Revisiting the Evidence on Trade Policy Preferences

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Abstract

Past literature has found evidence that labor market attributes affect individuals' trade policy preferences in a manner consistent with theories of international trade. This paper shows that, with the exception of education, these relationships between labor market attributes and trade policy preferences are not robust in US survey data. This suggests that either our proxies of labor market attributes are poor or our theories for what drives trade policy preferences need to be revisited.

JEL Codes: F13 – Commercial Policy; Protection; Promotion; Trade Negotiations; **D72 –** Models of Political Processes: Rent-Seeking, Elections, Legislatures, and Voting Behavior.

Key Words: Trade Protection; Skill; Political Economy.

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1. Introduction

Trade policy outcomes are fundamentally determined by individuals' preferences for trade policies, which are determined by how trade affects the income and welfare of individuals. While the majority of previous empirical work on trade policy outcomes has examined the position taken by political representatives or lobbies, more recent work has begun to explore individuals' survey responses or votes on trade policies directly. As Rodrik (1995) points out, understanding the formation of individual trade policy preferences is a fundamental input into the modeling of trade policy outcomes.

The recent literature analyzing individual responses has examined whether standard trade models' predictions of who gains and loses from trade protection correspond with individuals' stated preferences regarding trade policies. The almost exclusive focus has been on whether individuals' endowments (primarily their human capital skills) or their current industry of employment are correlated with their trade policy preferences. If workers are (perfectly) mobile across sectors, then their skill endowment matters for trade policy preferences, not their industry of employment. This corresponds to a two-factor Heckscher-Ohlin framework with associated Stolper-Samuelson effects, whereby workers with less (more) skill residing in a skill-abundant (skill-deficient) country will experience real income declines from freer trade and, thus, favor trade protection. In contrast, if workers cannot move between industries, then industry characteristics, not the workers' skill levels will determine how their income varies with trade and their resulting trade preferences. This corresponds to what is called a sector-specific or Ricardo-Viner model.

Prior literature has primarily examined these hypotheses using data on stated lobbying groups' positions on trade and votes by elected representatives, and generally concludes that industry characteristics, not human capital endowments, determine trade policies.[1] For our present purposes, a weakness is that these studies are likely capturing determinants of lobbying inputs, which is quite different from the trade policy preferences of voting constituents. Thus, it is not surprising that human capital endowment measures find little support.

A more recent literature has begun to examine these hypotheses using individuals' votes or stated preferences on surveys about free trade and trade protection, including Balistreri (1997), Scheve and Slaughter (2001a and 2001b), Beaulieu (2002a), and Mayda and Rodrik (2006). These individual survey studies generally find support for both human capital endowments and industry characteristics as determinants of individuals' support for trade protection, though the Scheve and Slaughter studies find support for only the effects of human capital endowments.

This paper provides evidence that the connection between trade policy preferences and labor market attributes may be more tenuous previously thought. Like Scheve and Slaughter (2001a and 2001b), I use data on individuals' responses to a question posed by the American National Election Studies (ANES) about whether the US should increase import restrictions or not. The ANES surveys provide much more detailed data on individual characteristics than other surveys used in the literature, including direct information on an individual's occupation and employment industry. My statistical analysis begins by replicating Scheve and Slaughter's results, but then expands their sample significantly to show initial evidence for both human capital endowments and industry trade exposure using their empirical specification. However, from this base specification, it is simple to show that the only robust variable used to proxy for

[1] Examples include Magee (1980) and Irwin (1994, 1996). However, as Beaulieu (2002b) points out, most studies of determinants of trade votes by legislators only explore whether industry characteristics of the legislator's constituents are correlated with trade votes and do not consider human capital (or other) endowments of the legislators' constituents. Kaempfer and Marks (1993), Baldwin and Magee (1998), and Beaulieu (2002b) find some evidence for both human capital endowments and industry composition of representative districts determining votes on trade bills by U.S. and Canadian political representatives.

labor market attributes (human capital endowments or industry characteristics) is the years of education of an individual.

The rest of the paper proceeds as follows. The next section provides details on the ANES data and base empirical specification I use. Section 3 presents the paper's empirical results, and section 4 concludes and discusses implications of the results for future work in this area.

