**Appendix A**

We test for balance between treatment groups in two different ways. First, we test for the probability of assignment to each treatment group (as opposed to the other two groups) conditional upon other covariates. Each of the three models is a logistic regression where the dependent variable takes on a value of 1 if the respondent is in the treatment group and a value of 0 otherwise. As the table illustrates, most of our covariates do not have a statistically significant effect on treatment assignment, with the notable exceptions of the bolded terms. This suggests that the randomization was carried out properly and none of these covariates influenced assignment to groups.

|  |
| --- |
|  |
|  | *Dependent variable:* |
|  |  |
|  | Treatment:Foreign | Treatment: Chinese | Treatment:no information |
|  | (1) | (2) | (3) |
|  |
| TAA per capita (logged and rescaled) | 0.110 | -0.0001 | -0.109 |
|  | (0.069) | (0.068) | (0.068) |
| # Unemployed per capita | -11.143 | 21.971 | -11.368 |
|  | (14.362) | (14.089) | (14.479) |
| Man | 0.111 | -0.100 | -0.011 |
|  | (0.142) | (0.143) | (0.145) |
| White | 0.096 | -0.131 | 0.034 |
|  | (0.158) | (0.158) | (0.160) |
| Age | 0.004 | -0.005 | 0.001 |
|  | (0.004) | (0.004) | (0.004) |
| Republican | -0.215 | 0.235 | -0.021 |
|  | (0.148) | (0.147) | (0.150) |
| Manufacturing | -0.074 | 0.099 | -0.026 |
|  | (0.148) | (0.149) | (0.151) |
| College | -0.110 | 0.161 | -0.051 |
|  | (0.137) | (0.137) | (0.139) |
| Constant | -0.539 | -1.033\*\*\* | -0.504 |
|  | (0.399) | (0.395) | (0.403) |
|  |
| Observations | 1,009 | 1,009 | 1,009 |
| Log Likelihood | -646.649 | -639.300 | -629.133 |
| Akaike Inf. Crit. | 1,311.299 | 1,296.600 | 1,276.265 |
|  |
| *Note:* | \*p\*\*p\*\*\*p<0.01 |

The second, and perhaps more appropriate, test of balance looks at the distribution of each covariate in each treatment group, compared with other treatment groups. If the randomization “worked”, we expect that the distributions of each covariate should be approximately equal. We conduct two-sided t-tests for each covariate, comparing each pair of treatment groups. The aim is to assure the means are roughly equal when we compare each treatment group. The table below shows the p-value for each t-test, indicating where we reject the null hypothesis that the difference of means is zero, meaning that the distributions may be systematically different. Bolded cells indicate p-values that are significant at conventional levels.

|  |  |  |  |
| --- | --- | --- | --- |
|  | foreign/Chinese | foreign/generic | Chinese/generic |
| TAA per capita (rescaled) | 0.424 | **0.052** | 0.234 |
| # Unemployed per capita | 0.280 | 0.739 | 0.175 |
| Man | 0.541 | 0.573 | 0.971 |
| White | 0.213 | 0.590 | 0.495 |
| Age (rescaled) | 0.109 | 0.514 | 0.366 |
| Republican | 0.286 | 0.732 | 0.482 |
| Manufacturing | 0.734 | 0.993 | 0.733 |
| College | 0.401 | 0.989 | 0.419 |

The only variable where the difference of means is large enough to reject the null hypothesis is the TAA per capita measure, and only when we compare the distributions between the foreign treatment and the ‘no information’ treatment. The distribution of each, along with a vertical line at the group mean, is displayed below. The average number of TAA claims per capita is higher in the foreign group than in the ‘no information’ group, although otherwise the distributions look largely similar.



The primary concern with an imbalance in the covariates is that any differences we find between the groups may be due not to the treatment, but to these underlying differences. In this case, if we find tha tAs it happens, we control for TAA Claims anyhow, as it is an important conditional variable. We also control for the other variables as they may confound the relationship between TAA Claims, nationalism, and the dependent variable.

