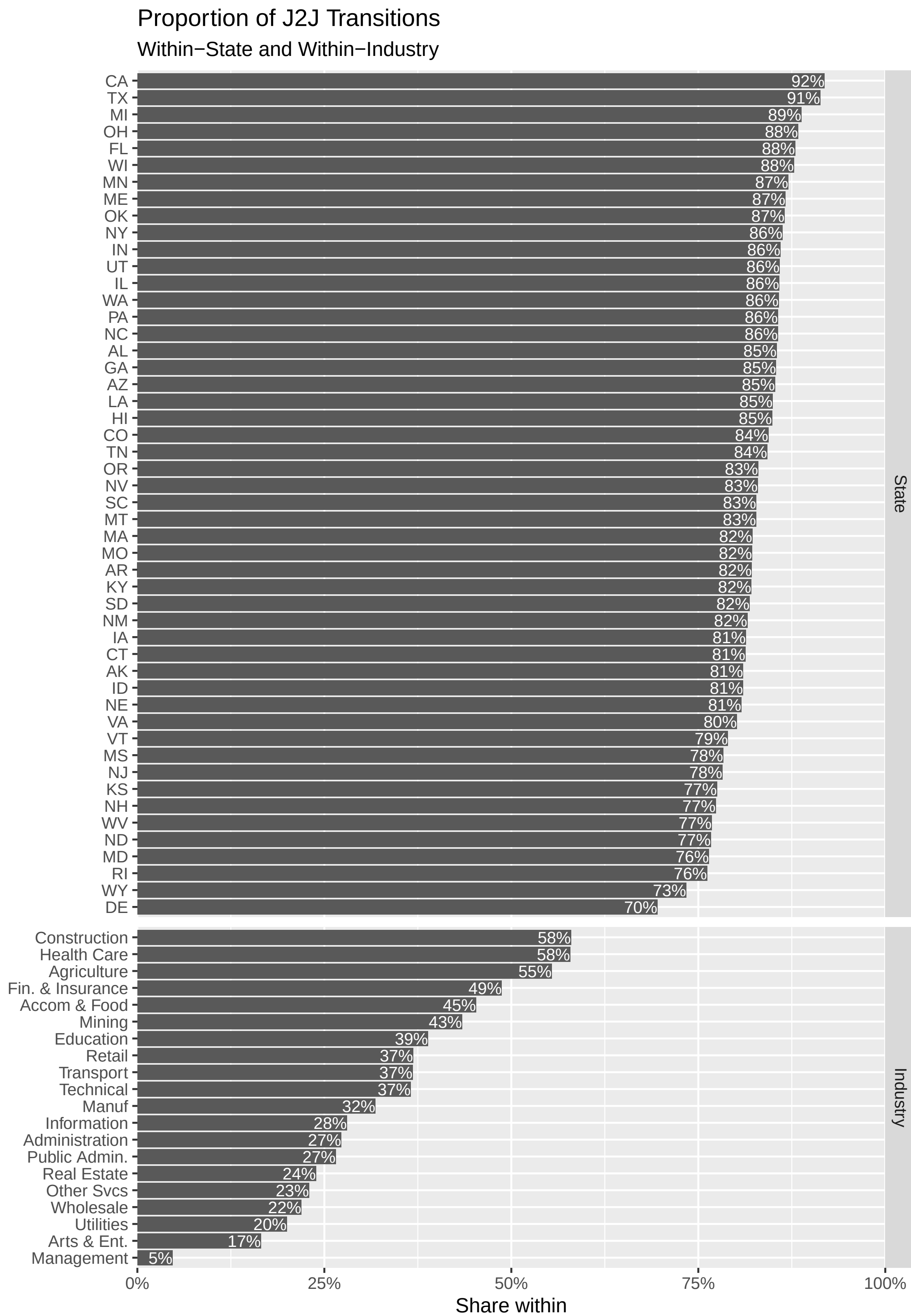


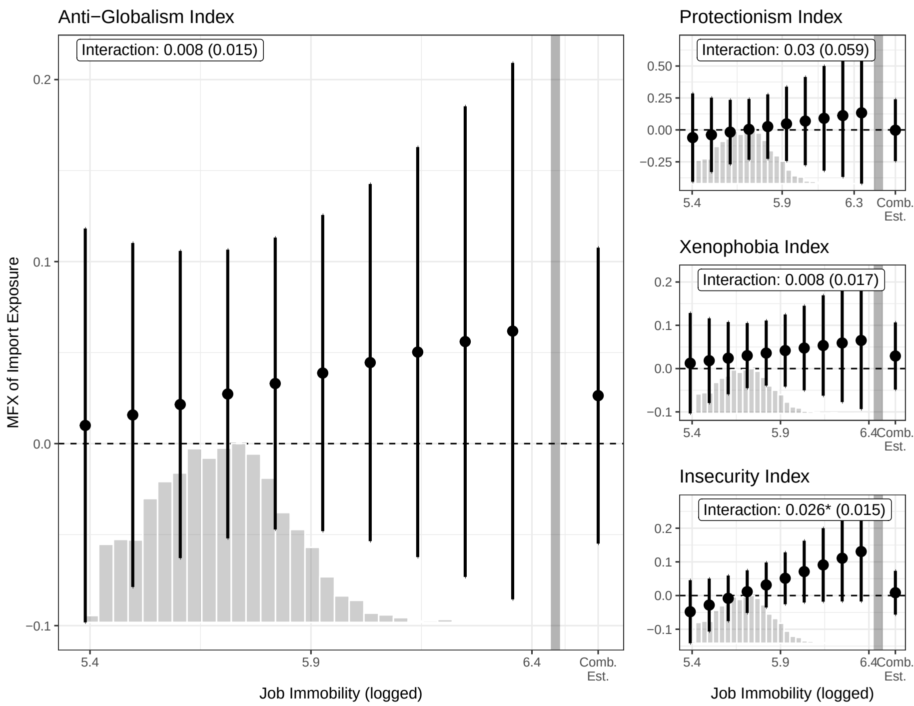
Figure SI.10: Proportion of transitions within



Average proportion of J2J transitions that occur within a state (top facet) or within an industry (bottom facet).

In this section, we replace the industry-level measure of the trade shock used in our analysis with the local measure pioneered by Autor, Dorn, and Hanson (2013). As illustrated in Figure SI.11, our results are severely attenuated. While the interaction remains in the expected direction for the measures of protectionism, xenophobia, and anti-globalism overall, the estimates are no longer significant at the 95% level of confidence. The only interaction coefficient that approaches standard significance thresholds is for the insecurity index, measuring the respondents' subjective concern about their labor market position.

Figure SI.11: Commuting Zone Level Analysis



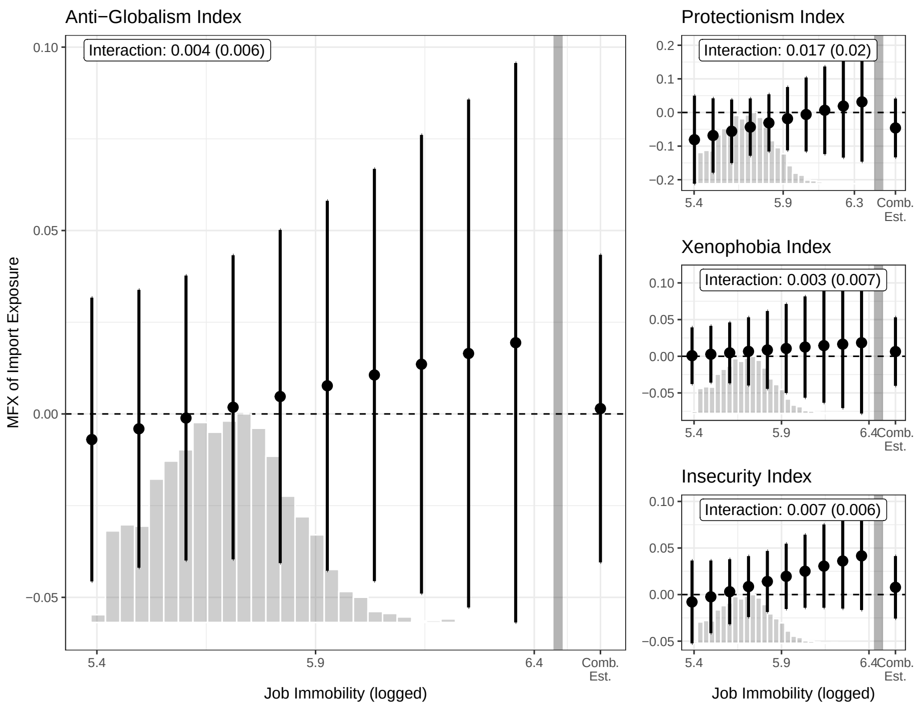
Main results estimated using commuting zone-level measure of import competition from Autor, Dorn, and Hanson (2013).

We also explore an extension in which we adopt the instrumental variables specification from Autor, Dorn, and Hanson (2013) wherein variation in the change in imports to the United States is instrumented using the prior decade's change in Chinese exports to other advanced industrial economies. The motivation for this instrumental variables strategy is to purge the change in Chinese imports to the United States of reciprocal demand. As such, the causal identification argument required for the exclusion restriction to hold is not really sensible for our application, since it is unlikely that reciprocal demand for goods is geographically correlated with beliefs about globalization among our respondents. Nevertheless, we plot these results in Figure SI.12, again revealing little systematic relationship between our main indices of interest and this geography-based measure of import competition.

We dig deeper into this finding by looking at the uninteracted relationship between our outcomes of interest and different measures used in the existing literature for capturing the local-level trade shock. Specifically, we compare our industry-level measure with the measure used by Autor, Dorn, and Hanson (2013) which captures the commuting zone level change in exposure to Chinese import competition between 1990 and 2007, a more geographically granular version of the same that captures the change at the county instead of the commuting zone, and a proxy measure for total trade-related layoffs obtained from applications for Trade Adjustment Assistance (TAA) benefits (Margalit 2011).

We plot the coefficients in Figure SI.13, examining how strongly correlated is each with the combined measures of xenophobia (and sub-aggregates for xenophobia expressed in economic terms, cultural terms, competition over public goods terms), subjective economic risk (and sub-aggregates for economic risk

Figure SI.12: Commuting Zone Level Analysis: IV



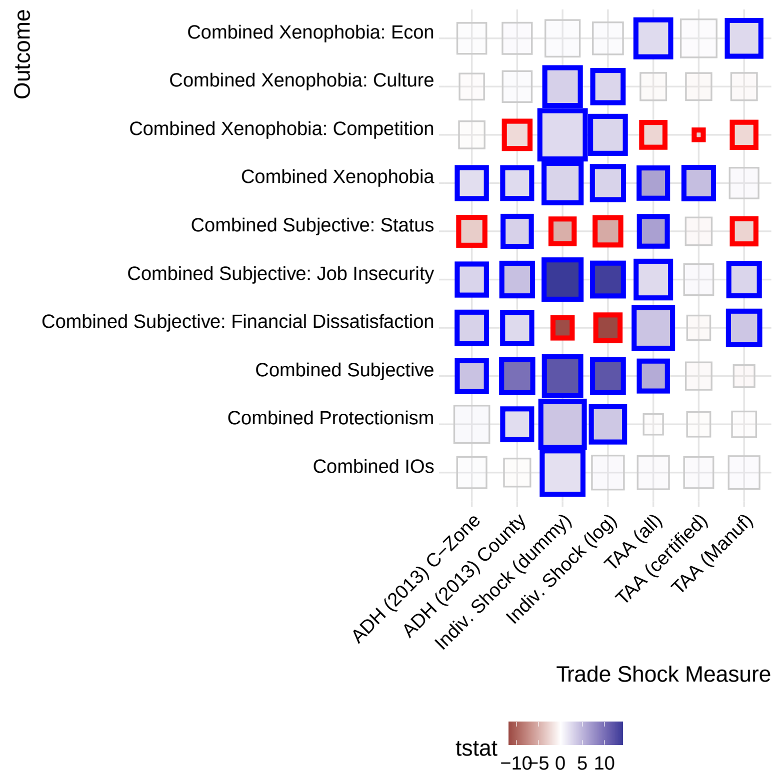
Main results estimated using commuting zone-level measure of import competition from Autor, Dorn, and Hanson (2013), instrumented by the prior decade's change in Chinese exports to other advanced economies.

expressed in terms of job insecurity, status, and finances), protectionism, and views of international organizations. Given the rich number of comparisons, we plot the coefficients as tiles, sized by the magnitude of the coefficient and colored by the t-statistic, with red indicating increasingly significant negative relationships, and blue indicating increasingly significant positive relationships. In addition, we highlight coefficients that are significant at the 95% threshold with thick borders.

As illustrated, the most robust relationships between the different survey measures of anti-globalist views and trade exposure is found for the industry-level measure used in our main analysis, followed by the county-level version of the local import competition measure developed by Autor, Dorn, and Hanson (2013). Interestingly, these industry-level measures of trade exposure are significantly *negatively* correlated with opinions relating to the respondent's status (whether they are worse off relative to their parents and their belief that they are lower-ranked in society), and with opinions about dissatisfaction with finances. Substantively, individuals who themselves work in industries that have experienced dramatic increases in competing imports from China are *less* likely to be dissatisfied with their finances, and *less* likely to see themselves as lower status. Yet these individuals are also *more* likely to express concerns about their job security.