2. Data and Empirical Specification

I create a dataset from the ANES surveys that follows Scheve and Slaughter (2001a) as closely as possible, while expanding beyond year 1992 (which is the only year they examine) to include survey years 1986, 1988, 1996 and 1998.[2] In all these years the ANES asked the same following question:

> ‘‘Some people have suggested placing new limits on foreign imports in order to protect American jobs. Others say that such limits would raise consumer prices and hurt American exports. Do you favor or oppose placing new limits on imports, or haven't you thought much about this?’’[3]

Following Scheve and Slaughter, I construct a dependent variable that assigns a "1" when the individual responds that they favor new limits on imports, and a "0" when they oppose new

[2] Scheve and Slaughter (2001b) also includes analysis of data from the year 1996, but finds quite similar evidence and comes to the same conclusions as Scheve and Slaughter (2001a); namely, that the evidence for the connection between the skill variables and trade policy preferences is strong and robust statistically, whereas the evidence for any industry trade exposure effect is quite weak.

[3] In 1990, the ANES survey asked a similar, but not identical, question that asked respondents to rank their preferences for new import limits over a range from 1 to 7, where "1" indicated "increase limits a lot", while "7" indicated "decrease limits a lot." Since it is not obvious how to correspond these responses into a binary variable in analogous fashion to my other survey years, I do not include this survey year. In 1986, the ANES survey first asked respondents if they had thought about import issues. Then, if they responded that they had, they were asked the same question about whether they favored or opposed new limits. I include respondents from this year in my sample as it is easy to construct a dependent variable in analogous fashion to my other survey years. Finally, I exclude the year 2000, the final year the question was asked, because the individual's county of residence is not reported in this year's survey. County residence is necessary for construction of a couple key independent variables discussed below.

limits.[4] A logit regression framework is used to account for the binary nature of the dependent variable.

I also follow Scheve and Slaughter in specifying my covariates and base specification. Scheve and Slaughter use two alternative measures of an individual's skill and two alternative measures of the trade exposure of the industry in which the individual works. Their measures of skill are years of education and wage levels. *Education Years* are directly asked of the individual in the ANES surveys across all years. Wage levels are not asked of ANES respondents, but instead they are asked to identify their occupation. Following Scheve and Slaughter, I take U.S. Bureau of Labor Statistics (BLS) data on average weekly wages by occupation to assign wage levels to individuals in the surveys based on their stated occupation. Because I have multiple years of surveys in my sample, I construct my wage data as a *Relative Occupation Wage* variable that is defined as an occupation's average wage relative to the average wage across all occupations in a given survey year. Scheve and Slaughter (2001a) simply used wage levels, which is appropriate (and equivalent to my construction) because they only examine a single survey year.

Like Scheve and Slaughter, the two measures of industry trade exposure I construct are the *Sector Tariff* and *Sector Net Export Share* of output (or sales) for a survey respondent's industry of employment. The ANES asks respondent's to identify the industry they work in, which are classified into 3-digit Census of Industry Codes (CIC). For tariff levels, I use the applied tariffs (duties collected divided by customs value of imports) found in U.S. trade data, available through the Schott and Feenstra datasets at the National Bureau of Economic Research (NBER) website. I construct the weighted average tariff by 4-digit Standard Industrial Classification (SIC) codes

[4] This excludes individuals who respond that they haven't thought much about the issue, as did Scheve and Slaughter (2001a and 2001b). Blonigen (2008) and Scheve and Slaughter (2001b) find that empirical estimates are

from the NBER data and then concord to 3-digit CIC codes. Non-traded sectors, as well as all service sectors, are assigned an import tariff of zero.[5] Net export shares for manufacturing are straightforward to construct using the NBER data for the trade flows (exports and imports by sector), and U.S. Census data for value of shipments. These data are constructed by SIC codes and then concorded to the CIC codes. Constructing net export shares for non-manufacturing sectors relied on a variety of sources, primarily U.S. Census data for shipments, NBER trade data for tradeable agriculture and mining sectors, and BEA data for tradeable service sectors. A data appendix describes the construction of this variable (and all my variables) in more detail. Non-tradeable sectors were assigned a net export share of zero. I expect a positive correlation between average tariffs in an individual's employment industry and their preference for import protection, and a negative correlation between their employment industry's net export share and their preference for import protection.