**Appendix B: Dealing with Grouped Data**

In our data, respondents are grouped in counties and counties (and therefore also respondents) are grouped in states. Our dependent variable is at the individual (respondent) level as is our treatment, but one of our conditioning variables (TAA claims per capita) is measured at the county level as is one of the control variables (# of unemployed per capita). (This is after we omit population as an independent regressor.) This introduces two potential problems. The first is that observations cannot reasonably be assumed to be independent within groups (violating the first i of the i.i.d. assumption of the logistic regression model), and the second is that there are unmeasured omitted variables between groups that may confound the relationships in question and introduce bias. In this section, we discuss robustness checks that deal with each.

The common way to deal with the violation of the independence assumption is to cluster the standard errors at the group level. The concern about not doing this is that our standard errors might be artificially deflated, resulting in rejections of the null hypothesis when we in fact should not. This is a concern about our data structure (individuals in counties in states), although it is less clear that it is a concern in our observed data, at least at the county level. Most counties (62.6%) have only one respondent. While these individuals are not independent of others in their county, this concern is alleviated in practice because there are no other individuals in their county for them to be non-independent of in our data. That said, there are a few counties that have quite a few respondents (Cook County, Illinois; Los Angeles County, California; Maricopa County, Arizona) and therefore we might expect this to be a problem. Accordingly, we estimate a model where we cluster the standard errors at the county level. We also estimate a model with the standard errors clustered at the state level. We also cluster the standard errors at the treatment level because Qualtrics aims for roughly equal assignment within treatment groups, which implies some form of conditional treatment assignment. This might mean that individuals are not truly independent within treatment groups.

A comparison of each of these clustered models with the model with the normal standard errors is below. (We use the vcovCL function in the sandwich package for R). In all three models, clustering the standard errors decreases our standard errors, increasing the statistical significance of our findings. This is most pronounced in Model 4, in which we cluster the standard errors by treatment. This suggests that our initial results were conservative, increasing our confidence in our findings. In the body of the paper, we cluster the standard errors by county.

|  |
| --- |
|  |
|  | *Dependent variable:* |
|  |  |
|  | Investment is Bad for the US(1 = investment is bad,0 = otherwise) |
| Clustering: | None | County | State | Treatment |
|  |
| Treatment: foreign | **2.351\*\*\*** | **2.351\*\*\*** | **2.351\*\*\*** | **2.351\*\*\*** |
|  | **(0.409)** | **(0.394)** | **(0.332)** | **(0.001)** |
| Treatment: Chinese | **3.197\*\*\*** | **3.197\*\*\*** | **3.197\*\*\*** | **3.197\*\*\*** |
|  | **(0.404)** | **(0.394)** | **(0.352)** | **(0.065)** |
| TAA claims per capita (rescaled) | **-0.465\*** | **-0.465\*** | **-0.465\*** | **-0.465\*\*\*** |
|  | **(0.279)** | **(0.256)** | **(0.269)** | **(0.042)** |
| # Unemployed per capita | 14.067 | 14.067 | 14.067 | 14.067 |
|  | (18.743) | (21.598) | (24.461) | (18.804) |
| Man | -0.265 | -0.265 | -0.265 | **-0.265\*** |
|  | (0.197) | (0.186) | (0.180) | **(0.157)** |
| White | -0.059 | -0.059 | -0.059 | -0.059 |
|  | (0.220) | (0.219) | (0.193) | (0.142) |
| Age (rescaled) | **0.313\*\*\*** | **0.313\*\*\*** | **0.313\*\*\*** | **0.313\*\*** |
|  | **(0.102)** | **(0.095)** | **(0.068)** | **(0.137)** |
| Republican | -0.110 | -0.110 | -0.110 | -0.110 |
|  | (0.200) | (0.186) | (0.195) | (0.332) |
| Manufacturing | -0.076 | -0.076 | -0.076 | -0.076 |
|  | (0.200) | (0.206) | (0.225) | (0.235) |
| College | -0.294 | -0.294 | **-0.294\*\*** | **-0.294\*** |
|  | (0.186) | (0.182) | **(0.135)** | **(0.158)** |
| Foreign x TAA per capita | 0.349 | 0.349 | 0.349 | **0.349\*\*\*** |
|  | (0.315) | (0.282) | (0.266) | **(0.069)** |
| Chinese x TAA per capita | 0.485 | **0.485\*** | 0.485 | **0.485\*\*\*** |
|  | (0.309) | **(0.292)** | (0.325) | **(0.036)** |
| Constant | -3.609\*\*\* | -3.609\*\*\* | -3.609\*\*\* | -3.609\*\*\* |
|  | (0.625) | (0.682) | (0.746) | (0.432) |
|  |
| Observations | 851 | 851 | 851 | 851 |
| Log Likelihood | -371.900 | -371.900 | -371.900 | -371.900 |
| Akaike Inf. Crit. | 769.799 | 769.799 | 769.799 | 769.799 |
|  |
| *Note:* | \*p\*\*p\*\*\*p<0.01 |

