New Evidence on the Formation of Individuals' Trade Policy Preferences

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Abstract

This paper revisits the issue of people's preferences for international trade protection examining survey data from the American National Election Studies. I first show that both an individual's skills and the international trade characteristics of their employment industry affects their trade policy preferences, in contrast to previous analysis using these data. Second, I document that many people do not feel informed enough to state a preference on trade protection, which is inconsistent with perfect information assumptions of standard political economy models. I examine the factors that correlate with being uninformed, and show that inferences from actual trade policy outcomes can be incorrect if one does not account for this uninformed group. Finally, I examine and find that individuals' retirement decisions have systematic effects on both their choice to be informed and their trade policy preferences. This highlights that there are significant life-cycle implications to trade policy preferences.

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1. Introduction

Trade policy outcomes are fundamentally determined by individuals' preferences for trade policies that, in turn, are determined by how trade affects the income and welfare of individuals. While the majority of empirical previous 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 a sector-specific model or what Scheve and Slaughter (2001) call a Ricardo-Viner framework.

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] A more recent literature has begun to examine these hypotheses using individuals' votes or stated preferences on surveys about free trade and trade protection, and include Balistreri (1997), Scheve and Slaughter (2001), 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 study (the only one using U.S. data) finds support for only the effects of human capital endowments.

The prior literature's focus on the human capital endowments versus industry characteristics debate has left a number of interesting issues unexplored. In this paper, I uncover a number of new empirical results that have important implications for the modeling of voters' support for trade protection and cast new light on prior findings. Like Scheve and Slaughter (2001), I use data on individual's responses to a question posed by the American National Election Studies (ANES) about whether the US should increase or decrease import restrictions. These data have much more detailed data on individual characteristics than other surveys used, including direct information on individuals' employment industry. These data also have a number of features that are unexploited by the Scheve and Slaughter (2001) study.

The first new issue I explore is the role of information. Many people in the survey (almost 30% of the sample) identify themselves as too poorly informed to express an opinion on trade policy. While Scheve and Slaughter eliminate responses from these uninformed individuals in their study, I show that there are systematic factors that explain which individuals fall into this group, with less-skilled, lower income, and female individuals more likely to feel "uninformed"

[1] Examples include Magee (1980) and Irwin (1994, 1996). However, as Beaulieu (2002b) points out, most studies of determinants of trade votes by legislators do not even control for human capital (or other) endowments of the legislators constituents, but simply assume that industry characteristics and composition of the representatives "district" are primary determinants. Kaempfer and Marks (1993), Baldwin and Magee (1998), and Beaulieu (2002b)

on the issue of trade protection. In addition, controlling for this systematic selection of individuals affects statistical inferences about which factors make an average "informed" individual more likely to support trade protection. This evidence of uninformed individuals among the population suggests that political economy trade models should consider the effect of systematic "costs" of various populations to inform themselves. Modeling these effects may translate into quite different implications for the economy-wide support for various trade policies. As an example, I show how this systematic selection of individuals into informed and uninformed groups can explain recent findings by Bradford (2008) that U.S. trade protection levels are highest for the medium-skilled industries, not the lowest skilled industries, as might be predicted by a simple Heckscher-Ohlin framework.[2]

A second main focus of the paper is examination of the effects of a life-cycle change, retirement, on an individual's trade policy preferences. Retirement may affect both an individual's decision to inform themselves and their trade policy preference once they are informed. Importantly, retirement means that the individual is no longer in the workforce, which likely means a significant change in their source of income. For example, individuals who were in trade sensitive industries are now likely to have income sources that are less trade-sensitive. In addition, non-participation in the workforce may make it more costly for individuals to inform themselves. My empirical estimates show that while retired individuals are not different from

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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.

[2] My information story is one explanation for how pressure for trade protection (and ultimate protection outcomes) may be non-linear in human skill. This contrasts with recent theoretical work by Blanchard and Willmann (2008) that endogenizes individuals' choices of skill acquisition in general equilibrium models of trade and finds potential equilibria where "middle-skilled" workers' wages in a skill-abundant country face pressure from trade liberalization, whereas both low- and high-skilled workers potentially gain from trade liberalization. Below I provide indirect evidence against the Blanchard and Willmann mechanism and in support of my explanation. In particular, the non-linear relationship in human skills and support for trade protection is present when examining who supports trade protection across all individuals (both informed and non-informed), but not when examining only informed individuals. This suggests that actual trade policy decisions is non-linear in skills, not because trade liberalization would not hurt low-skill workers, but because a disproportionate number of them are not informed on the issue.