A secondary focus of Scheve and Slaughter is examination of the hypothesis that home-owners in trade-sensitive locations will be more likely to prefer trade protection. This is because homes are often an important asset for individuals and home values depend on economic activity in the immediate location. Following Scheve and Slaughter, I use Census data to calculate the share of the individual's county's employment in two-digit SIC sectors with above-median tariffs (called *County Trade Exposure*).[6] I interact this county exposure share variable with a binary

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qualitatively very similar when one includes these individuals and employs a sample selection correction.

[5] Pooling individuals in non-tradeable sectors with those in tradeable ones may be a concern if these groups systematically differ in their views of trade policy. However, my results are qualitatively identical when I exclude individuals from non-traded sectors.

[6] The county location of an individual is identified by the ANES survey through 1998. Scheve and Slaughter alternatively proxy for the trade exposure of an individual's county with the share of county employment in two-digit SIC sectors with above-median net-import balances (which they label as *County 2 Exposure*). Both they and I get qualitatively identical results regardless of whether one uses the county exposure variable tied to high tariff industries (which they label *County 1 Exposure*) or to high net-import balance industries (*County 2 Exposure*). Thus, for brevity, I only report results using the *County 1 Exposure* variable. I use the same 2-digit SIC industries as used by Scheve and Slaughter (2001) for these variables based on 1992 data.

variable indicating whether the individual owns a house, which is asked directly by the ANES survey in all my sample years, and denote this variable as *County Trade Exposure* × *House*. By the hypotheses developed in Scheve and Slaughter, a positive correlation is expected between this variable and the likelihood that an individual prefers new import limits.

Finally, after initial estimates, I will also include other individual characteristics in my regression specifications, including age, gender, race, political party affiliation, union membership, and household income levels which come directly from the ANES survey questions. Table 1 provides summary statistics of all the variables used in this study's analysis.

3. Empirical Results

In this section, I start by presenting the base statistical results that are estimated from identical specifications as those in Scheve and Slaughter (2001a). I then examine the robustness of these results. Since a number of the variables are at different levels of aggregation, I calculate standard errors using a four alternative methods: 1) unclustered, but corrected using a general White's correction that yields what are typically called "robust" standard errors, 2) clustered at the industry level, 3) clustered at the occupation level, and 4) two way clustering by industry and occupation using the methods proposed by Cameron, Gelbach and Miller (2010). In my tables of results, I report the minimum and maximum standard error I obtain over these four alternatives.

Columns 1 through 4 of Table 2 provide logit estimates of the determinants of an individual's preference for higher import restrictions using identical specifications and sample year (1992) to that in Scheve and Slaughter (2001a). The results are qualitatively identical to those in Scheve and Slaughter (2001a) – specifically, models 9, 10, 13, and 14 in Table 5 of their paper.[7] Both measures of skill (*Education Years* and *Relative Occupation Wage*) are statistically significant and indicate important effects on trade policy preferences. However, as found by Scheve and Slaughter, measures of the trade exposure of an individual's employment industry (*Sector Tariff* and *Sector Net Export Share*) are not significant in explaining trade policy preferences. Thus, this initial evidence is consistent with a model with intersectoral factor mobility assumed in Heckscher-Ohlin models where skills determine welfare impacts of trade policy, while inconsistent with a sector-specific (or Ricardo-Viner) model where factors are immobile between sectors and trade exposure would affect individual welfare and, hence, their trade policy preferences. As in Scheve and Slaughter (2001a; 2001b), I also find that individuals who own homes in trade sensitive areas are much more likely to favor new import restrictions.

I next run the same specification, but this time with the full sample of years available, and report these estimates in columns 5 through 8 of Table 2.[8] I also add dummy variables for each year to control for any common year-specific effects on all individuals' trade policy preferences. The surprising result is that while the skill variables come in with similar magnitude and statistical significance, the industry trade exposure variables are now correct sign and statistically significant. These findings that both skill and industry matter contrast with Scheve and Slaughter (2001a and 2001b), but are consistent with Beaulieu's (2002a) results using Canadian survey data, and suggest that labor is neither perfectly mobile nor perfectly immobile.[9]

[7] I get qualitatively identical results to Scheve and Slaughter for all specifications reported in their paper, but just show these for the sake of brevity. Full "replication" results are available upon request.

[8] For ease of comparison across specifications, I keep the number of observations the same in the full sample of years by dropping observations for which *any* of my skill or industry variables have missing values. These results are virtually identical to the alternative where I drop missing variables for only the specific skill and industry variable in the specification.