Taken together, we posit that these patterns might reflect an important distinction between one's current versus one's future labor market position. Shocks that threaten the welfare of individuals who are currently well-off are those most likely to activate the anti-globalist views we document in the main paper. We leave this as an important avenue of future research, although we argue that this finding is consistent with the broad conclusions we draw in our paper.

Figure SI.13: Robustness: Alternative trade shock measures and subjective risk and attitudes



Relationship between anti-globalist bundle of views (y-axis) and different measures of trade exposure (x-axis). Each tile represents a coefficient, and is sized by its absolute value. Negative coefficients are indicated in red while positive are indicated in blue. Significant coefficients are further highlighted by thick borders.

6.3 Geography-vs-Industry Revisited

In sum then, we show that the industry-specific measure of trade shocks is more prognostic of attitudes than the now-conventional import penetration measure proposed by Autor, Dorn, and Hanson (2013). In addition, we also demonstrate that the geography-specific component of our proposed immobility measure drives the majority of the heterogeneous variation in the relationship between attitudes and import competition. However, this naturally raises the question of why we rely on a purely industry-based measure of trade shocks, given that our measure of job immobility is driven primarily by variation in geography.

We posit that these differences reflect the substantive differences in how individuals process information about their labor market position. When it comes to trade shocks, we argue that our industry-specific measure improves on the Autor, Dorn, and Hanson (2013) measure because it removes *uncertainty* about the causes of economic dislocation. Individuals living in commuting zones that are home to many import competing industries are likely negatively affected by the adverse spillovers as these industries lay off workers, affecting unemployment more generally along with housing prices and other social goods. However, since many individuals may not work in these particular industries, we posit it is harder for them to pinpoint the cause of their increasing precariousness relative to those who actually work in said industries. Furthermore, the inverse of the ADH measure also holds: namely that it ignores at-risk workers who live in commuting zones that are not defined by many import competing industries. We argue that these workers, by virtue of their industry of employment, are nevertheless aware of and sensitive to import competition's threat to their job, but are missed in the ADH measure. As such, by removing the intermediate geographic assignment step that translates changes in national imports competing by industry to individual respondents, we get a more precise measure of who is threatened by free trade.

Conversely, the primacy of geography over industry in the immobility measure simply reflects the realities of how these two dimensions of job transition translate into costs. Based on the data, geographic relocation is simply less common – and, therefore we posit, more costly – than industry transitions.

7 Full Tables

We present the full tables for the regressions on labor market immobility and exposure below, where each table is labeled according to its corresponding figure in the main text.

Table SI.3: Subjective Concern regression results: Figure 4

Model:	Overall Subjective Concern (1)	Job Insecurity (2)	Low Status (3)	Financial Dissatisfaction (4)
Variables				
Import Exposure	0.022^{*}	0.012	0.002	-0.010
	(0.012)	(0.013)	(0.013)	(0.011)
Job Immobility	-0.022^{***}	-0.007	-0.008	-0.012^{*}
	(0.006)	(0.007)	(0.007)	(0.006)
Mar: Widowed	0.182^{***}	0.075^{**}	0.060^{**}	0.217^{***}
	(0.021)	(0.031)	(0.026)	(0.024)
Mar: Divorced	0.316^{***}	0.073^{***}	0.187^{***}	0.426^{***}
	(0.016)	(0.018)	(0.020)	(0.017)
Mar: Separated	0.396^{***}	0.149^{***}	0.191^{***}	0.487^{***}
	(0.033)	(0.035)	(0.039)	(0.032)
Mar: Never Married	0.250^{***}	0.077^{***}	0.045^{**}	0.345^{***}
	(0.017)	(0.018)	(0.018)	(0.017)
Educ: High School	0.240^{***}	0.095^{***}	-0.164^{***}	0.402^{***}
	(0.016)	(0.017)	(0.019)	(0.017)
Educ: Less than HS	0.411^{***}	0.264^{***}	-0.231^{***}	0.587^{***}
	(0.019)	(0.022)	(0.025)	(0.020)
Educ: Some Coll	0.185^{***}	0.050^{***}	-0.097^{***}	0.315^{***}
	(0.016)	(0.017)	(0.018)	(0.016)
Race: Black	0.157^{***}	0.089^{***}	0.081^{***}	0.139^{***}
	(0.020)	(0.022)	(0.024)	(0.020)
Race: Other	0.024	0.024	-0.012	0.026
	(0.025)	(0.027)	(0.029)	(0.024)
Gender: Female	0.063^{***}	0.080^{***}	0.007	0.045^{***}
	(0.012)	(0.014)	(0.013)	(0.013)
Party: Democrat	-0.022	0.004	-0.011	-0.020
	(0.020)	(0.022)	(0.024)	(0.020)
Party: Lean Dem	0.022	0.024	-0.008	0.013
	(0.022)	(0.024)	(0.026)	(0.023)
Party: Independent	0.0009	-0.001	-0.010	0.037^{*}
	(0.021)	(0.024)	(0.025)	(0.021)
Party: Lean Rep	-0.067^{***}	-0.055^{**}	-0.019	-0.052^{**}
	(0.023)	(0.026)	(0.028)	(0.025)
Party: Republican	-0.124^{***}	-0.082^{***}	-0.022	-0.123^{***}
	(0.021)	(0.023)	(0.025)	(0.022)
Party: Strong Rep	-0.132^{***}	-0.103^{***}	0.034	-0.177^{***}
	(0.022)	(0.027)	(0.026)	(0.024)
Party: Other	0.048	0.090^{*}	-0.028	0.019
	(0.043)	(0.049)	(0.050)	(0.046)
Age: 30-40yrs	0.005	0.036^{*}	0.005	0.058^{***}
	(0.019)	(0.020)	(0.022)	(0.020)
Age: 40-50yrs	0.009	0.046^{**}	-0.060^{***}	0.117^{***}
	(0.021)	(0.022)	(0.023)	(0.022)
Age: 50-64yrs	0.094^{***}	0.053^{**}	-0.072^{***}	0.140^{***}
	(0.020)	(0.022)	(0.024)	(0.022)
Age: 65+yrs	0.284^{***}	0.111^{***}	-0.123^{***}	0.013
	(0.022)	(0.033)	(0.027)	(0.024)
Born: Not US	0.050^{*}	0.044	0.011	0.047^{*}
	(0.028)	(0.033)	(0.034)	(0.028)
Parents Born: Both US	-0.006	-0.009	0.029	-0.007
	(0.025)	(0.031)	(0.031)	(0.027)
Parents Born: One Foreign	-0.022	0.011	0.007	-0.063^{*}
	(0.032)	(0.038)	(0.040)	(0.035)
# of Children	0.035^{***}	-0.004	0.041^{***}	0.052^{***}
	(0.006)	(0.008)	(0.008)	(0.007)
C-zone: % Manuf (1990)	0.010	-0.003	-0.006	0.012
	(0.011)	(0.012)	(0.013)	(0.011)
C-zone: % College Deg (1990)	-0.016	-0.009	0.016	-0.037^{***}
	(0.011)	(0.012)	(0.012)	(0.011)
C-zone: % Foreign (1990)	0.019	0.028^{*}	0.019	0.013
	(0.015)	(0.017)	(0.018)	(0.016)
C-zone: % Black (1990)	-0.023^{**}	-0.031^{**}	0.021	-0.029^{**}
	(0.011)	(0.013)	(0.014)	(0.012)
C-zone: % Hispanic (1990)	-0.020	-0.010	0.019	-0.049^{***}
	(0.016)	(0.018)	(0.020)	(0.017)
Import Exposure × Job Immobility	0.035^{***}	0.022^{***}	0.021^{***}	0.015^{**}
	(0.006)	(0.007)	(0.007)	(0.007)
Fixed-effects				
stab	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
indus1DIG	Yes	Yes	Yes	Yes
Fit statistics				
Observations	29,613	23,605	21,964	27,804
R^2	0.12	0.08	0.09	0.13
Within R^2	0.08	0.02	0.02	0.10

Clustered (clust) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table SI.4: Globalization Sentiment regression results: Figure 5

Model:	Overall Subjective Concern (1)	Job Insecurity (2)	Low Status (3)	Financial Dissatisfaction (4)
Variables				
Import Exposure	0.012	0.026	-0.031	0.038
	(0.047)	(0.055)	(0.049)	(0.057)
Job Immobility	-0.035***	-0.013$^{\cdot}$	-0.027***	-0.013
	(0.007)	(0.008)	(0.007)	(0.008)
Mar: Widowed	0.171***	0.054$^{\cdot}$	0.214***	0.060*
	(0.021)	(0.031)	(0.024)	(0.026)
Mar: Divorced	0.310***	0.071***	0.423***	0.187***
	(0.016)	(0.018)	(0.017)	(0.020)
Mar: Separated	0.383***	0.132***	0.480***	0.192***
	(0.033)	(0.035)	(0.033)	(0.039)
Mar: Never Married	0.228***	0.067***	0.335***	0.042*
	(0.016)	(0.018)	(0.017)	(0.019)
Educ: High School	0.220***	0.080***	0.380***	-0.156***
	(0.016)	(0.017)	(0.017)	(0.019)
Educ: Less than HS	0.366***	0.233***	0.539***	-0.222***
	(0.020)	(0.023)	(0.021)	(0.026)
Educ: Some Coll	0.179***	0.050**	0.305***	-0.090***
	(0.016)	(0.017)	(0.017)	(0.018)
Race: Black	0.169***	0.090***	0.144***	0.084***
	(0.020)	(0.022)	(0.020)	(0.024)
Race: Other	0.025	0.018	0.031	-0.009
	(0.024)	(0.027)	(0.025)	(0.029)
Gender: Female	0.090***	0.105***	0.042**	0.0005
	(0.013)	(0.014)	(0.013)	(0.014)
Born: Not US	0.046$^{\cdot}$	0.054	0.041	0.011
	(0.028)	(0.033)	(0.028)	(0.034)
Parents Born: Both US	-0.012	-0.008	-0.008	0.028
	(0.025)	(0.031)	(0.027)	(0.031)
Parents Born: One Foreign	-0.024	0.018	-0.066$^{\cdot}$	0.007
	(0.032)	(0.038)	(0.035)	(0.040)
Party: Democrat	-0.026	-0.0004	-0.017	-0.012
	(0.020)	(0.022)	(0.021)	(0.024)
Party: Lean Dem	0.015	0.022	0.015	-0.008
	(0.022)	(0.025)	(0.023)	(0.026)
Party: Independent	-0.0008	0.005	0.037$^{\cdot}$	-0.009
	(0.021)	(0.024)	(0.021)	(0.025)
Party: Lean Rep	-0.062**	-0.048$^{\cdot}$	-0.043$^{\cdot}$	-0.017
	(0.023)	(0.027)	(0.025)	(0.029)
Party: Republican	-0.123***	-0.079***	-0.117***	-0.020
	(0.021)	(0.023)	(0.022)	(0.025)
Party: Strong Rep	-0.123***	-0.089**	-0.172***	0.034
	(0.022)	(0.027)	(0.024)	(0.026)
Party: Other	0.048	0.085$^{\cdot}$	0.018	-0.026
	(0.042)	(0.048)	(0.045)	(0.050)
Age: 30-40yrs	0.020	0.035$^{\cdot}$	0.070***	0.007
	(0.019)	(0.020)	(0.020)	(0.022)
Age: 40-50yrs	0.023	0.037$^{\cdot}$	0.130***	-0.057*
	(0.020)	(0.022)	(0.022)	(0.023)
Age: 50-64yrs	0.105***	0.033	0.156***	-0.069**
	(0.020)	(0.022)	(0.022)	(0.024)
Age: 65+yrs	0.286***	0.033	0.028	-0.118***
	(0.022)	(0.032)	(0.024)	(0.027)
# of Children	0.036***	-0.004	0.052***	0.041***
	(0.007)	(0.008)	(0.007)	(0.008)
C-zone: % Manuf (1990)	0.008	-0.005	0.010	-0.008
	(0.011)	(0.012)	(0.011)	(0.013)
C-zone: % College Deg (1990)	-0.013	-0.006	-0.035**	0.015
	(0.011)	(0.012)	(0.011)	(0.012)
C-zone: % Foreign (1990)	0.022	0.033*	0.014	0.019
	(0.015)	(0.017)	(0.016)	(0.018)
C-zone: % Black (1990)	-0.025*	-0.031*	-0.028*	0.019
	(0.011)	(0.013)	(0.012)	(0.015)
C-zone: % Hispanic (1990)	-0.021	-0.014	-0.047**	0.018
	(0.016)	(0.018)	(0.017)	(0.020)
Import Exposure $\times$ Job Immobility	0.091***	0.065**	0.049**	0.046*
	(0.017)	(0.020)	(0.018)	(0.021)
Fixed-effects				
State	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
NAICS 2-Digit	Yes	Yes	Yes	Yes
Fit statistics				
Observations	29,613	23,605	27,804	21,964
R^2	0.14	0.09	0.14	0.09
Within R^2	0.07	0.02	0.09	0.01