others in whether they are informed about trade policy, neither their human capital skills nor the trade exposure of their former occupation industry matter anymore for their trade policy preferences. These results have obvious implications in the coming years as the baby boomer generation hits retirement age. U.S. Census Bureau estimates suggest that the percent of U.S. population 65 and older will increase from 13% in 2010 to almost 20% by 2030.[3]

Finally, in using Scheve and Slaugher (2001) as a starting point for my study, I uncover that their results are sensitive to alternative specifications of their empirical model. In particular, their result that the import exposure of an individuals' occupation does not affect trade policy preferences is sensitive to expanding the sample beyond 1992. Once other years are added to the sample, *both* human capital skills and the trade exposure of an individuals' industry matter for trade policy preferences.

The paper proceeds as follows. In the next section, I present relevant hypotheses about how workers' skills, industry trade exposure, information acquisition, and retirement affect their stated preferences for trade policy. Section 3 describes my data and empirical approach, section 4 presents my statistical results, and section 5 concludes.

2. Hypotheses

2.1. Skills, occupation industry, and trade preferences

Trade-focused political economy models either assume that labor is freely mobile across sectors within a country or that agents (laborers or capitalists) have endowments that are specific to their own industry and cannot be transferred across industries/sectors. An example of the

[3] These calculations are based on population projections found at http://www.census.gov/population/www/projections/usinterimproj/.

former model is the standard Heckscher-Ohlin 2×2×2 framework which yields the well-known Stolper-Samuelson result -- a rise in the price of one of the two goods will increase the real return of the factor endowment that the good uses relatively intensely, and lower the real return of the other factor. Thus, for example, in a model with skilled and unskilled labor as the two factors of production, a rise in the price of the good employing relatively more unskilled labor will benefit all unskilled laborers (regardless of sector). And by the Heckscher-Ohlin theorem, a country with a relatively greater proportion of skilled labor in its workforce (i.e., a developed country) would be exporting the skilled-labor-intensive good and importing the unskilled-labor-intensive good. Thus, if you ask workers in a developed country, such as the US, whether they prefer new import limits, a model with freely mobile workers across sectors predicts that unskilled workers will favor such limits (which would raise the domestic relative price of the unskilled-intensive product), while skilled workers will oppose new import limits.

This is in contrast with a model where factors are sector-specific, not mobile, across sectors. In these models, workers and/or capital owners will have incentives to lobby for import protection when their sector faces greater imports from other countries. If they are successful, price increases from the import limits will provide benefits to only the factors of production being employed in the sector at the expense of factors in other sectors. In contrast, factor owners (either labor or capital) in exporting sectors will oppose limits on imports. In these models then, whether an individual's occupation industry faces competitive pressure from imports will determine their stance on import limits.

In summary, correlation between trade policy preferences and individuals' skills (or human capital endowment), with no correlation between the individual's industry of occupation (and the import competition it faces), rejects the sector-specific model in favor of a model with

freely mobile labor. Alternatively, evidence that industry of occupation, not skills, correlates with individuals' trade policy preferences supports sector-specific models and rejects models of freely-mobile factors. Evidence for both suggests that mobility of factors across sectors is only partially true in some manner, and calls for further investigation.[4] No evidence for either skills or occupation industry correlating with trade policy preferences would suggest that trade policy models need to begin anew in their assumptions.

2.2. The Role of Information

Current political economy models used to address trade policy issues almost invariably assume that individuals have full information about the state of the world. In reality, this means that an individual knows, depending on the assumed underlying model, their relative skill type and their country's relative factor endowment differences, or the nature of import competition for their occupation industry. In practice, however, obtaining this information may involve non-trivial costs and may lead an individual to choose to be uninformed on the issue. The decision to become informed then depends on expected costs and benefits of information acquisition.