[9] Enlarging the sample also has significant impact on the marginal effect of trade exposure in the county for home owners, which falls to about 30% of its former magnitude and is now only significant at the 5% level, rather than the 1% level.

The magnitude of both the skill variables and industry trade exposure variables are economically significant as well. A one-standard deviation increase in the *Relative Occupation Wage* of an individual decreases their likelihood to favor new import limits by 5.8 percentage points (from a mean of about 62%), while a one-standard deviation increase in *Education Years* decreases an individual's likelihood of favoring trade protection by 10.8 percentage points, ceteris paribus. Using column 5's estimates, a one-standard deviation in the *Sector Tariff* increases an individual's likelihood of favoring trade protection by 2.4 percentage points. Using column 6's estimates, a one-standard deviation in the *Sector Net Export Share* decreases an individual's preference for trade protection by 4.7 percentage points.

However, as columns 1 and 2 of Table 3 next show, these results are not robust to including both measures of human capital endowment (*Relative Occupation Wage* and *Education Years*) and both measures of industry trade exposure (*Sector Tariff* and *Sector Net Export Share*) in the same specification. This simple change leads *Relative Occupation Wage* to be statistically insignificant in the 1992 sample (column 1) and even the incorrect sign (and statistically significant) in the full sample results (column 2). *Sector Tariff* and *Sector Net Export Share* now have incorrect signs in the 1992 sample, and are only marginally statistically significant at standard confidence levels (depending on the standard error one chooses) in the full sample. The exception is the variable *Education Years*, which remains statistically significant at the 1% level in both the 1992 and full samples and has a very similar magnitude to the base specifications.[10]

In column 3 of Table 3, I include a full set of demographic variables to the specification in column 2, including age, gender, relative income levels, race variables, political party and union

[10] The correlation between *Education Years* and *Relative Occupation Wage* is 0.51, while the correlation between *Sector Tariff* and *Sector Net Export Share* is -0.36. Interactions between the skill and industry variables (e.g., *Education Years* × *Sector Tariff*) are also statistically insignificant when included in the specification and have virtually no impact on the magnitude of the education effect.

affiliation.[11] Our results are qualitatively identical – the coefficient on *Education Years* is only slightly lower, but remains statistically significant at the 1% level, while the other labor market attributes are marginally significant at best.

There are interesting relationships revealed in the coefficients on our demographic variables, with gender, political party, union affiliation, and income all estimated to have statistically and economically significant effects on trade policy preferences. While the average individual in the sample is 62% likely to support new import limits, marginal effects suggest that females are 9.5 percentage points more likely than males to support new import limits, everything else equal. Likewise, having a union member in the household increases the respondent's probability of supporting new import limits by around 10 percentage points. Democrats are over 6 percentage points more likely to support new import limit relative to independents (the excluded category), as well as relative to Republicans. Finally, individuals with household income below the 50th percentile are 5-6 percentage points more likely to support new import limits than individuals with household incomes above the 50th percentile.[12]

One previously unexplored concern with estimating the relationship between education and trade preferences is that the education variable is unusually distributed. For example, there are very few individuals with less than 12 years of education with a large mass of individuals with exactly 12 years of education – high school graduates. Thus, it may be a poor assumption that the education effect on trade preferences is a monotonic linear relationship. As an alternative, I create categorical variables to indicate education groupings that are often used in labor market

[11] The income variables are measured at the household level, not the individual level, and thus are not that highly correlated with the *Relative Occupation Wage* variable. A linear regression of the *Relative Occupation Wage* on the household income variables yields an R^2 around 0.10. Thus, it is not surprising that the *Relative Occupation Wage* is virtually unchanged whether one includes the income variables in the demographic controls or not.

[12] To be precise, statistical tests cannot reject that the coefficients on income in the first (lowest) and second quartiles are identical, nor can they reject that the coefficient on the third quartile is different from the excluded

studies: 1) Less than high school, 2) High school graduate, 3) Some college, 4) College graduate, and 5) Graduate education. Column 4 of Table 3 provides re-estimates of the specifications in column 3, replacing the *Education Years* variable with dummy variables for the first four of these education groupings, excluding the last category to avoid perfect multicollinearity.