Clustered (clust) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

Table SI.5: Protectionism regression results: Figure 6

Model:	Overall: Trade Agreements are Bad (1)	America should not follow NAFTA decisions (2)	America does not benefit from NAFTA (3)	Overall: Trade's Economics are Bad (4)	Jobs lost to trade are better (5)	Free trade does not lead to better products (6)
Variables						
Import Exposure	0.059	0.125**	-0.094*	0.109***	0.024	0.121***
	(0.037)	(0.055)	(0.049)	(0.037)	(0.183)	(0.038)
Job Immobility	0.012	0.014	-0.045	0.010	0.075	0.013
	(0.019)	(0.027)	(0.036)	(0.021)	(0.075)	(0.024)
Mar: Widowed	0.003	0.015	-0.052	-0.053	0.338	-0.124
	(0.068)	(0.104)	(0.144)	(0.076)	(0.489)	(0.079)
Mar: Divorced	0.002	0.022	0.056	-0.010	-0.172	-0.036
	(0.050)	(0.073)	(0.095)	(0.051)	(0.238)	(0.058)
Mar: Separated	0.011	0.038	-0.014	-0.094	0.157	-0.104
	(0.099)	(0.145)	(0.196)	(0.102)	(0.412)	(0.125)
Mar: Never Married	0.004	0.046	0.176	-0.006	-0.115	-0.022
	(0.063)	(0.088)	(0.115)	(0.054)	(0.213)	(0.062)
Educ: High School	0.263***	0.243***	0.229**	0.025	-0.466**	0.114*
	(0.054)	(0.072)	(0.102)	(0.053)	(0.183)	(0.061)
Educ: Less than HS	0.195***	0.210**	0.105	0.122	-0.288	0.175**
	(0.070)	(0.098)	(0.176)	(0.077)	(0.273)	(0.087)
Educ: Some Coll	0.222***	0.209***	0.233**	0.062	-0.066	0.122**
	(0.051)	(0.068)	(0.095)	(0.049)	(0.207)	(0.056)
Race: Black	-0.029	-0.101	0.066	0.021	-0.174	0.075
	(0.062)	(0.082)	(0.133)	(0.062)	(0.236)	(0.069)
Race: Other	0.016	0.044	0.083	-0.025	-0.106	0.040
	(0.079)	(0.107)	(0.155)	(0.081)	(0.359)	(0.087)
Gender: Female	-0.040	-0.048	-0.022	0.050	-0.038	0.094*
	(0.043)	(0.057)	(0.082)	(0.044)	(0.165)	(0.050)
Party: Democrat	0.119*	0.034	0.390***	-0.122*	-0.366	-0.113
	(0.063)	(0.084)	(0.111)	(0.066)	(0.236)	(0.079)
Party: Lean Dem	0.191***	0.178*	0.389***	0.016	-0.274	-0.033
	(0.074)	(0.104)	(0.148)	(0.075)	(0.293)	(0.088)
Party: Independent	0.315***	0.274***	0.551***	0.025	-0.057	-0.020
	(0.072)	(0.093)	(0.132)	(0.073)	(0.311)	(0.084)
Party: Lean Rep	0.225***	0.174	0.475***	-0.143*	-0.415	-0.178*
	(0.086)	(0.108)	(0.149)	(0.078)	(0.260)	(0.092)
Party: Republican	0.205***	0.082	0.498***	-0.150*	-0.136	-0.264***
	(0.070)	(0.098)	(0.130)	(0.077)	(0.259)	(0.091)
Party: Strong Rep	0.277***	0.118	0.664***	-0.204***	-0.430	-0.278***
	(0.076)	(0.092)	(0.123)	(0.073)	(0.326)	(0.083)
Party: Other	0.182	0.204	0.397	-0.154	0.268	-0.168
	(0.142)	(0.204)	(0.449)	(0.157)	(0.559)	(0.197)
Age: 30-40yrs	0.121**	0.216**	0.121	0.114*	0.036	0.149**
	(0.061)	(0.094)	(0.120)	(0.064)	(0.302)	(0.070)
Age: 40-50yrs	0.151**	0.256**	0.051	0.156**	0.302	0.127*
	(0.070)	(0.105)	(0.132)	(0.065)	(0.316)	(0.074)
Age: 50-64yrs	0.163**	0.229**	0.172	0.105	0.146	0.114
	(0.066)	(0.096)	(0.123)	(0.065)	(0.298)	(0.075)
Age: 65+yrs	0.156**	0.205*	0.362**	0.142*		0.137
	(0.073)	(0.105)	(0.147)	(0.083)		(0.089)
Born: Not US	-0.028	-0.085	0.044	-0.112	0.178	-0.189*
	(0.092)	(0.125)	(0.161)	(0.090)	(0.415)	(0.104)
Parents Born: Both US	0.231**	0.212	0.305**	0.074	0.211	0.148
	(0.091)	(0.130)	(0.154)	(0.082)	(0.444)	(0.097)
Parents Born: One Foreign	0.127	0.056	0.544***	-0.105	-0.151	-0.051
	(0.114)	(0.151)	(0.182)	(0.111)	(0.570)	(0.128)
# of Children	-0.0008	-0.021	0.051	0.015	-0.126	0.037
	(0.024)	(0.032)	(0.046)	(0.024)	(0.100)	(0.027)
C-zone: % Manuf (1990)	0.007	-0.001	0.138*	0.047	0.083	0.061
	(0.039)	(0.051)	(0.077)	(0.036)	(0.159)	(0.043)
C-zone: % College Deg (1990)	-0.052	-0.032	0.119	0.009	0.043	-0.002
	(0.036)	(0.055)	(0.077)	(0.040)	(0.162)	(0.044)
C-zone: % Foreign (1990)	0.032	0.030	0.044	0.047	-0.225	0.061
	(0.045)	(0.078)	(0.106)	(0.059)	(0.202)	(0.065)
C-zone: % Black (1990)	-0.081**	-0.102	-0.097	-0.101**	-0.120	-0.072
	(0.036)	(0.064)	(0.110)	(0.045)	(0.199)	(0.053)
C-zone: % Hispanic (1990)	-0.052	-0.062	0.024	0.008	0.325	-0.086
	(0.053)	(0.091)	(0.122)	(0.069)	(0.228)	(0.068)
Import Exposure × Job Immobility	0.040**	0.047*	0.060**	0.015	0.127	-1.72×10^{-5}
	(0.019)	(0.027)	(0.028)	(0.026)	(0.083)	(0.030)
Fixed-effects						
stab	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
indus1DIG	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,751	1,490	798	2,711	253	2,169
R^2	0.12	0.13	0.18	0.09	0.30	0.08
Within R^2	0.04	0.05	0.10	0.02	0.15	0.04

Clustered (clust) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table SI.6: Xenophobia regression results: Figure 7 - Economy

Model:	Overall: Xenophobic Economy (1)	Overall: Xenophobic Competition (2)	Overall: Xenophobic Cultural Threat (3)
Variables			
Import Exposure	-0.013	-0.022	0.004
	(0.022)	(0.024)	(0.025)
Job Immobility	0.006	-0.001	0.026**
	(0.012)	(0.013)	(0.012)
Mar: Widowed	0.025	0.006	0.137***
	(0.045)	(0.052)	(0.047)
Mar: Divorced	0.014	-0.009	-0.009
	(0.031)	(0.034)	(0.035)
Mar: Separated	0.016	-0.129**	-0.012
	(0.060)	(0.063)	(0.063)
Mar: Never Married	-0.016	-0.140***	-0.008
	(0.032)	(0.038)	(0.033)
Educ: High School	0.337***	0.231***	0.450***
	(0.030)	(0.033)	(0.033)
Educ: Less than HS	0.426***	0.270***	0.600***
	(0.038)	(0.045)	(0.040)
Educ: Some Coll	0.241***	0.215***	0.316***
	(0.027)	(0.032)	(0.031)
Race: Black	0.042	-0.035	0.034
	(0.039)	(0.044)	(0.039)
Race: Other	-0.149***	-0.115**	-0.046
	(0.052)	(0.056)	(0.058)
Gender: Female	0.019	0.018	0.005
	(0.024)	(0.026)	(0.026)
Party: Democrat	0.109***	0.134***	0.035
	(0.037)	(0.043)	(0.039)
Party: Lean Dem	0.049	0.008	-0.092*
	(0.043)	(0.050)	(0.047)
Party: Independent	0.164***	0.155***	0.130***
	(0.041)	(0.046)	(0.043)
Party: Lean Rep	0.163***	0.278***	0.078
	(0.046)	(0.054)	(0.050)
Party: Republican	0.182***	0.324***	0.168***
	(0.040)	(0.046)	(0.044)
Party: Strong Rep	0.165***	0.338***	0.226***
	(0.043)	(0.052)	(0.049)
Party: Other	0.173*	0.062	0.070
	(0.092)	(0.098)	(0.100)
Age: 30-40yrs	0.008	0.093**	-0.006
	(0.035)	(0.044)	(0.037)
Age: 40-50yrs	-0.008	0.097**	-0.067*
	(0.038)	(0.045)	(0.040)
Age: 50-64yrs	-0.0007	0.129***	-0.028
	(0.040)	(0.049)	(0.043)
Age: 65+yrs	-0.050	0.195***	0.052
	(0.047)	(0.052)	(0.050)
Born: Not US	-0.373***	-0.161**	-0.195***
	(0.054)	(0.064)	(0.057)
Parents Born: Both US	0.272***	0.257***	0.245***
	(0.052)	(0.062)	(0.054)
Parents Born: One Foreign	0.148**	0.124	0.142**
	(0.068)	(0.078)	(0.066)
# of Children	0.018	0.014	0.033**
	(0.013)	(0.015)	(0.014)
C-zone: % Manuf (1990)	-0.014	0.019	0.031
	(0.021)	(0.023)	(0.024)
C-zone: % College Deg (1990)	-0.066***	-0.022	-0.057***
	(0.020)	(0.024)	(0.022)
C-zone: % Foreign (1990)	0.008	0.020	0.042
	(0.028)	(0.035)	(0.030)
C-zone: % Black (1990)	-0.006	0.040	-0.0005
	(0.021)	(0.025)	(0.024)
C-zone: % Hispanic (1990)	-0.058*	-0.043	-0.032
	(0.031)	(0.038)	(0.033)
Import Exposure × Job Immobility	0.038***	0.037***	0.019
	(0.012)	(0.014)	(0.012)
Fixed-effects			
stab	Yes	Yes	Yes
Year	Yes	Yes	Yes
indus1DIG	Yes	Yes	Yes
Fit statistics			
Observations	6,043	4,752	5,998
R^2	0.36	0.34	0.26
Within R^2	0.10	0.08	0.10

Clustered (clust) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table SI.7: Xenophobia regression results: Figure 7 - Economy

Model:	Immigrants do not improve America's economy (1)	Immigrants take jobs away from Americans (2)	Immigrants lead to lower economic growth (3)	Immigrants lead to higher unemployment (4)
Variables				
Import Exposure	-0.011	-0.028	0.0005	-0.027
	(0.031)	(0.026)	(0.067)	(0.055)
Job Immobility	0.012	0.025	-0.027	0.014
	(0.018)	(0.018)	(0.030)	(0.031)
Mar: Widowed	0.049	0.043	-0.028	0.048
	(0.068)	(0.063)	(0.113)	(0.148)
Mar: Divorced	0.0008	0.004	0.113	-0.007
	(0.046)	(0.048)	(0.079)	(0.079)
Mar: Separated	-0.0004	0.014	0.095	-0.027
	(0.081)	(0.089)	(0.148)	(0.155)
Mar: Never Married	-0.031	0.036	-0.219**	0.080
	(0.051)	(0.047)	(0.087)	(0.079)
Educ: High School	0.334***	0.333***	0.164**	0.373***
	(0.044)	(0.047)	(0.073)	(0.076)
Educ: Less than HS	0.418***	0.608***	0.091	0.431***
	(0.059)	(0.057)	(0.098)	(0.090)
Educ: Some Coll	0.226***	0.241***	0.184***	0.338***
	(0.039)	(0.040)	(0.070)	(0.075)
Race: Black	0.034	0.196***	-0.261**	0.062
	(0.056)	(0.057)	(0.107)	(0.098)
Race: Other	-0.174**	-0.113	-0.365**	-0.422**
	(0.075)	(0.074)	(0.148)	(0.169)
Gender: Female	0.147***	0.022	-0.105	0.043
	(0.036)	(0.036)	(0.068)	(0.062)
Party: Democrat	0.171***	0.096*	0.054	0.230**
	(0.057)	(0.056)	(0.101)	(0.089)
Party: Lean Dem	0.145**	0.033	0.042	0.183
	(0.065)	(0.062)	(0.114)	(0.126)
Party: Independent	0.217***	0.226***	0.151	0.153
	(0.060)	(0.060)	(0.114)	(0.121)
Party: Lean Rep	0.194***	0.178**	0.064	0.296***
	(0.071)	(0.072)	(0.125)	(0.109)
Party: Republican	0.183***	0.184***	0.218*	0.290***
	(0.061)	(0.062)	(0.113)	(0.103)
Party: Strong Rep	0.138**	0.159**	0.088	0.313***
	(0.066)	(0.066)	(0.124)	(0.118)
Party: Other	0.293**	0.216*	0.169	0.206
	(0.122)	(0.121)	(0.233)	(0.242)
Age: 30-40yrs	0.008	-0.027	-0.061	0.161*
	(0.054)	(0.053)	(0.092)	(0.084)
Age: 40-50yrs	-0.043	-0.026	-0.050	0.058
	(0.055)	(0.057)	(0.095)	(0.094)
Age: 50-64yrs	-0.131**	0.013	0.171	0.107
	(0.059)	(0.060)	(0.109)	(0.104)
Age: 65+yrs	-0.215***	-0.044	0.133	-0.116
	(0.068)	(0.071)	(0.130)	(0.123)
Born: Not US	-0.404***	-0.433***	-0.269	-0.209
	(0.076)	(0.078)	(0.163)	(0.224)
Parents Born: Both US	0.341***	0.363***	0.131	0.060
	(0.075)	(0.075)	(0.134)	(0.185)
Parents Born: One Foreign	0.234**	0.169*	0.058	0.042
	(0.101)	(0.099)	(0.154)	(0.222)
# of Children	0.015	0.015	0.005	-0.006
	(0.020)	(0.020)	(0.037)	(0.037)
C-zone: % Manuf (1990)	0.025	-0.0005	-0.106*	-0.044
	(0.031)	(0.029)	(0.054)	(0.065)
C-zone: % College Deg (1990)	-0.079**	-0.064**	-0.118**	-0.119**
	(0.031)	(0.032)	(0.052)	(0.050)
C-zone: % Foreign (1990)	0.055	0.097**	-0.031	-0.038
	(0.045)	(0.046)	(0.074)	(0.059)
C-zone: % Black (1990)	-0.015	-0.048	-0.084	0.069
	(0.036)	(0.038)	(0.055)	(0.042)
C-zone: % Hispanic (1990)	-0.126**	-0.113**	-0.043	-0.051
	(0.049)	(0.050)	(0.076)	(0.056)
Import Exposure × Job Immobility	0.041**	0.037**	0.051*	0.013
	(0.018)	(0.017)	(0.030)	(0.031)
Fixed-effects				
stab	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
indus1DIG	Yes	Yes	Yes	Yes
Fit statistics				
Observations	3,392	3,447	1,257	1,295
R^2	0.18	0.18	0.14	0.11
Within R^2	0.11	0.12	0.08	0.06