For simplification, assume the *ex ante* expected benefits of acquiring information are identical across individuals, but costs of information acquisition may vary. I hypothesize that a number of observed individual characteristics will correlate with higher costs of information acquisition. First, lower education levels will increase the personal cost of an individual to obtain and understand the relevant information. Second, controlling for education levels, lower income will make individuals less likely to inform themselves. In other words, these two hypotheses simply follow from the idea that both intellectual and financial resources are necessary to inform

[4] The sector-specific model can be seen as a short-run version of the Heckscher-Ohlin framework. Thus, Mayda and Rodrik (2006) suggest that evidence for both is consistent with a world where some voters have a short-run

one self. These predictions are in line with a recent political economy literature on the role of information and individuals' decisions to vote in an election.[5]

It is now straightforward to see that costly information acquisition can lead to a much different mapping of welfare effects of trade policy outcomes to expressed trade policy preferences, particularly if skills drive individual welfare effects, than a world where everyone is fully informed. For example, suppose that there is sufficient labor mobility that skills matter for individuals' trade policy outcomes and that individuals' differing skills are distributed continuously over an interval of finite length. Further, assume that in a skilled abundant country such as the United States, the net costs of eliminating import restrictions and adopting free trade (changes in wage income plus changes in consumer prices) are continuously decreasing in skill – the benefits of import protection are highest for the least-skilled. This is depicted in the top panel of Figure 1, which graphs the net benefits of import protection by skill level.[6] This graph represents the extent to which an individual of a certain skill level will favor or oppose import restrictions, assuming all agents are informed about this relationship. The individual with the skill level associated with a zero net benefit is indifferent to trade protection.

Now assume that the costs of information acquisition about free trade costs are decreasing in skill, while expected benefits of information acquisition are constant, as discussed above. This is depicted graphically in the lower panel of Figure 1. Individuals with skill levels below s* will choose to not inform themselves and, by default, have an expected net benefit of import protection equal to zero. This creates a non-linearity in expected net benefits of import protection, which is shown by the wider lines in the upper panel of Figure 1. If the critical s*

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perspective, whereas others have a longer-run perspective.

[5] Such papers include Larcinese (2007a; 2007b) which examine voter's use of information and turnout in Britain. There are other papers that explore information acquisition and voter turnout (see, for example, Fedderson and

occurs before the skill level where actual net benefits of import protection are zero, we get a pattern whereby the medium-skill individuals (ones who are high-skilled enough to be informed, but low-skilled enough to have a net benefit of import protection) will favor import protection, whereas the low- and high-skilled individuals will not advocate (or even oppose) import protection. If less-skilled individuals are more likely to benefit from import protection, but less likely to inform themselves on the issue, they may not be any more likely to vote for trade protection than skilled workers. Translating this into a representative democracy setting, legislators representing less-skilled workers may not be more likely to vote for trade protection even if import protection would benefit these less-skilled workers.

This is obviously a very particular example to show just one way in which information acquisition can affect the expected benefits of import protection and, ultimately, trade policy outcomes. As mentioned, prior literature has constructed trade models with perfect information where net benefits of import protection may not be a continuously decreasing function of skill for a developed country. However, as we will show below, our data are consistent with the model depicted in Figure 1, where stated preferences for trade protection are decreasing in skill for fully informed individuals, but the overall sample of stated preferences by individuals for import protection take this specific non-linear shape because so many low-skill individuals in the sample are uninformed.

2.3. Life-cycle considerations: Retirement

Standard political economy models assume that agents have a consistent source of labor (or capital) income. However, retirement represents a real-life event where individuals

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Pesendorfer, 1996), but this is the first paper I am aware of that examines a particular policy question, rather than general election turnout.

significantly reduce or completely stop employment and, hence, their source of income significantly moves away from employment income to other sources. Statistics calculated by the Employee Benefit Research Institute using data from the 2004 U.S. Consumer Population Survey shows retirees' income sources to consist of the following primary components on average: 1) 40% from social security benefits from the federal government, 2) 19.4% from continued employment, 3) 16.8% from personal asset holdings, 4) 9.3% from public-sector defined-benefit (i.e., pension) plans, and 5) 9.2% from private-sector defined-benefit plans.[7]

From these statistics, it is clear that the majority of a retirees' income source is no longer tied to an employment industry – it is only important for income coming from continued employment (19.4%) or from a private-sector defined-benefit plan (9.2%), where presumably the private sector entity is their former employer. Likewise, their skill would only matter for their income from employment (19.4%) after retirement. These data suggest that there will be a significant reduction of skills and employment industry as determinants of an individual's income after retirement towards income sources (social security, personal-asset holdings, and public-sector defined-benefit plans) that should roughly correlate with the overall growth of the economy. In terms of Figure 1, the net benefits schedule in the top panel should flatten out as the major proportion of retirees' income is no longer tied to their skills, translating into little variation in trade policy preferences across skill groups. Similarly, I hypothesize that retirement should significantly decrease the effect of the trade exposure of the individual's (former) employment industry on their trade policy preferences.