The results in column 4 are consistent with those in column 3, but also show the importance of modeling the nonlinearities inherent in the education variable. The results show that individuals in the three lowest education groups are statistically more likely to favor new import limits relative to individuals with education in graduate school, while there is no difference in preferences for trade policy between college graduates and those going on to graduate school. The marginal effects connected to these coefficient estimates indicate that these are very large effects. Individuals in *any* of the education categories below a college degree are 15 to 25 percentage points more likely to favor new import levels than individuals with at least a college degree, ceteris paribus. This large change in support for new import limits once one obtains a college degree is a much different implication than the linear estimates, where the marginal effects indicate that each additional year of education decreases an individual's preference for new import limits by about 3.5 percentage points. The coefficient estimates and statistical (in)significance of the other labor market variables (*Relative Occupation Wage, Sector Tariff, and Sector Net Export Share*) are qualitatively identical regardless of how we specify the education variable.

As an additional robustness check, I also ran the column 3 specification of Table 3 separately for each year of the sample (results available upon request). These results clearly show the relative fragility of the labor market attributes other than *Education Years*, as they all switch

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fourth (highest) quartile. However, the coefficients on the two lowest quartiles are each statistically different from both the third and fourth quartiles at standard confidence levels.

signs across years and are rarely statistically significant. In contrast, the coefficient on *Education Years* ranges from -0.116 to -0.181 in magnitude and is statistically significant at the 1% level for every separate year in the sample.[13]

Labor market skills map into specific occupations and industry of employment for individuals. For example, the average years of education for machinery operators in the printing industry is likely quite different from that of a manager in the finance industry. The ANES asks individuals their occupation and industry of employment, which allows me to introduce a rich set of over 600 industry-by-occupation fixed effects into the specification. If the education effect on trade policy preferences is driven to some extent by its connection to labor market skills, the education effect may not be robust to including this extensive set of industry-by-occupation fixed effects are taken into account. As a final robustness check, columns 5 and 6 of Table 3 provide results when I estimate the same specification in columns 3 and 4 of Table 3, but with a fixed-effects, or conditional, logit estimation procedure using these industry-by-occupation categories. Specification tests indicate that these fixed effects are statistically important, yet our results are qualitatively very similar to those when we do not control for these effects (compare with columns 3 and 4). In particular, while the coefficients on the other labor market variables continue to be statistically insignificant in the conditional logit estimates, the marginal effect of the education variables across these two specifications continues to be statistically significant at the 1% level though falls a bit in magnitude.

[13] These large swings in coefficient estimates do not stem from large changes in the distribution of these variables across years, as descriptive statistics for the covariates are quite stable across years.

4. Conclusion and Discussion

This paper provides evidence that the relationship between labor market attributes of individuals and their stated trade policy preferences is more tenuous than previously thought. The only proxy for labor market attributes that is a robust correlate with trade policy preferences is an individual's education level, and it is possible that this education effect is driven by aspects of education beyond its implications for an individual's labor market outcome. These results should be at least a bit disconcerting to trade economists as differential labor market outcomes is the main mechanism by which our standard trade models predict heterogeneous trade policy preferences across workers/individuals.

There are three possible paths for future research. The first is to examine the extent to which our current proxies for labor market skills and trade exposure may be significantly mis-measured or mis-specified. Perhaps there are better measurements of labor market attributes that can be specified to account for the effects that are currently absorbed by the industry-by-occupation fixed effects. Alternatively, it may be that the types of workers and tasks that are systematically helped or harmed by trade policy may not be separated out very well by our typical categorizations of industries and occupations. A second related path is to examine whether the dependent variable is poorly measured and modifications of the survey question could provide sharper connections to labor market outcomes.

A final path is to revisit our theories in light of what the data suggest are significant correlates of trade policy preferences. As one can see from the results in Table 3, when we include demographic and political control variables, there are a number of variables that appear to be quite robust determinants of trade policy preferences. However, none of them have obvious connections to hypotheses that stem from our traditional economic models of trade. Gender has a large effect on trade policy preferences with women nearly 10 percentage points more likely to favor new import limits even after controlling for education, income, political affiliation, industry-by-occupation fixed effects, etc. This strong gender bias has been found in other studies as well (e.g., Beaulieu and Napier, 2008, and Rodrik and Mayda, 2005), but there is no suggested hypothesis for why this exists. Ideological variables, such as membership in the Democratic party or in a union also makes an individual much more likely to support new import limits. Many would not find this surprising, as people affiliated with these political groups are often thought to have attributes (such as a blue collar job or lower income) that would lead to such a membership and also correlate with trade preferences. But then it is highly surprising that the marginal effect of these political affiliations remains strong and large even after controlling for a rich set of demographic, industry, and occupational controls. Finally, there is significant statistical support of income effects on trade policy preferences (individuals from households with lower income are more likely to support new import limits), even after controlling for industry-by-occupation effects, wages and education levels. Rodrik and Mayda (2005) find similar effects and note that there is no economic theory for these income effects that are independent of labor market outcomes.