Clustered (clust) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table SI.8: Xenophobia regression results: Figure 7 - Competition

Model:	Gov spends too much assisting immigrants (1)	Illegal immigrants should not get work permits (2)	Immigrants should not receive special favors (3)	Immigrants get too demanding (4)
Variables				
Import Exposure	-0.019	-0.032	0.003	-0.004
	(0.042)	(0.053)	(0.060)	(0.054)
Job Immobility	0.024	-0.031	0.020	-0.026
	(0.028)	(0.032)	(0.028)	(0.027)
Mar: Widowed	0.079	-0.219*	-0.142	0.049
	(0.115)	(0.128)	(0.092)	(0.124)
Mar: Divorced	0.046	-0.066	0.079	0.055
	(0.084)	(0.082)	(0.073)	(0.072)
Mar: Separated	-0.074	-0.030	-0.088	-0.143
	(0.161)	(0.165)	(0.148)	(0.139)
Mar: Never Married	0.027	-0.182**	-0.142*	-0.101
	(0.094)	(0.088)	(0.082)	(0.076)
Educ: High School	0.228***	0.010	0.424***	0.511***
	(0.084)	(0.069)	(0.069)	(0.072)
Educ: Less than HS	0.364***	-0.027	0.403***	0.642***
	(0.105)	(0.100)	(0.101)	(0.082)
Educ: Some Coll	0.210***	0.057	0.385***	0.336***
	(0.075)	(0.084)	(0.078)	(0.070)
Race: Black	0.176	-0.101	-0.447***	0.123
	(0.108)	(0.112)	(0.120)	(0.095)
Race: Other	-0.359***	-0.024	-0.184	-0.098
	(0.131)	(0.177)	(0.163)	(0.165)
Gender: Female	-7.59×10^{-5}	-0.128**	-0.012	0.106*
	(0.059)	(0.065)	(0.055)	(0.061)
Party: Democrat	0.394***	0.180*	0.201*	0.163*
	(0.089)	(0.103)	(0.112)	(0.088)
Party: Lean Dem	0.096	0.063	0.096	-0.048
	(0.127)	(0.119)	(0.126)	(0.109)
Party: Independent	0.476***	0.155	0.357***	0.147
	(0.094)	(0.127)	(0.116)	(0.113)
Party: Lean Rep	0.404***	0.186*	0.315**	0.436***
	(0.120)	(0.111)	(0.141)	(0.112)
Party: Republican	0.531***	0.388***	0.472***	0.411***
	(0.105)	(0.111)	(0.105)	(0.096)
Party: Strong Rep	0.736***	0.282**	0.490***	0.371***
	(0.109)	(0.115)	(0.134)	(0.116)
Party: Other	0.639*	0.085	-0.352	-0.179
	(0.350)	(0.245)	(0.318)	(0.263)
Age: 30-40yrs	0.125	0.038	-0.013	0.120
	(0.096)	(0.095)	(0.090)	(0.093)
Age: 40-50yrs	0.203**	0.013	-0.040	0.046
	(0.101)	(0.104)	(0.100)	(0.105)
Age: 50-64yrs	0.196**	-0.004	0.109	0.245**
	(0.095)	(0.110)	(0.097)	(0.116)
Age: 65+yrs	0.155	0.075	0.298***	0.407***
	(0.118)	(0.117)	(0.112)	(0.128)
Born: Not US	-0.237	-0.076	0.152	-0.086
	(0.152)	(0.179)	(0.166)	(0.158)
Parents Born: Both US	0.613***	0.300**	0.124	0.074
	(0.141)	(0.150)	(0.157)	(0.140)
Parents Born: One Foreign	0.600***	0.017	0.146	0.058
	(0.225)	(0.201)	(0.185)	(0.176)
# of Children	0.0003	0.055*	0.040	0.016
	(0.034)	(0.033)	(0.033)	(0.034)
C-zone: % Manuf (1990)	0.080	-0.010	-0.025	-0.008
	(0.054)	(0.052)	(0.060)	(0.058)
C-zone: % College Deg (1990)	0.007	0.077	-0.029	-0.086*
	(0.061)	(0.053)	(0.058)	(0.051)
C-zone: % Foreign (1990)	0.066	-0.038	0.017	-0.062
	(0.092)	(0.077)	(0.085)	(0.080)
C-zone: % Black (1990)	-0.075	-0.014	0.095	0.143**
	(0.086)	(0.058)	(0.060)	(0.056)
C-zone: % Hispanic (1990)	0.037	0.019	-0.024	0.073
	(0.125)	(0.070)	(0.078)	(0.087)
Import Exposure × Job Immobility	0.087***	0.071**	0.021	0.036
	(0.026)	(0.029)	(0.025)	(0.025)
Fixed-effects				
stab	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
indus1DIG	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,096	1,286	1,312	1,275
R^2	0.28	0.09	0.17	0.18
Within R^2	0.19	0.06	0.12	0.13

Clustered (clust) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table SI.9: Xenophobia regression results: Figure 7 - Culture

Model:	Immigrants do not make U.S. open to new ideas (1)	Immigrants don't improve American society (2)	Immigrants make it harder to keep united (3)	Exposure to foreign culture damages our own (4)
Variables				
Import Exposure	-0.031	0.006	0.002	-0.013
	(0.043)	(0.057)	(0.046)	(0.049)
Job Immobility	0.019	0.004	0.0008	0.043
	(0.020)	(0.031)	(0.021)	(0.032)
Mar: Widowed	0.022	0.046	0.206**	0.399***
	(0.080)	(0.139)	(0.081)	(0.142)
Mar: Divorced	-0.033	-0.044	0.018	0.047
	(0.056)	(0.089)	(0.062)	(0.077)
Mar: Separated	0.161	-0.038	-0.064	0.099
	(0.107)	(0.157)	(0.107)	(0.158)
Mar: Never Married	-0.022	-0.068	-0.030	-0.048
	(0.057)	(0.088)	(0.062)	(0.085)
Educ: High School	0.379***	0.497***	0.377***	0.467***
	(0.054)	(0.078)	(0.056)	(0.083)
Educ: Less than HS	0.550***	0.525***	0.413***	0.852***
	(0.076)	(0.130)	(0.065)	(0.121)
Educ: Some Coll	0.285***	0.267***	0.228***	0.248***
	(0.046)	(0.079)	(0.054)	(0.079)
Race: Black	0.114	0.056	0.070	0.368***
	(0.078)	(0.092)	(0.068)	(0.093)
Race: Other	-0.070	-0.047	-0.082	0.005
	(0.095)	(0.135)	(0.103)	(0.140)
Gender: Female	0.094**	-0.006	0.075	-0.165***
	(0.042)	(0.064)	(0.047)	(0.061)
Party: Democrat	0.085	0.170*	-0.053	0.082
	(0.075)	(0.090)	(0.064)	(0.093)
Party: Lean Dem	-0.004	-0.058	-0.084	-0.235*
	(0.085)	(0.119)	(0.080)	(0.125)
Party: Independent	0.110	0.222**	-0.011	0.270**
	(0.079)	(0.096)	(0.070)	(0.106)
Party: Lean Rep	0.106	0.057	0.067	0.023
	(0.089)	(0.127)	(0.081)	(0.118)
Party: Republican	0.211***	0.225**	0.151**	0.197*
	(0.081)	(0.103)	(0.074)	(0.103)
Party: Strong Rep	0.187**	0.307***	0.154*	0.403***
	(0.082)	(0.093)	(0.087)	(0.106)
Party: Other	0.236*	0.167	-0.317*	0.084
	(0.140)	(0.268)	(0.184)	(0.245)
Age: 30-40yrs	-0.051	0.040	-0.008	0.059
	(0.066)	(0.102)	(0.064)	(0.106)
Age: 40-50yrs	-0.117*	-0.024	-0.089	0.009
	(0.069)	(0.106)	(0.068)	(0.097)
Age: 50-64yrs	-0.108	0.015	0.064	-0.013
	(0.072)	(0.107)	(0.073)	(0.111)
Age: 65+yrs	-0.056	-0.197	0.072	0.169
	(0.087)	(0.131)	(0.084)	(0.118)
Born: Not US	-0.237**	-0.159	0.008	-0.053
	(0.098)	(0.163)	(0.116)	(0.147)
Parents Born: Both US	0.391***	0.387***	0.241**	-0.082
	(0.097)	(0.148)	(0.103)	(0.132)
Parents Born: One Foreign	0.236**	0.175	0.191*	-0.238
	(0.118)	(0.190)	(0.114)	(0.175)
# of Children	0.090***	0.045	0.013	0.046
	(0.022)	(0.036)	(0.024)	(0.037)
C-zone: % Manuf (1990)	-0.049	0.220***	0.068	0.032
	(0.040)	(0.059)	(0.048)	(0.058)
C-zone: % College Deg (1990)	-0.051	0.057	-0.035	-0.187***
	(0.039)	(0.067)	(0.039)	(0.064)
C-zone: % Foreign (1990)	-0.038	0.072	0.027	0.039
	(0.053)	(0.092)	(0.054)	(0.096)
C-zone: % Black (1990)	-0.028	0.081	0.037	0.105
	(0.043)	(0.099)	(0.046)	(0.090)
C-zone: % Hispanic (1990)	0.017	-0.025	0.019	-0.138
	(0.054)	(0.104)	(0.054)	(0.109)
Import Exposure × Job Immobility	0.054**	-0.002	0.019	0.041
	(0.024)	(0.033)	(0.021)	(0.037)
Fixed-effects				
stab	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
indus1DIG	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,321	1,107	2,485	1,090
R^2	0.15	0.20	0.13	0.23
Within R^2	0.10	0.11	0.06	0.18

Clustered (clust) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

8 Job Immobility compared to other measures

Our proposed measure incorporates three dimensions of job immobility: tasks, industry, and geography. However, there is a flourishing literature that examines the sensitivity of political beliefs and opinions to occupation-based measures of labor market vulnerability. Important contributions to this literature have been made by Owen and Quinn (2016) and Owen and Johnston (2017) (see also Owen 2020). These approaches focus specifically on two characteristics of an individual's occupation: routine task intensity (RTI) and offshorability. The results demonstrate a persistent association between an individual's labor market vulnerability and a battery of politically-relevant opinions, including support for trade protection, belief that trade leads to better products becoming available, attitudes toward multinational corporations, and finally beliefs that immigrants take jobs away from local workers. They find consistent support for their interaction term that captures the marginal effect of job routineness on beliefs across workers in differing levels of offshorability on all outcomes, excepting views toward immigrants.