The second concern -- that there is unmeasured heterogeneity between groups -- is equally concerning but also complicated by the small number of respondents in some counties and some states. In addition to the county concerns listed above, seventeen states have fewer than ten individuals grouped within them, and we have only one respondent in Wyoming. This makes fixed effects (including dummies for state and county) less advisable, since small numbers of observations within groups leads to high-variance (if unbiased) estimates (see Clark and Linzer 2015). County fixed effects also drastically reduce the degrees of freedom. Instead, we estimate a model with both county and state random effects (random intercepts). Random effects models allow for ‘shrinkage’, borrowing strength from other units and pulling the group estimates in toward the overall mean. Convergence concerns for the random effects model requires us to rescale certain variables (TAA claims per capita and age) to more closely resemble the scale of the other variables in our model, which are mostly dummies. We re-scale each to have a mean of zero and a standard deviation of one. The models below compare the original model in the paper (without clustered errors), a model with state dummies, and a model with random intercepts by state. (The models with county dummies and random intercepts by county would not properly converge despite our best efforts, due to most of the counties having very observations. In lieu of this, we also run a model where we include dummies for the counties with more than ten respondents. The choice of ten is arbitrary – our conclusions aren’t highly sensitive to it.)

|  |
| --- |
|  |
|  | *Dependent variable:* |
|  |  |
|  | Investment is Bad for the US(1 = investment is bad,0 = otherwise) |
|  | *Logistic* | *Random intercepts* | *Logistic* |
|  |  |  |  |
|  | (1) | (2) | (3) | (4) |
|  |
| Treatment: foreign | **2.351\*\*\*** | **2.354\*\*\*** | **2.388\*\*\*** | **2.368\*\*\*** |
|  | **(0.409)** | **(0.410)** | **(0.429)** | **(0.419)** |
| Treatment: Chinese | **3.197\*\*\*** | **3.212\*\*\*** | **3.388\*\*\*** | **3.290\*\*\*** |
|  | **(0.404)** | **(0.407)** | **(0.425)** | **(0.415)** |
| TAA claims per capita (rescaled) | **-0.465\*** | **-0.474\*** | **-0.584\*** | -0.373 |
|  | **(0.279)** | **(0.281)** | **(0.319)** | (0.299) |
| # Unemployed per capita | 14.067 | 12.715 | -2.190 | 2.201 |
|  | (18.743) | (20.069) | (25.798) | (19.827) |
| Man | -0.265 | -0.261 | -0.232 | -0.297 |
|  | (0.197) | (0.198) | (0.212) | (0.200) |
| White | -0.059 | -0.083 | -0.287 | -0.175 |
|  | (0.220) | (0.230) | (0.242) | (0.225) |
| Age (rescaled) | **0.313\*\*\*** | **0.318\*\*\*** | **0.369\*\*\*** | **0.310\*\*\*** |
|  | **(0.102)** | **(0.103)** | **(0.112)** | **(0.104)** |
| Republican | -0.110 | -0.103 | -0.062 | -0.100 |
|  | (0.200) | (0.202) | (0.220) | (0.205) |
| Manufacturing | -0.076 | -0.094 | -0.185 | -0.146 |
|  | (0.200) | (0.207) | (0.223) | (0.207) |
| College | -0.294 | -0.291 | -0.304 | -0.221 |
|  | (0.186) | (0.188) | (0.202) | (0.193) |
| Miami-Dade County, FL |  |  |  | -1.017 |
|  |  |  |  | (0.647) |
| Los Angeles County, CA |  |  |  | **-1.201\*** |
|  |  |  |  | **(0.645)** |
| Cook County, IL |  |  |  | **1.085\*** |
|  |  |  |  | **(0.558)** |
| San Diego County, CA |  |  |  | -0.084 |
|  |  |  |  | (0.711) |
| New York County, NY |  |  |  | -0.648 |
|  |  |  |  | (0.810) |
| Maricopa County, AZ |  |  |  | -0.719 |
|  |  |  |  | (1.103) |
| Clark County, NV |  |  |  | **2.341\*\*\*** |
|  |  |  |  | **(0.787)** |
| Foreign x TAA per capita | 0.349 | 0.345 | 0.272 | 0.344 |
|  | (0.315) | (0.316) | (0.353) | (0.333) |
| Chinese x TAA per capita | 0.485 | 0.482 | 0.512 | 0.444 |
|  | (0.309) | (0.311) | (0.353) | (0.328) |
| Constant | -3.609\*\*\* | -3.568\*\*\* | -3.855\*\*\* | -3.279\*\*\* |
|  | (0.625) | (0.652) | (1.426) | (0.648) |
|  |
| State FEs | No | No | Yes | No |
| Observations | 851 | 851 | 851 | 851 |
| Log Likelihood | -371.900 | -371.834 | -336.525 | -361.061 |
| Akaike Inf. Crit. | 769.799 | 771.668 | 785.049 | 762.122 |
| Bayesian Inf. Crit. |  | 838.118 |  |  |
|  |
| *Note:* | \*p\*\*p\*\*\*p<0.01 |