Retirement may also affect whether individuals inform themselves about trade policies. On one hand, it may be more costly to inform oneself once one is no longer (or significantly less

[6] I thank Scott Taylor for suggesting the construction of this graphical model to better illustrate these concepts.
[7] These calculations can be found at: http://www.ebri.org/pdf/programs/policyforums/may2004/ristats.pdf.

involved) in the workforce. Relatedly, the expected benefit of informing oneself about returns to one's own skill set or employment industry from certain trade policies will have gone down considerably. This leads to the hypothesis that retirement will lead individuals to be less likely to acquire information about trade policy impacts, everything else equal. Potentially mitigating or reversing these effects, is the notion that the opportunity cost of time has declined for retirees, making them more likely to acquire information on public policy questions.

3. Data and Empirical Specification

To test these various hypotheses, I create a dataset from the ANES surveys that follows Scheve and Slaughter (2001) 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. 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?''[8]

Scheve and Slaughter (2001) construct a dependent variable for their analysis which assigns a "1" when the individual responded that they favor new limits on imports, and a "0" when they oppose new limits. In my analysis below, I begin with this same dependent variable construction. Given

[8] 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.

that the dependent variable is binary, Scheve and Slaughter (2001) use a logistic regression as their empirical specification. I use a probit specification which yields qualitatively identical empirical estimates, but more easily allows a specification extension to address the issue I raise next.

Constructing a dependent variable in the manner just described leaves out a potentially important group of respondents – those who do not feel they know enough about the issue to express a "favor" or "oppose" opinion. I label these individuals as "uninformed" on the issue of import limits and, in fact, they comprise a significant portion of the overall sample – 27.2%. Scheve and Slaughter do not include these respondents in their sample, but modeling whether an individual is informed or not is important for two reasons. First, understanding the attributes that correlate with an individual's choice to be uninformed is important and has direct implications for models of political economy that invariably assume informed agents. Second, if there is correlation between the types of individuals who choose to be uninformed and those that favor or oppose new import limits, then statistical inferences on only the informed groups (as in Scheve and Slaughter, 2001) will suffer from sample selection bias. To directly address these issues, I run a probit specification with a Heckman-style sample selection that first estimates the determinants of whether an individual has thought about new import restrictions and, second, whether they favor such import restrictions conditional on whether they have thought about the topic.

I use identical control regressors as those employed by Scheve and Slaughter (2001), constructing them in analogous fashion to the greatest extent possible. Scheve and Slaughter (2001) use two alternative measures of an individual's skill and two alternative measures for the trade exposure of the industry in which the individual works. Their measures of skill are years of

education and wage levels. Years of education 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.[9] Following Scheve and Slaughter (2001) 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 Wage" variable that is an occupation's wage relative to the average wage across all occupations in a given survey year. Scheve and Slaughter (2001) simply used wage levels, which is appropriate (and equivalent to my construction) because they only examine a single survey year.

Like Scheve and Slaughter (2001), the two measures of industry trade exposure I construct are the tariff level and 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 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. 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

[9] Retired and unemployed persons in the sample are asked to identify the occupation of their last job. I get qualitatively identical results throughout my analysis whether I sample all individuals or sample only working

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.

Scheve and Slaughter (2001) have a secondary focus of their paper that examines the hypothesis that home owners in trade-sensitive locations will be more likely to prefer trade protection. This is because a house is often an important asset for individuals and house values depend on economic activity in the immediate location. Following Scheve and Slaughter (2001) 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 Exposure*).[10] I then interact this county exposure share variable with a binary variable indicating whether the individual owns a house, which is asked directly by the ANES survey in all my sample years, denoted as *County Exposure* × *House*. By the hypotheses developed in Scheve and Slaughter, I expect a positive correlation 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 as a robustness check, including age, gender, race, political party affiliation, and union membership which come directly from the ANES survey questions. Table 1 provides summary statistics of all the variables used in this study's analysis.

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individuals.

[10] 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*).

4. Empirical Results

In this section, I present my statistical results. I begin with estimates that stem from identical specifications as those in Scheve and Slaughter (2001) using only 1992 data, as in that paper, and obtain qualitatively identical results to their paper. I then examine the robustness of these results by first expanding the sample to all available years. I next model the uniformed individuals, providing evidence of the characteristics that correlate with whether or not an individual is uninformed or not, as well as exploring the robustness of other results when accounting for uninformed individuals. I then explore the relationship between skills and trade policy preferences, allowing for a non-linear relationship. Finally, I examine the impact of retirement on information acquisition and trade policy preferences.