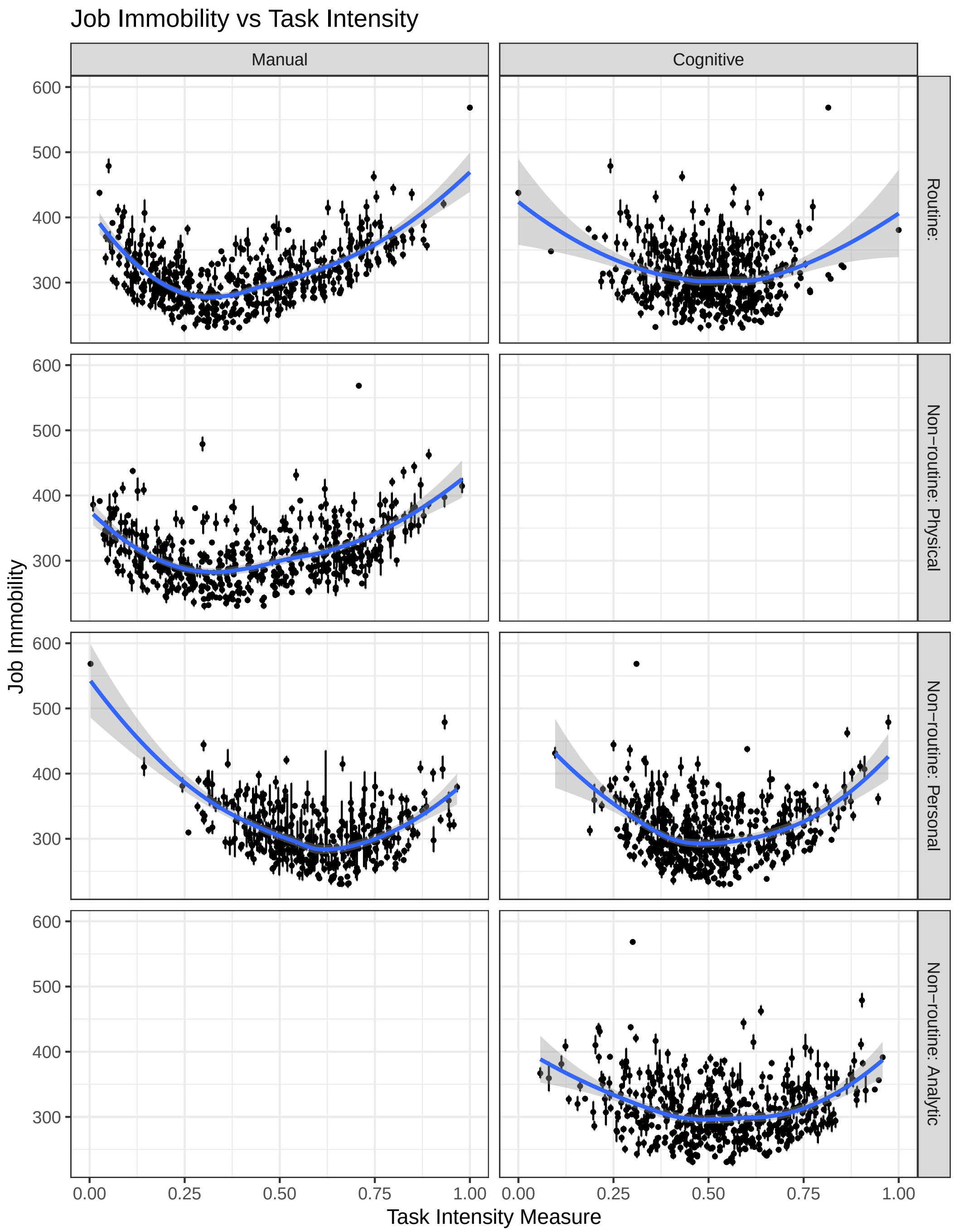
Conceptually, one might expect our measure to be highly correlated with these occupation-specific measures of vulnerability. After all, we share a common interest in labor market position and how those in vulnerable positions adopt different views on politically relevant issues. Yet at the same time, our measure incorporates two additional dimensions of labor market vulnerability that the measures proposed in existing work neglect: geography and industry. Furthermore, our approach treats all measures of task intensity equally, focusing only on whether two occupations have (dis)similar intensities in certain tasks and skills.

Indeed, simple descriptive correlations (see Figure SI.14) indicate that our proposed risk measure diverges dramatically from occupation-specific measures of task intensity, and do so in revealing patterns. Specifically, our proposed measure of job immobility has an inverse-U shaped relationship with all measures of task intensity. Substantively, this reflects the nature of our measure, which defines immobility as increasing with more silo-ed occupations (i.e., those that use a given dimension of tasks either intensively or un-intensively). Note, however, the difference in the location of the nadir of our immobility measure by dimension. Whereas cognitive intensity of all dimensions minimizes job immobility at around 0.5, manual tasks exhibit a stark difference between routine and non-routine physical tasks – for which job immobility is minimized at lower levels – and non-routine personal tasks – for which job immobility is minimized at higher levels.

These patterns reflect crucial differences between our proposed measure and those that rely on occupation-specific measures of task intensity. Most importantly, our measure defines individuals as higher-risk if they work in occupations that are *either* low or highly intensive in routine tasks, especially manual work. Second, we highlight the pattern in which occupations that require relatively little routine manual tasks, or non-routine physical tasks, are where our immobility measure is minimized. Conversely, our measure is minimized among workers in occupations that require non-routine personal manual tasks relatively intensively. We posit that these differences reflect differences in the distribution of these occupations across geography and industry. Specifically, routine manual tasks are found in industries which are more centralized in particular industries and in particular locations in the United States, with little state-to-state or industry-to-industry flows. As such, occupations that require these skills relatively intensively are more immobile compared to occupations that use routine cognitive skills relatively intensively, since the latter are more diffuse, reducing the relocation costs across geography and industry. Conversely, we find no systematic pattern linking our measure of job immobility to the offshorability measure, as illustrated in Figure SI.15.

How do these differences translate into differences in our substantive findings? To test, we re-analyze all the main results, replacing our moderator of job immobility with measures of manual and cognitive routine task intensity, as well as with the offshorability measure. We plot the interaction coefficients in Figure SI.16, illustrating that the significant positive interaction terms – reflecting an increased propensity to espouse anti-globalist views or concerns about one's labor market position – are predominantly found with our measure, but not the alternatives. The major exception to this pattern is the interaction

Figure SI.14: Task Intensity and Job Immobility Scatter Plots

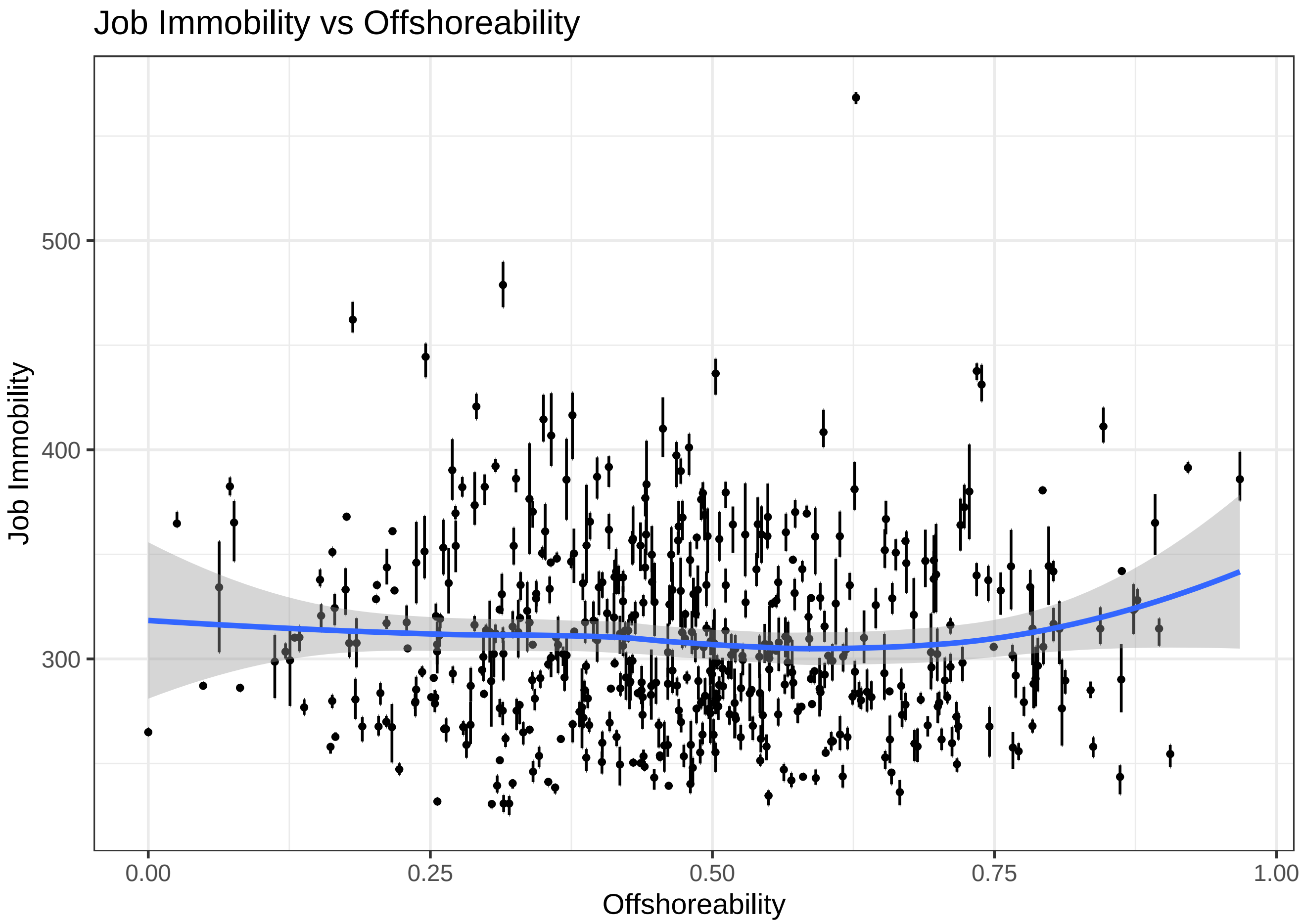


Scatter plots comparing each occupation's task intensity (x-axes) to the average job immobility measure (y-axes). Vertical bars indicate two standard deviations of job immobility, capturing the dispersion of the latter measure due to the location of respondents by state and by industry. Task intensity dimensions are divided into manual and cognitive (columns) and further subdivided by routine and non-routine tasks (rows).

term on manual RTI for protectionist views, which is positive, statistically significant, and of a magnitude commensurate to our job immobility measure. Interestingly, working in an offshorable occupation makes respondents *less* likely to espouse protectionist views in response to increasing import competition, although these estimates are not statistically significant at conventional thresholds.

As a final test of the robustness of our results, we re-run our main analyses controlling for the respon-

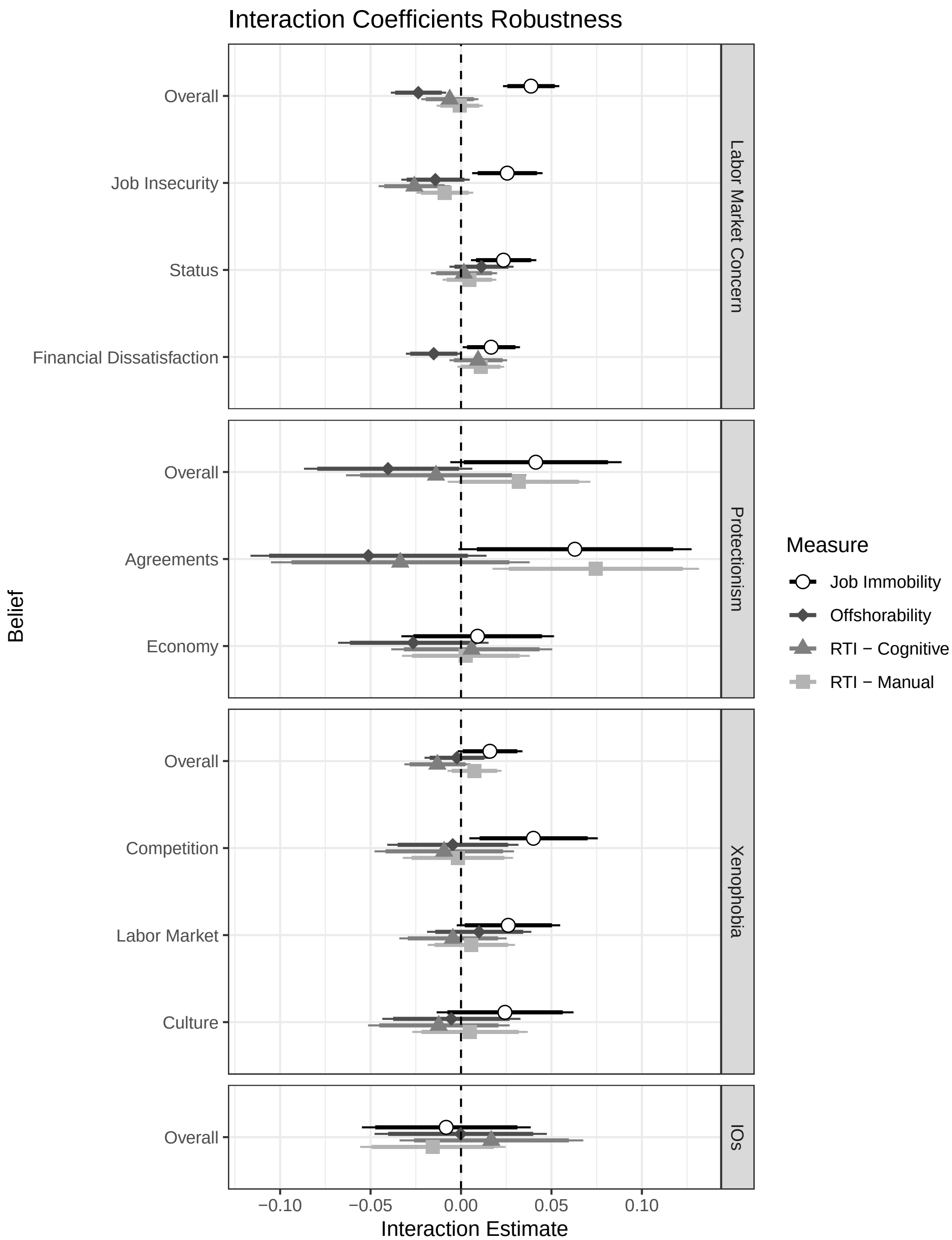
Figure SI.15: Offshorability and Job Immobility Scatter Plots



Scatter plots comparing each occupation's offshorability (x-axis) to the average job immobility measure (y-axis). Vertical bars indicate two standard deviations of job immobility, capturing the dispersion of the latter measure due to the location of respondents by state and by industry.