Although the random intercepts model slightly inflates the standard errors, our substantive conclusions do not differ when comparing the random intercepts model with the logistic regression that does not account for unit effects. The interaction terms are not significant at conventional levels in either model, although the interaction between Chinese treatment and TAA claims per capita are close in both models (p=.12 in both models). Including state fixed effects inflates the standard errors even more, but not enough, again, to change our conclusions. The interaction terms are still not statistically significant in this model. The model that includes a dummy for the most-represented counties increases the standard errors more than the baseline and random intercepts models, but less than the state fixed effects model. The only finding that changes in this model is that the effect of TAA claims in the generic, or ‘no information’, treatment group (the omitted category, represented by the independent TAA claims variable) is smaller and no longer statistically significant. In this model, the Foreign x TAA interaction term is closer to significance than in any of the other models (p=.30 instead of p>.4 in the others), but the Chinese x TAA interaction is further from significance (p=.18). Our claims in the paper hold in all of these robustness checks – including about the offsetting effect of the interaction terms – and the only thing that is really in flux is the significance of the one interaction term (which was not significant in the model with controls in the original paper either).

**Appendix C: Three-Way Interaction Model**

Split samples, as used in the body of the paper, can be useful for presenting results and commenting on substantive significance. They help us understand whether there are differences between treatment groups within each group (nationalists and non-nationalists). They don’t, however, help us understand whether the differences between the two groups (nationalists and non-nationalists) are statistically significant. Doing this requires running a three-way interaction model. The regression equation (omitting controls for the sake of space) for that model is as follows:

$$y= β\_{0}+β\_{1}foreign+β\_{2}Chinese+β\_{3}TAA+β\_{4}nationalism+β\_{5}foreign×nationalism+$$

$$ β\_{6}Chinese×nationalism+β\_{7}foreign×TAA+ β\_{8}Chinese×TAA+β\_{9}nationalism×TAA+$$

$$ β\_{10}foreign×nationalism×TAA+β\_{11}Chinese×nationalism×TAA$$

The results of this logistic regression model are displayed in the table below. Standard errors are clustered by county.