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Table 1: Descriptive Statistics

Variable	Mean	Standard Deviation
<u>**Dependent variable**</u>		
Supports New Import Limits	0.621	0.485
<u>**Independent variables in trade protection preference regression**</u>		
Relative Occupation Wage	1.139	0.334
Education Years	13.329	2.680
Sector Tariff	0.007	0.024
Sector Net Export Share	-0.006	0.114
County Trade Exposure	0.063	0.063
County Trade Exposure × House	0.044	0.060
<u>**Additional independent variables as controls in trade vote regression**</u>		
Age (in years)	45.958	16.607
Female	0.444	0.497
African American	0.092	0.288
Asian American	0.016	0.126
Hispanic	0.058	0.233
Native American	0.039	0.193
Democrat	0.369	0.483
Republican	0.298	0.457
Union Membership in Household	0.199	0.399
Household Income – First (Lowest) Quartile	0.175	0.380
Household Income – Second Quartile	0.242	0.429
Household Income – Third Quartile	0.248	0.432

Notes: These are descriptive statistics for the full sample of years (1986, 1988, 1992, 1996, and 1998) and are based on 5224 observations. All variables, with the exception of *Relative Occupation Wage*, *Sector Tariff*, and *Sector Net Export Share*, come from survey data by the American National Election Studies. Data from the U.S. Bureau of Labor Statistics on wages are used to construct the *Relative Occupation Wage* and are concorded to individuals' reported occupation categories. Data from the U.S. Bureau of Labor Statistics on wages are used to construct the *Relative Occupation Wage* variable and are concorded to individuals' reported occupation categories. U.S. trade and industry data are used to construct *Sector Tariff* and *Sector Net Export Share* and are concorded to the individual's employment industry. See data appendix for further details.

Table 2: Re-estimating Scheve and Slaughter – 1992 Sample and Full Sample of Years

	1992 Sample Only				Full Sample of Years			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Relative Occupation Wage	-0.719	-0.693			-0.838	-0.861		
	(0.172,0.265)	(0.174,0.251)			(0.097,0.122)	(0.089,0.120)		
Education Years			-0.206	-0.201			-0.186	-0.187
			(0.027,0.035)	(0.027,0.035)			(0.020,0.025)	(0.019,0.025)
Sector Tariff	1.860		-0.196		5.269		2.888	
	(2.696,4.081)		(2.590,4.014)		(0.875,1.779)		(1.044,1.570)	
Sector Net Export Share		-0.371		0.082		-1.036		-0.703
		(0.593,0.756)		(0.605,0.780)		(0.208,0.304)		(0.225,0.276)
County Trade Exposure	-0.984	-0.776	-1.731	-1.551	0.680	0.879	0.383	0.485
	(1.474,1.687)	(1.486,1.723)	(1.424,1.694)	(1.566,1.699)	(0.651,0.935)	(0.644,0.810)	(0.665,0.948)	(0.653,0.869)
County Trade Exposure × House	5.171	5.468	5.552	5.819	1.517	1.502	1.559	1.548
	(1.285,1.620)	(1.211,1.631)	(1.326,1.687)	(1.319,1.703)	(0.785,0.841)	(0.738,0.826)	(0.811,0.881)	(0.810,0.877)
Year Dummies	No	No	No	No	Yes	Yes	Yes	Yes
Pseudo R^2	0.020	0.020	0.052	0.051	0.020	0.019	0.043	0.043
Chi-squared Statistic	30.91	30.75	68.00	65.60	125.74	124.12	217.53	219.22
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1404	1378	1417	1390	5224	5224	5224	5224

Notes: Dependent variable is an indicator variable for whether an individual supports new import limits. Standard errors in brackets below coefficients are the lowest and highest standard errors from four alternative assumptions: unclustered robust, clustered by industry, clustered by occupation, and two-way clustering by industry and occupation. Columns 1 through 4 correspond to models 9, 10, 13, and 14, respectively, in Table 5 of Scheve and Slaughter (2001a), whereas columns 5 through 8 provide estimates for the full sample of years – 1986, 1988, 1992, 1996, and 1998.