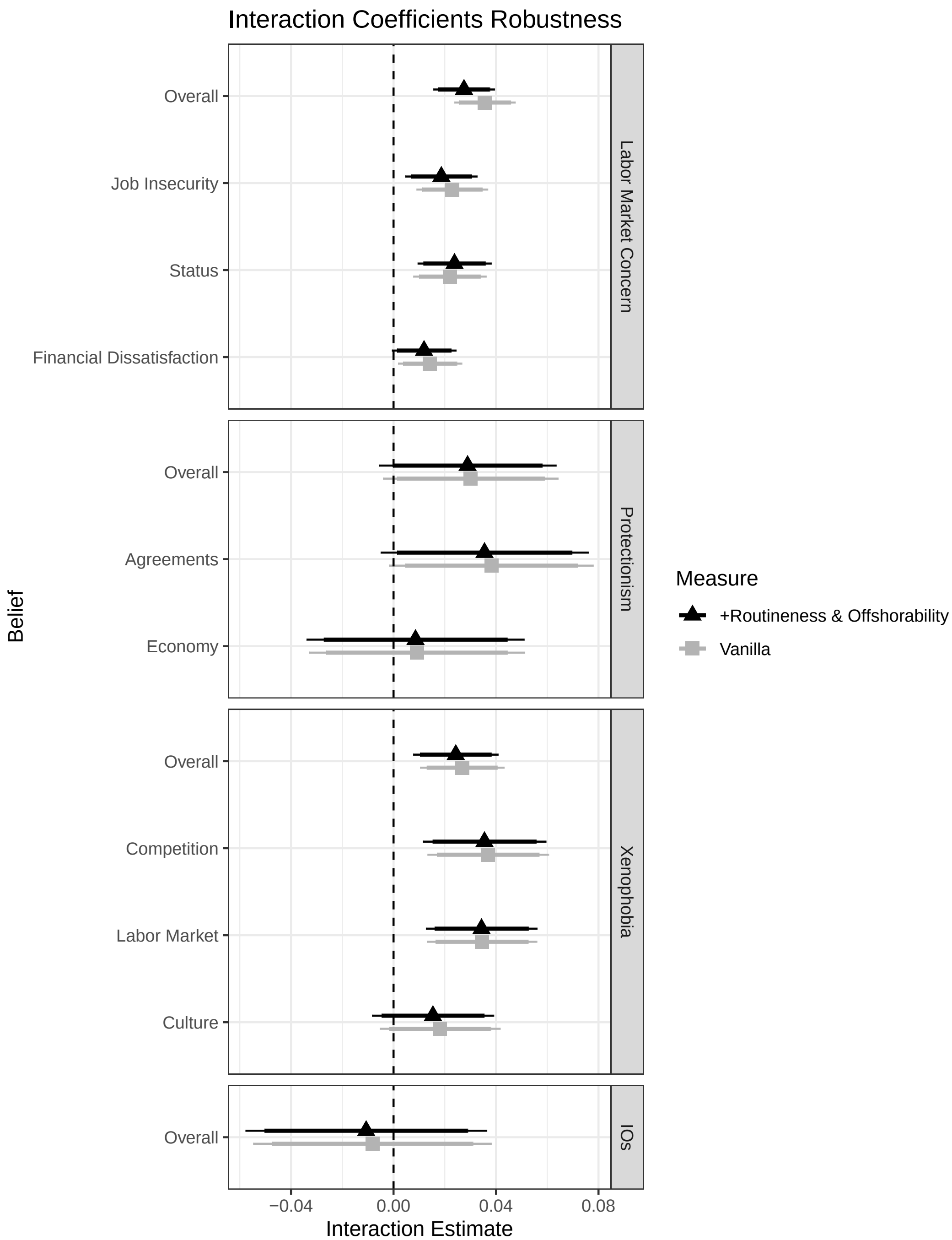
dent's task routineness and offshorability described above. We plot the main results with and without these included controls in Figure SI.17, revealing minimal changes to our estimates.

Figure SI.16: Comparing Job Immobility and RTI / Offshorability



Coefficient estimates (x-axis) of the interaction term capturing the extent to which exposure to import competition with China is increasingly prognostic of a bundle of anti-globalist views (y-axis) among respondents with higher levels of job immobility (white circles), offshorability (dark gray diamonds), cognitive RTI (grey triangles), and manual RTI (light grey squares).

Figure SI.17: RTI Control Robustness

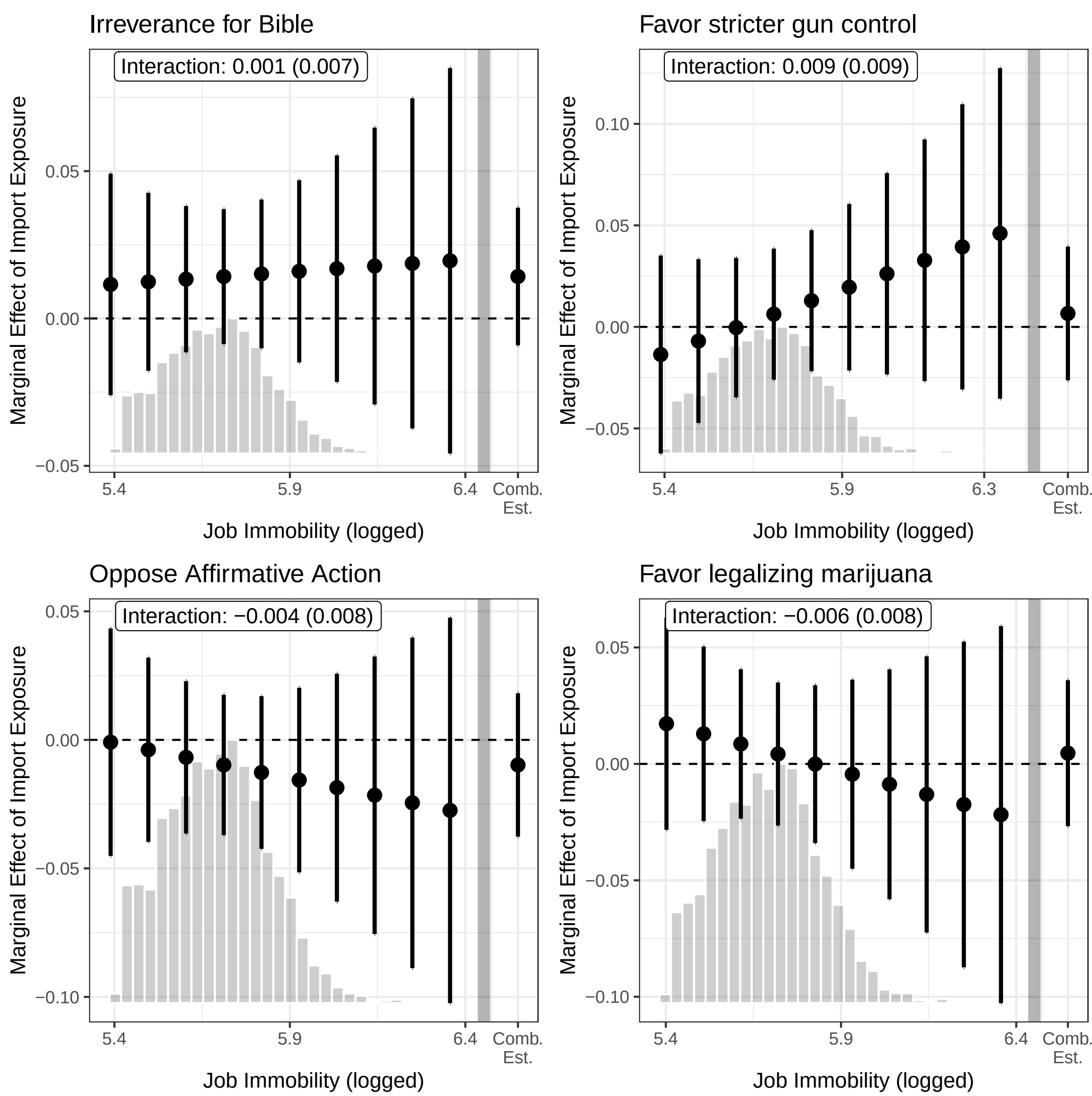


Coefficient estimates (x-axis) of the interaction term capturing the extent to which exposure to import competition with China is increasingly prognostic of a bundle of anti-globalist views (y-axis) among respondents with higher levels of job immobility, controlling for the measures of routineness and offshorability summarized in Figures SI.14 and SI.15.

9 Placebo Tests

Our main results presume that the twin experiences of job immobility and import competition prime respondents to adjust their views on a bundle of opinions related to globalization. However, it may be that these pressures simply make respondents more sensitive to all political opinions. To investigate, we run a series of four placebo tests, in which we identify questions asked consistently over the period of analysis about topics substantively unrelated to the flow of goods and people across international borders. Specifically, we predict views on gun control, legalization of marijuana, the Bible, and affirmative action as a function of job immobility interacted with import competition. As illustrated in Figure SI.18, none of these outcomes are meaningfully related with import competition, nor is this null marginal effect meaningfully influenced by the respondent's job immobility.

Figure SI.18: Placebo tests



Marginal effects of import competition (y-axes) on a battery of placebo opinions (panels) across levels of occupational immobility (x-axes), R^i_{jns}. Interaction coefficient and standard error indicated in top-left of each panel.

10 Perceptions of Labor Market Insecurity

Our main results demonstrate two patterns we argue are consistent with our story of import competition interacting with occupational immobility to influence a bundle of politically relevant beliefs on globalization via the pathway of increased anxiety. First, we show that respondents exposed to import competition whose occupational immobility is high are more likely to indicate subjective concern with their labor market position. This result indicates that the pathway is open. Second, we show that this same interaction specification also predicts differences in views on trade and immigration that cohere to a bundled set of anti-globalist views.

Given our empirical setting, causally identifying just the overall relationship between labor market insecurity and anti-globalist views is challenging. Further identifying the average causal mediation effect (ACME) that operates via the *perception* of these labor market pressures requires even more heroic assumptions. In the following section, we provide suggestive – albeit unidentified – evidence of this pathway, via three complementary analyses.

First, we make the heroic assumption that sequential ignorability holds, and re-run our main specification, replacing our measure of job immobility with subjective assessments of labor market risk. Formally, we estimate an interacted specification of the form:

$$y^i_{nst} = \alpha_s + \delta_t + \beta_1 IE^i_{nt} + \beta_2 SUBJ^i_t + \beta_3 IE^i_{nt} \times SUBJ^i_t + \beta_4 \mathbf{X}^i + \beta_5 \mathbf{C}^i_{t_{pre}} + \epsilon^i_{nst} \qquad \text{(SI.2)}$$

Note that this specification can be interpreted in two ways, although neither are supported by the data. First, we might imagine this as a moderator analysis, in which case the $SUBJ^i_t$ variable should be considered pre-treatment to the import competition measure (which is clearly implausible). Second, we might imagine this as a naive mediation analysis, in which case the $SUBJ^i_t$ variable would be assumed to be causally affected by import competition, and furthermore that it is unconfounded conditional on the observed value of the import competition treatment (sequential ignorability).

Despite these clear data limitations, we nevertheless present our estimates from equation (SI.2) in Figure SI.19. As illustrated, there is little evidence of a systematic relationship between import competition and subjective assessments of labor market insecurity. While the interaction terms are positive, they are noisily estimated. Furthermore, none of the marginal effect coefficients are differ significantly from zero at conventional thresholds. Given the number of possible confounders that might influence self-reported feelings of labor market anxiety, these results should be viewed with a grain of salt.

An alternative approach to probing the mechanism of anxiety is via instrumental variable analysis. Specifically, we treat the interaction between import competition and occupational immobility as an instrumental variable for the respondent's subjective assessment of the fragility of their position in the labor market, which we then use to predict their views on the same bundle of anti-globalist beliefs. Mechanically, this use of an IV means that we only exploit variation in the subjective assessment of labor market risk that is correlated with the interaction between import competition and job immobility. But theoretically, we are unlikely to validate the necessary exclusion restriction assumption, which states that import competition and job immobility can *only* influence anti-globalist beliefs via the pathway of the respondent's subjective assessment.

Nevertheless, when we exploit only the variation in these self-reported feelings of labor market anxiety that is associated with import competition and occupational immobility, we find much stronger evidence linking subjective experiences and anti-globalist views. Figure SI.20 displays the coefficients from our IV regression where each point is sized and labeled according to the first-stage strength of the instrument (import competition interacted with occupational immobility). We further separate out which components of the immobility measure matter most, moving from the full measure in the left facet, to focusing only on the industry-based component (center panel) and the geography-based component (right panel). As indicated by the larger first-stage F-statistics, it seems that labor market anxiety is most strongly associated with the geographic component of occupational immobility, and that this aspect of self-reported

Figure SI.19: Marginal effect plots of interacting the trade shock measure with self-reported labor market anxiety.