4.1. Base Results

In columns 1 through 4 of Table 2, I provide probit estimates of the determinants of an individual's preference for higher import restrictions using identical specifications to that in Scheve and Slaughter (2001), where I alternate using education and relative wages as measures of an individual's skills and using tariff rates or net imports as a share of sales as measures of the trade exposure of an individual's employment industry. For ease of understanding the economic significance of my regressors on the dependent variable, I show marginal effects and their associated standard errors in these tables, where the reported marginal effects provide the change in the dependent variable (probability of favoring new import restrictions in decimal form) for a one-unit change in the regressor.

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.

My results are qualitatively identical to those in Scheve and Slaughter (2001) – specifically, models 9, 10, 13, and 14 in Table 6 of their paper.[11] Both measures of skill are statistically significant and indicate important effects on trade policy preferences. As found by Scheve and Slaughter (2001), trade exposure of an individual's employment industry is not significant in explaining trade policy preferences. Thus, the 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 not mobile between sectors and trade exposure would affect individual welfare and, hence their trade policy preferences. As in Scheve and Slaughter (2001), I also find that individuals who own homes in trade sensitive areas are much more likely to favor new import restrictions.

4.2. Expanding the sample

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. 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 generally statistically significant – the exception is the *Sector Tariff* variable in the column 7 specification which has a p-value of 0.165. These findings that both skill and industry matter contrast with Scheve and Slaughter (2001), but are consistent with Beaulieu's (2002a) results using Canadian

[11] 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.

survey data, and suggest that workers do not see themselves as either perfectly mobile or perfectly immobile.

The magnitude of the 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 55%), while a one-standard deviation increase in *Education Years* decreases an individual's likelihood of favoring trade protection by 10.6 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 3.2 percentage points.

4.3. Controlling for information acquisition

To this point, my specification has not controlled for whether an individual has thought about trade policy issues. In Table 3, I present estimates from a probit regression where the dependent variable is "1" if the individual has thought about trade protection and "0" if they have not. As discussed in section 2, I assume that whether an individual has thought about trade protection depends largely on the costs of information acquisition, which are decreasing in education and income. To control for income, I use ANES reported household income to construct and include dummy variables for whether an individual's household income is in the lower quartile, second quartile, or third quartile for that sample year.[12] I also include a number of demographic variables that are readily available from the ANES survey, including age, gender,

[12] I exclude a dummy variable for household income in the top quartile to avoid perfect multicollinearity with an included constant term in the regression.

ethnicity, political affiliation and labor union participation.[13] Finally, I also include an indicator variable for whether the individual voted in the most recent past election, since an individual would be presumably more likely to inform themselves on issues in preparation for voting.

Table 3 provides results from the probit estimation using the dependent variable indicating whether an individual has thought about trade protection. The variables used to proxy for information costs come in with expected signs and are statistically significant. The estimated marginal effects suggest that each additional year of education adds 2.6 percentage points to the likelihood that an individual will have thought about trade protection (from a mean around 70%).[14] Individuals in the lowest household income quartile are 7.0 percentage points less likely to have thought about trade protection than the highest household-income quartile, while those in the second quartile are 4.5 percentage points less likely. There is no statistical difference between those in the highest and second-highest household income quartiles. Thus, as hypothesized, low-education and low-income individuals are less likely to acquire information about trade protection.

The demographic variables provide quite interesting statistical results. First, an individual is more likely to have thought about trade protection as they age – ten years of age makes an individual about 2 percentage points more likely to have informed themselves enough to provide an opinion on new import limits. Ethnicity is estimated to have some impact as well, with African Americans and Hispanics less likely to have thought about trade protection, ceteris paribus. Political affiliations do not have any statistical impact, while union membership

[13] These are the same demographic variables that Scheve and Slaughter (2001) use for robustness checks in their work. In unreported results, I also included other variables from the trade policy preference equation, including the *Sector Net Export Share* and *County Exposure* variables. These could possibly come in significantly if expected benefits of information acquisition depend on how individuals are affected by trade policy. However, none of these variables are statistically significant in the thought regression.

increases the likelihood of having thought about trade policy by 2.4 percentage points. As expected, voting in the past election is also strongly correlated with feeling currently informed about trade policy, increasing the likelihood by 5.9 percentage points. Finally, gender has an unexpectedly large effect, with women 17 percentage points lower in their likelihood of thinking about trade protection than men, ceteris paribus (i.e., after controlling for age, income, race, and education). Such a large gap brings up the possibility of an alternative interpretation for my results. Perhaps these estimates are not only uncovering who becomes informed about trade policies, but also who is confident enough to offer an opinion on trade policies.