Table 3: Education is the Only Robust Labor Market Determinant of Trade Policy Preferences

	Logit				Conditional Logit	
Variables	**1992 Sample**	**Full Sample**	**Full Sample with Controls**	**Full Sample with Controls: Education Categories**	**Full Sample with Controls**	**Full Sample with Controls: Education Categories**
Relative Occupation Wage	0.005	-0.206	0.011	0.129	1.598	1.564
	(0.148,0.227)	(0.093,0.125)	(0.058,0.115)	(0.077,0.113)	(0.702,1.289)	(0.659,1.309)
Education Years	-0.202	-0.171	-0.152		-0.114	
	(0.025,0.036)	(0.015,0.026)	(0.015,0.025)		(0.024,0.026)	
Education - Less Than High School				1.118		0.947
				(0.128,0.248)		(0.195,0.259)
Education - High School				1.126		1.015
				(0.108,0.191)		(0.089,0.202)
Education - Some College				0.778		0.713
				(0.106,0.177)		(0.139,0.174)
Education - Bachelor's Degree				0.147		0.243
				(0.075,0.162)		(0.091,0.175)
Sector Tariff	-0.294	1.937	1.375	1.705	8.982	9.306
	(3.594,4.934)	(0.952,1.633)	(0.623,1.904)	(0.580,1.849)	(7.103,8.588)	(7.016,8.664)
Sector Net Export Share	0.061	-0.594	-0.529	-0.466	-0.182	-0.173
	(0.659,1.008)	(0.247,0.310)	(0.233, 0.310)	(0.234,0.305)	(0.618,0.905)	(0.647,0.926)
County Trade Exposure	-1.476	0.337	0.022	0.141	0.702	0.734
	(1.482,1.700)	(0.674,0.942)	(0.506,0.747)	(0.552,0.744)	(0.704,0.812)	(0.726,0.786)
County Trade Exposure * House	5.687	1.641	1.714	1.632	1.346	1.294
	(1.296,1.706)	(0.768,0.849)	(0.750,0.826)	(0.785,0.830)	(0.939,1.000)	(0.943,1.042)
Age			0.003	0.005	0.005	0.007
			(0.002,0.004)	(0.002,0.003)	(0.003,0.003)	(0.002,0.003)

Female			0.416	0.402	0.392	0.351
			(0.051,0.094)	(0.052,0.089)	(0.074,0.082)	(0.073,0.082)
Asian American			-0.150	-0.130	-0.196	-0.170
			(0.114,0.301)	(0.133,0.307)	(0.180,0.305)	(0.183,0.310)
African American			0.113	0.127	0.158	0.152
			(0.117,0.255)	(0.118,0.255)	(0.160,0.245)	(0.161,0.244)
Hispanic			-0.177	-0.142	-0.086	-0.070
			(0.133,0.167)	(0.131,0.157)	(0.170,0.191)	(0.165,0.180)
Native American			0.103	0.092	0.149	0.154
			(0.154,0.187)	(0.154,0.180)	(0.150,0.209)	(0.142,0.207)
Democrat			0.278	0.290	0.313	0.318
			(0.062,0.075)	(0.061,0.071)	(0.065,0.087)	(0.064,0.083)
Republican			0.013	0.013	-0.026	-0.032
			(0.056,0.067)	(0.057,0.068)	(0.059,0.071)	(0.062,0.071)
Union			0.461	0.433	0.342	0.323
			(0.065,0.085)	(0.067,0.085)	(0.075,0.084)	(0.077,0.085)
Income in 1st (lowest) Quartile			0.217	0.235	0.205	0.208
			(0.057,0.102)	(0.061,0.102)	(0.045,0.106)	(0.045,0.105)
Income in 2nd Quartile			0.270	0.226	0.233	0.203
			(0.056,0.086)	(0.068,0.086)	(0.054,0.087)	(0.062,0.087)
Income in 3rd Quartile			0.124	0.084	0.133	0.104
			(0.074,0.080)	(0.075,0.080)	(0.090,0.103)	(0.091,0.100)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.051	0.044	0.087	0.093		
Chi-squared Statistic	65.02	230.55	486.02	557.10	288.24	313.58
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1378	5224	5224	5224	5224	5224

Notes: Dependent variable is an indicator variable for whether an individual supports new import limits. Standard errors in brackets below coefficients are the lowest and highest standard errors from four alternative assumptions: unclustered robust, clustered by industry, clustered by occupation, and two-way clustering by industry and occupation. The excluded education category is individuals with at least some graduate education.