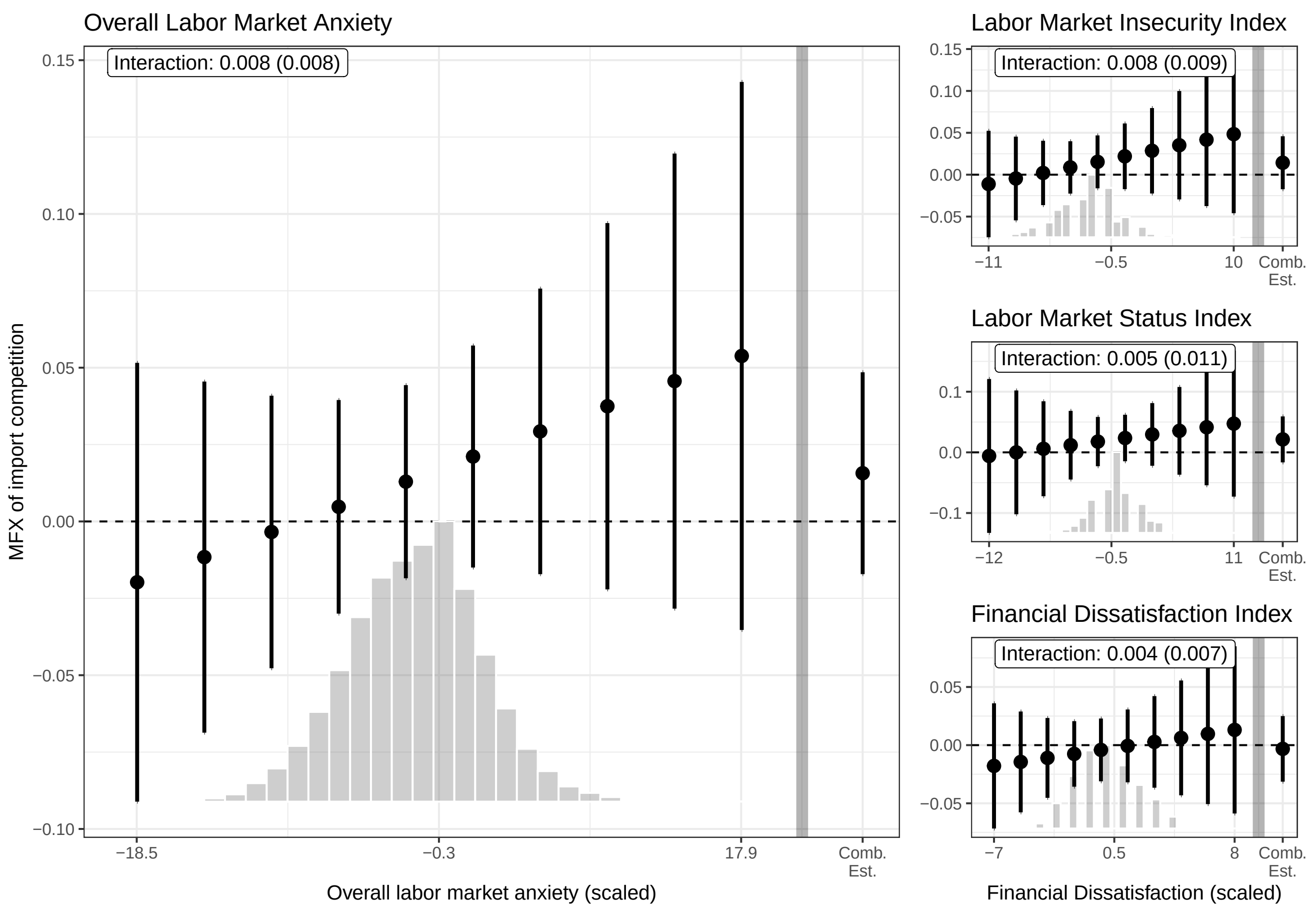
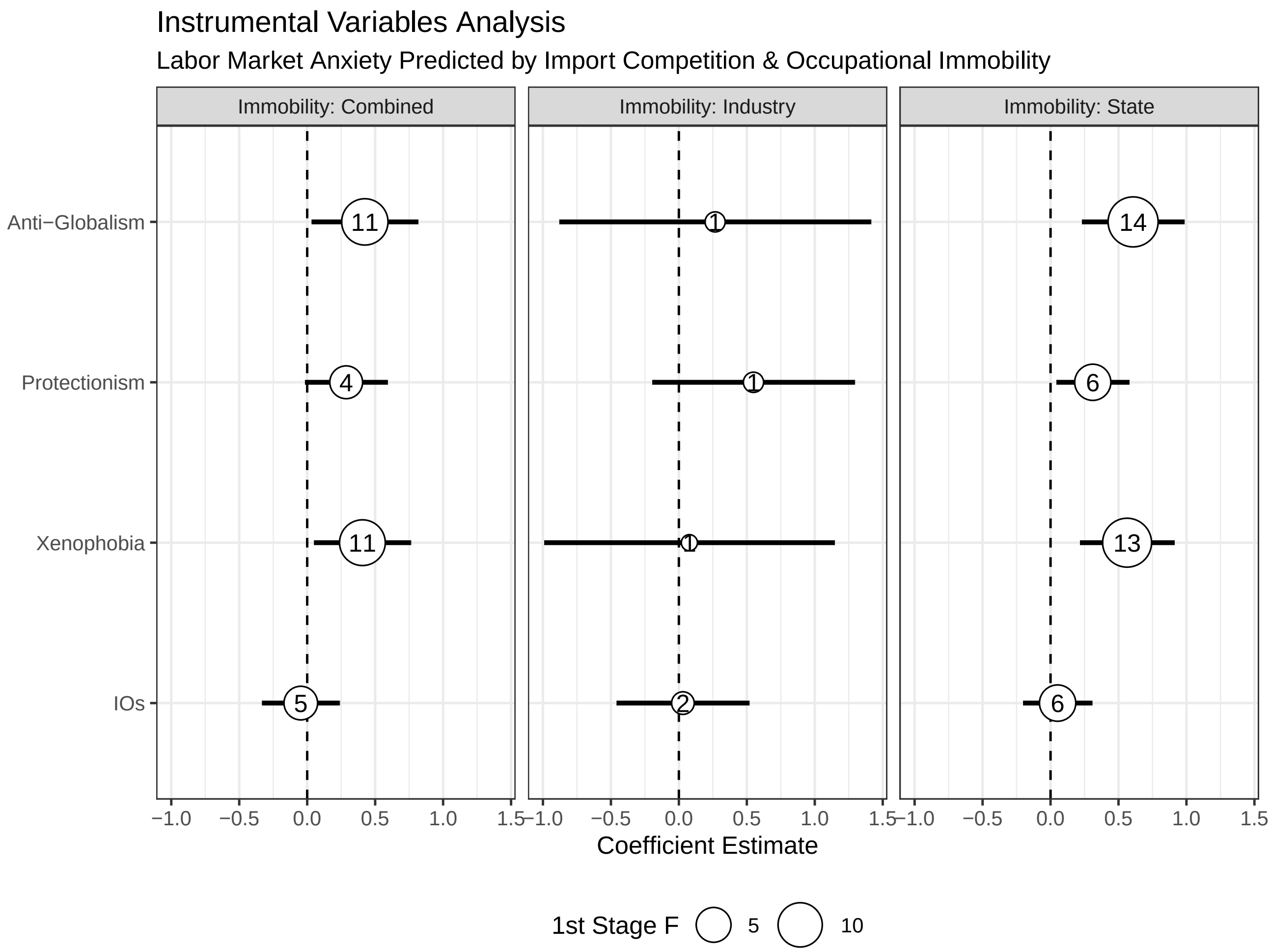


Figure SI.20: IV results predicting attitudes toward anti-globalist bundles (y-axes) based on the component of self-reported labor market anxiety that is predicted by import competition interacted with occupational immobility, where the latter is separated out into its industry-based dimension (center panel), its geography-based dimension (right panel), and the combination of the two (left panel).



anxiety is highly prognostic of anti-globalist views, in particular xenophobia and protectionism. Again, we find little evidence of an association with attitudes toward international organizations.

11 Shift Share Interpretation

Our interaction specification is characteristic of the "shift-share" or Bartik approach, where a time varying component (the change in imports per worker, or shift) is distributed across regions or districts (share). To describe this connection, we reproduce some of the core equations from our main text.

Recall that our primary component of risk weights the euclidean distance (d_{jk}) between any two occupations j (the respondent i's current or most recent occupation) and k (a potential new occupation), with the share of occupation k in the respondent's current state or industry. For example, for occupation j in state s, we take the weighted average distance between j and all other occupations k where the weights are given by k's share of total employment in the respondent's current state s. Formally:

$$\sigma_{js} = \sum_{k \in \mathcal{J}} \left(d_{jk} * \frac{L_{ks}}{L_s} \right)$$

where L_{ks} is the total jobs in occupation k in state s, and L_s is the total jobs in state s. This yields an immobility measure σ_{js} which is larger for when an individual is employed in an occupation j that uses very different skills from other occupations in the same state.

An analogous measure can be weighted instead by the share of all jobs in her industry n that are of occupation k.

$$\sigma_{jn} = \sum_{k \in \mathcal{J}} \left(d_{jk} * \frac{L_{kn}}{L_n} \right)$$

These two measures represent the difficulty an individual i may face in finding a new job in the same state or industry that the respondent is currently employed in. Unfortunately, data availability means that we cannot calculate the three-way share of occupation k in industry n in state s. If we only relied on these measures, it would be tantamount to assuming that labor is completely immobile between states or across industries.

To relax this assumption, we augment these with the job-to-job data. These data allow us to calculate the above metrics for any state q and any industry m by weighting these choices based on the empirically observed job flows. Denote a job flow from i's home state s to q by ΔL_{sq} (and analogously from i's industry n to m by ΔL_{nm}). Denote the sum of labor outflows from i's state s to all other states as $P_{s \to q}$, and from i's industry n to all other industries by $P_{n \to m}$.

Define

$$\sigma_{jsq} = \sum_{k} \left(d_{jk} * \frac{L_{kq}}{L_q} * P_{s \to q} \right)$$

Analogously, for occupation j in industry n, we take the weighted average distance between j and all other occupations k in a different industry m, where the weights are given by the share of total J2J flows that go from n to m. Formally:

$$\sigma_{jnm} = \sum_{k} \left(d_{jk} * \frac{L_{km}}{L_m} * P_{n \to m} \right)$$

Each of these immobility components σ_{js}, σ_{jsq}, σ_{jn}, and σ_{jnm} correspond to different barriers to transitioning between a job in occupation j in industry n in state s and a new job. σ_{js} captures the difficulty in finding new work in the same state. σ_{jsq} captures the difficulty in finding new work in a different state. σ_{jn} captures the difficulty in finding new work in the same industry. And σ_{jnm} captures the difficulty in finding new work in a different industry.

Summing across all potential US states, we obtain a measure of occupational immobility for an individual working in occupation j in state s:

$$\begin{aligned}
\sigma_{js}^{\mathcal{S}} &= \sum_q \sigma_{jsq} \\
&= \sum_q \sum_k \left(d_{jk} * \frac{L_{kq}}{L_q} * P_{s \to q} \right)
\end{aligned} \tag{SI.3}$$

Summing across all industries provides a measure of industry-based occupational immobility:

$$\begin{aligned}
\sigma_{jn}^{\mathcal{N}} &= \sum_m \sigma_{jnm} \\
&= \sum_m \sum_k \left(d_{jk} * \frac{L_{km}}{L_m} * P_{n \to m} \right)
\end{aligned} \tag{SI.4}$$

We calculate our final measure of occupational immobility as simply the mean[2] of these two measures.

$$\sigma_{jns}^{i} = \frac{1}{2} \left(\sigma_{js}^{\mathcal{S}} + \sigma_{jn}^{\mathcal{N}} \right) \tag{SI.5}$$

From equations SI.3 and SI.4, we can write the interactions as follows:

$$\begin{aligned}
\sigma_{js}^{\mathcal{S}} * \Delta M_{nt} &= \sum_q \left[\sum_k \left(d_{jk} * L_{kq} * P_{s \to q} \right) \right] * \frac{\Delta M_{nt}}{L_q} \\
\sigma_{jn}^{\mathcal{N}} * \Delta M_{nt} &= \sum_m \left[\sum_k \left(d_{jk} * L_{km} * P_{n \to m} \right) \right] * \frac{\Delta M_{nt}}{L_m}
\end{aligned}$$

The change in imports per worker in a state or an industry (the shift) is allocated to workers differentially – with more to those workers with higher immobility. A greater share of the shift is allocated to workers whose jobs are more distant to other jobs in task, geography or industry space. Notice that the volume of imports in an industry is effectively normalized by the size of the industry or state with the interaction term.