|  |
| --- |
|  |
|  | *Dependent variable:* |
|  |  |
|  | Investment is Bad for the US(1 = investment is bad,0 = otherwise) |
|  |
| Treatment: foreign | **2.352\*\*\*** |
|  | **(0.459)** |
| Treatment: Chinese | **3.066\*\*\*** |
|  | **(0.461)** |
| TAA claims per capita (rescaled) | **-0.586\*** |
|  | **(0.305)** |
| Nationalism | -0.262 |
|  | (0.807) |
| Unemployed per capita | 14.262 |
|  | (21.529) |
| Man | -0.261 |
|  | (0.187) |
| White | -0.094 |
|  | (0.218) |
| Age (rescaled) | **0.019\*\*\*** |
|  | **(0.005)** |
| Republican | -0.093 |
|  | (0.197) |
| Manufacturing | -0.084 |
|  | (0.211) |
| College | -0.289 |
|  | (0.179) |
| Foreign x TAA per capita | **0.539\*** |
|  | **(0.320)** |
| Chinese x TAA per capita | **0.716\*\*** |
|  | **(0.352)** |
| Foreign x nationalism | -0.063 |
|  | (0.916) |
| Chinese x nationalism | 0.501 |
|  | (0.955) |
| TAA per capita x nationalism | **0.630\*** |
|  | **(0.329)** |
| Foreign x TAA per capita x nationalism | **-0.975\*\*** |
|  | **(0.454)** |
| Chinese x TAA per capita x nationalism | **-0.902\*\*** |
|  | **(0.419)** |
| Constant | -4.408\*\*\* |
|  | (0.737) |
|  |
| Observations | 851 |
| Log Likelihood | -369.610 |
| Akaike Inf. Crit. | 777.221 |
|  |
| *Note:* | \*p\*\*p\*\*\*p<0.01 |

Yet that table on its own does not really answer the question: are the effects of TAA claims within each treatment group statistically different between nationalists and non-nationalists?

Each of the variables, the terms, and its interpretation is summarized in the table below.

|  |  |  |
| --- | --- | --- |
| **Variable** | **Term(s)** | **Interpretation** |
| b0 |  | average DV for generic/’no information' treatment when no job loss and not nationalist |
| b1 | foreign | effect of Foreign treatment if no job-loss and not nationalist |
| b2 | Chinese | effect of Chinese treatment if no job loss and not nationalist |
| b3 | TAA | effect of job loss in generic/’no information’ treatment if not nationalist |
| b4 | nationalism | effect of nationalism in generic/’no information’ treatment if no job loss |
| b5 | foreign x nationalism | effect of Foreign treatment for nationalists if no job loss |
| b6 | Chinese x nationalism | effect of Chinese treatment for nationalists if no job loss |
| b7 | foreign x TAA | effect of job loss in foreign treatment if not nationalist |
| b8 | Chinese x TAA | effect of job loss in Chinese treatment if not nationalist |
| b9 | nationalism x TAA | effect of job loss in generic/’no information’ treatment for nationalists |
| b10 | foreign x nationalism x TAA | effect of job loss in foreign treatment for nationalists |
| b11 | Chinese x nationalism x TAA | effect of job loss in Chinese treatment for nationalists |

Thus, to test whether the effects in the three treatment groups are statistically significant, we have to conduct a Wald test comparing different sets of coefficients. The comparison of $β\_{8}$ and $β\_{11}$ tells us if the effect of job loss in the Chinese treatment is different among nationalists and non-nationalists. The p-value for the Wald test is 0.089, indicating that the difference is statistically significantly at the p=.10 level. The comparison of $β\_{7}$ and $β\_{10}$ tells us if the effect of job loss in the foreign treatment is different among nationalists and non-nationalists. The p-value for this comparison is 0.09, indicating, again, statistical significance at conventional levels. The comparison of $β\_{9}$ and $β\_{3}$tells us if the effect of job loss in the ‘no information’ treatment is different among nationalists and non-nationalists. In this case, p=0.15, indicating that the effect of job loss between nationalists and non-nationalists is the ‘no information’ treatment group is not statistically significant at conventional levels.