Data Appendix

Many of the variables used in this study come directly from questions in the ANES survey, including our dependent variable, as well as the following regressors: *Education Years*, *House*, *Age*, *Female*, *African American*, *Asian*, *Hispanic*, *Native American*, *Democrat*, *Republican*, *Union Membership*. The income question in the survey had respondents report where their income fell across a number of given ranges. I use the information on how many in the survey fell into each range, to construct variables indicating whether an individual's household income as in the first, second, or third quartile of income range responses for the given survey year.

A number of the variables used in this study required combining ANES survey responses with other data. *Relative Occupation Wage* is constructed by combining individuals' responses on their occupation, which are coded according to 1980 Census Occupation Codes and matching that to U.S. Bureau of Labor Statistics (BLS) on average weekly wages by occupation from Current Population Survey data. This is identical to the procedure used by Scheve and Slaughter (2001a and 2001b). However, because there are multiple years in the sample, I normalize wages by dividing each of the occupation wages by the average wage across occupations for a given year.

To construct the *Sector Tariff* variable I first obtain data on applied tariff rates at the 4-digit Standard Industrial Classification (duties divided by customs value of imports) reported in U.S. trade data. These data, compiled by Robert Feenstra and co-authors from official U.S. Customs data, can be found at the data page of the National Bureau of Economic Research (NBER): www.nber.org/data. I then create a concordance between 4-digit SIC and the 3-digit Census Industry Code reported in the ANES survey to match tariff data to the survey respondents' reported industry/sector. (Concordance available upon request) The data construction for this variable differs from Scheve and Slaughter in using applied tariff rates, rather then tariff rate schedules, due to the relative inaccessibility of tariff rate schedules over my sample years. Like Scheve and Slaughter, I record a "0" tariff for all non-traded goods, as well as traded service sectors.

Construction of the *Net Export Share* variable follows Scheve and Slaughter closely, but was more involved than any of the other variables and relied on a variety of data sources due to having to span many years of data. Import and export data by 4-digit SIC sector are available for traded industries in agriculture, mining, and manufacturing from the NBER data mentioned above. Data on imports and exports for traded service sectors come from an October 2001 *Survey of Current Business* article titled "Cross-border trade in services, 1986-2000." All other sectors are considered non-tradeable and are assigned a "0" for their net export share. For the traded sectors, we also needed a measure of sector size to normalize the net export data in order to create our measure of *Net Export Share*. For manufacturing industries, we use the value of shipments of a sector reported annually in the U.S. Census' *Annual Survey of Manufactures*. For non-manufacturing sectors, the Census has, at best, 5-year censuses that I used to interpolate and extrapolate shipment values for years corresponding to our sample. These include the *Census of Mining*, *Census of Construction*, and censuses of a variety of service sectors which one can access at the following U.S. Census webpage: http://www.census.gov/svsd/www/economic.html. Shipment value data for our agricultural sectors were proxied by "cash receipts" and were taken from http://www.ers.usda.gov/Data/FarmIncome/FinfidmuXls.htm.

Finally, my measure of county exposure to trade (*County Exposure 1*) in this paper, follows Scheve and Slaughter's methodology. I use the U.S. Bureau of Labor Statistics data provided in their Quarterly Census of Employment and Wages, which provides employment by U.S. county by SIC sectors covering agriculture, manufacturing and mining. I then calculate the employment share of the ten 2-digit SIC sectors with the highest tariffs in total county employment – these ten sectors by Scheve and Slaughter's calculations are SIC 21, 22, 23, 28, 30, 31, 32, 34, 38, and 39. *County Exposure 2* is calculated in the same manner, except using the fourteen 2-digit SIC sectors that Scheve and Slaughter find have the highest net imports – SIC 22, 23, 24, 25, 26, 29, 30, 31, 32, 33, 34, 36, 37, and 39.