12 International Organizations

We find consistent evidence suggesting that two dimensions of the anti-globalist wave correlated with import competition among those whose jobs are least mobile: protectionism and xenophobia. However, we find no support for similar patterns on the third theorized dimension of the anti-globalist wave: attitudes toward international organizations. In our manuscript, we suggest that these null results may reflect the lack of coherent elite cues or party ownership on this dimension of globalization (Katitas 2019, Kuk, Seligsohn, and Zhang 2022). Instead, we posit that the constitutive dimensions of anti-IO attitudes are better explained by the traditional left-right ideological dimension as it exists in the United States.

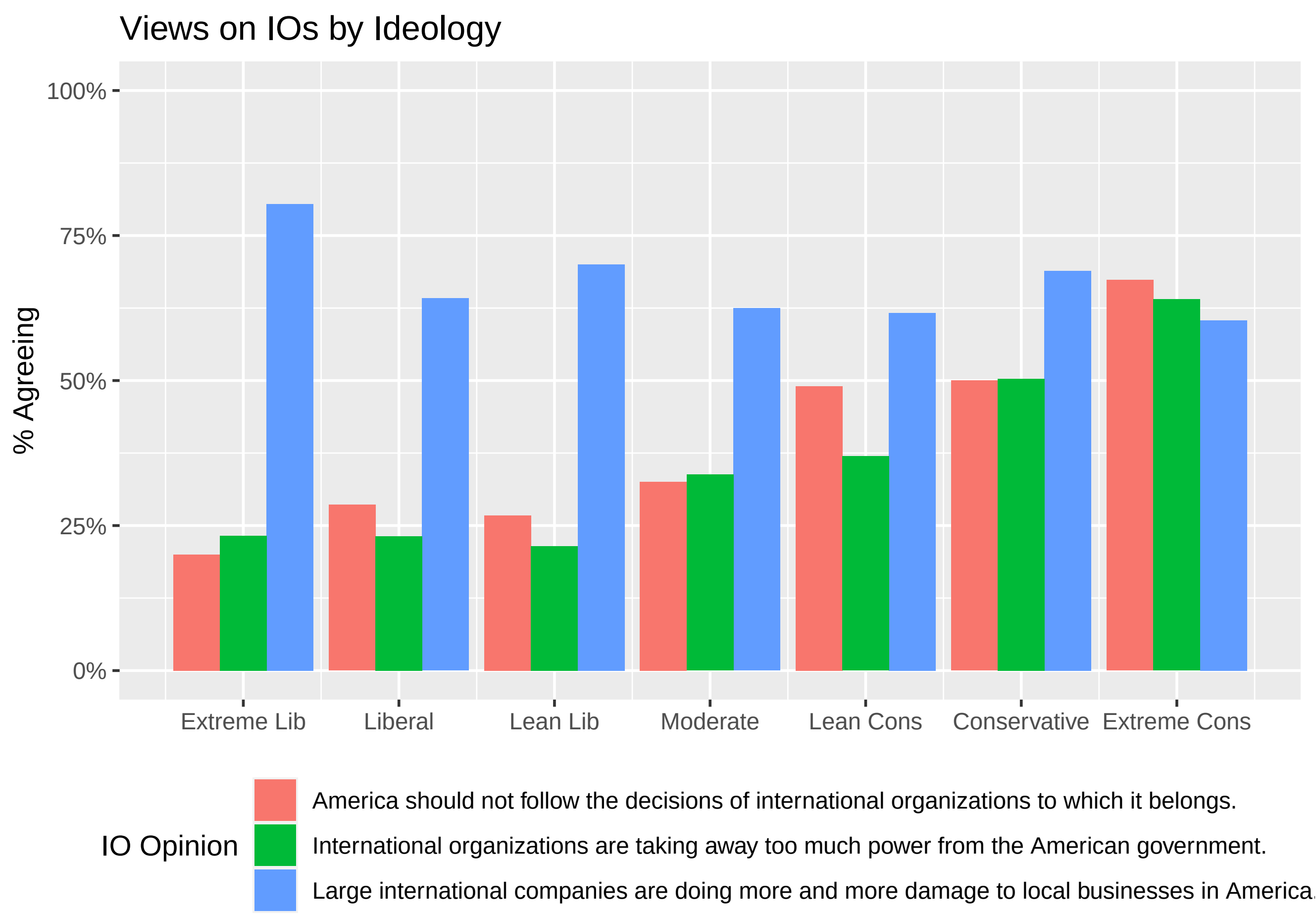
Specifically, attitudes toward international companies are subsumed by liberal antipathy toward large corporations, while attitudes toward the relative power of international organizations are subsumed by the conservative-owned dimension of American sovereignty and independence in international affairs. With ideology explaining the majority of views on these dimensions, there is little variation left for our measures of trade shocks and job immobility to explain.

We provide descriptive evidence in support of this conclusion in Figure SI.21, which summarizes the proportion of respondents agreeing with three anti-globalist measures (y-axis) by self-reported ideology (x-axis). As illustrated, we confirm that views on international organizations are roughly correlated

[2] Unfortunately job data that is binned by occupation, state, and industry together is not available.

with self-reported ideology, showing that negative views of international companies are stronger on the ideological left, while attitudes toward international organizations – specifically their infringement on U.S. sovereignty – are more negative on the ideological right.

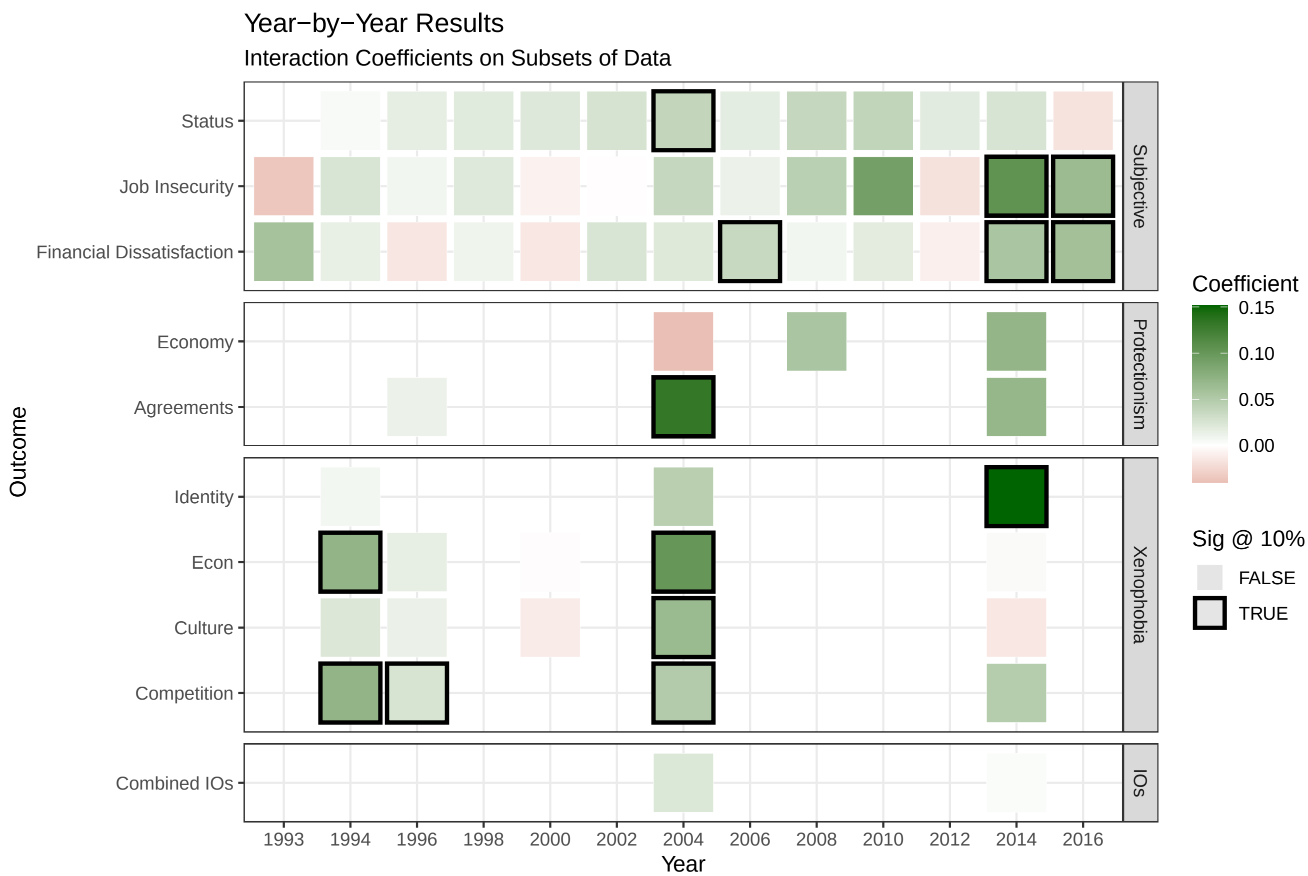
Figure SI.21: Proportion of respondents agreeing with three questions about international organizations (y-axis), divided by ideology (x-axis).



13 Year-by-Year Results

Our main analysis pools our data over all survey waves in which different outcomes of interest were asked. We account for secular trends over time via year fixed effects. However, we can also re-run our main specification year-by-year, as visualized in Figure SI.22 where each tile indicates the interaction coefficient and is outlined in thick black bars where it is significant at the 90% level of confidence.

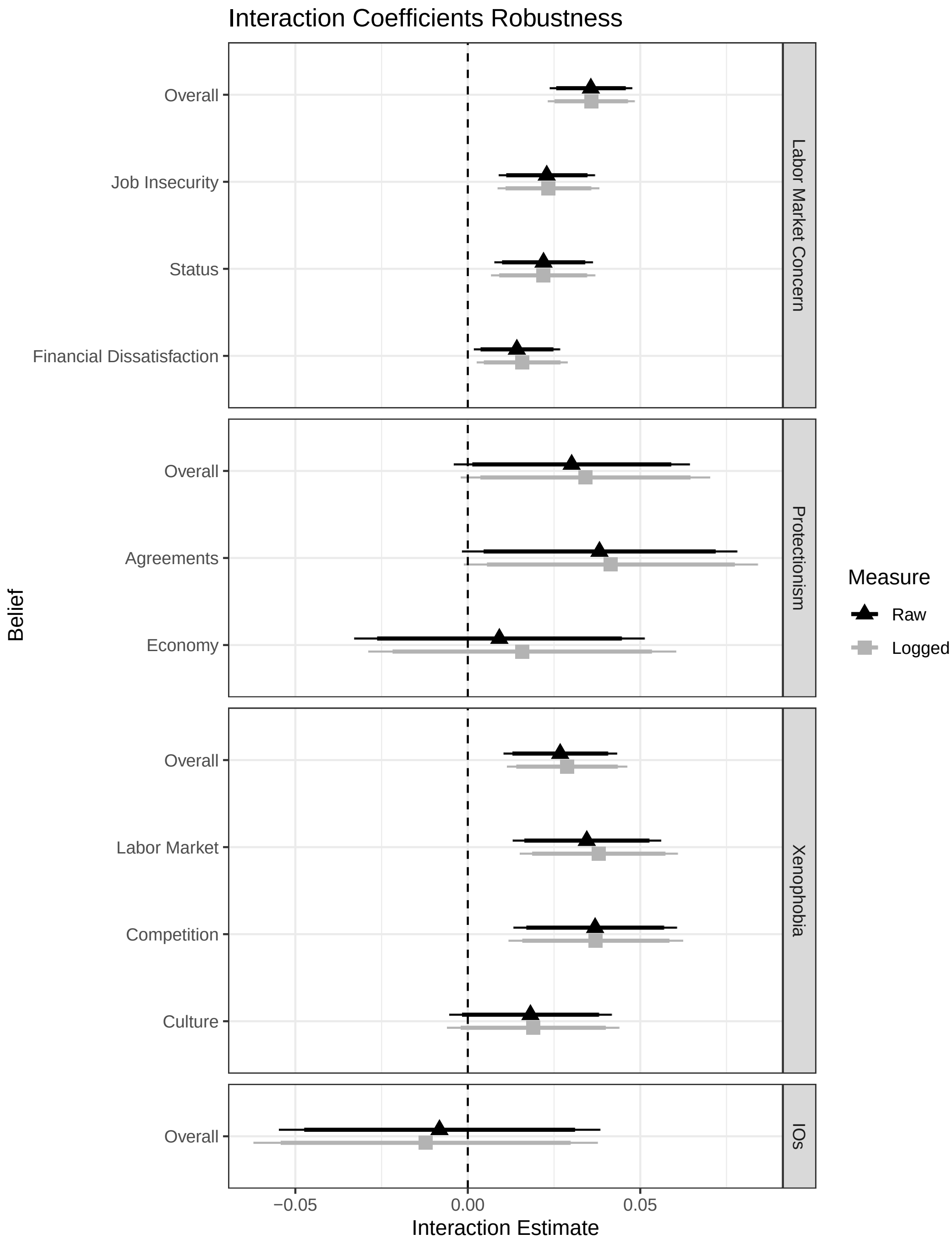
Figure SI.22: Year-by-year results (x-axis) for different outcomes (y-axis). Tiles are colored by interaction coefficient, and outlined in black for those that are statistically significant at the 90% level of confidence.



14 Logged Immobility

Our main results logged the job immobility measure to compensate for mild skew in the data. Below, we confirm that our results are insensitive to this decision.

Figure SI.23: Interaction coefficient robustness to decision whether to log the job immobility measure.



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