To examine this further, I collect data on a couple variables from the ANES survey that may be good proxies of whether individuals inform themselves: 1) whether an individual has discussed politics with friends or family in the past week, and 2) whether the individual has read a newspaper in the past week. I then run a probit specification using these two variables separately as dependent variables on the same regressor matrix used in the specification in Column 1 to explain whether an individual has thought about import restrictions. The marginal effects from these separate probit regressions are reported in with the Columns 2 and 3 of Table 3. I find that all three dependent variables have many correlates in common. Age, education, income, and voting in the last election are positively correlated with all three, while being female means a significantly lower probability for all three. These results then provide some confirmatory evidence that information acquisition (not simply some other factor, such as an individual's confidence) is a true underlying reason why some individuals suggest they are not informed enough to offer an opinion on import restrictions. The robust and large effect of gender on information acquisition is a new result that complements a related recent literature that finds

[14] This correlation between education and information acquisition about trade policies may also explain why less-educated individuals answer to trade policy questions have found to be more sensitive to how the survey question is

women are more likely to favor trade protection (see Beaulieu and Napier, 2008, and Burgoon and Hiscox, 2008).

In summary, variables proxying for information acquisition costs, as well as some interesting demographic variables, are quite significant in explaining variation in individuals' likelihoods of being informed about trade policies. I next want to explore how this selection of individuals affects both my estimates of trade policy preferences, as well as some evidence on trade outcomes.

Table 4 provides re-estimates of the determinants of individuals' trade policy preferences after controlling for sample selection bias due to conditioning on only those who have thought about trade policy. In technical terms, I re-estimate the same specification as columns 5 through 8 using a two-step Heckman sample selection correction, where the sample selection equation is the one used in Table 3. I also include the same demographic variables in the trade policy preference specification as I use in the selection equation, except for whether a person voted in the last election – this variable serves as my exclusion restriction.[15] Theoretically, prior experience voting in a general election should not have any significant impact on one's views on any one particular issue, such as trade policy. And, empirically, I do not find any statistically significant correlation between voting in the past election and whether one supports import protection or not. While statistical tests confirm that there is a sample selection bias in these data[16], I find that the bias is fairly small in economic magnitude, as I get qualitatively identical

framed. (see Hiscox, 2006)

[15] Due to statistical convergence difficulties, I must exclude the variable indicating female gender in the trade policy preference specification when using education to proxy for skills. I do include the female gender variable in the trade policy specification when proxying for skills with relative wages, and the gender variable comes in statistically insignificant. This contrasts with previous research (mentioned earlier) that finds that women are more protectionist than men.

[16] A likelihood ratio test rejects independence of the two equations at the 1% significance level in all specifications.

results on the determinants of trade policy preferences with or without a sample selection correction.

4.4. Explaining the non-linear relationship between skills and trade policies

As mentioned in the introduction, Bradford (2008) recently shows that trade policy outcomes in the U.S. are non-linear in skills, with the lowest- and highest-skilled industries having significantly lower tariff rates than medium-skilled industries. Are individuals' trade policy preferences, like these trade policy outcomes, also non-linear in skills in this same way? In answering this question with my data, I show that information acquisition is a key factor in explaining this non-linear pattern and is consistent with the model results depicted in Figure 1.

To explore this issue, I first categorize individuals into standard education classifications that represent progressively higher degrees of education: 1) less than high school, 2) high school degree, 3) some college, 4) college bachelor's degree, and 5) graduate or professional degree beyond college degree.[17] I then replace *Education Years* in my specification with dummy variables for whether an individual falls into one of these categories (excluding the last category to avoid perfect multicollinearity with the constant term) and run this on alternative data samples and dependent variables in Table 5.[18]

Column 1 of Table 5 provides estimates when I estimate this new specification on only those individuals in my sample who felt sufficiently informed to provide an opinion on whether they favor new import limits. Column 2 provides estimates when I also include a sample-selection correction when estimating preferences for this informed group. In both sets of

[17] I get qualitatively identical results by simply adding a term that squares an individual's *Education Years*, but find this construction of education categories is easier for immediate interpretation and presentation.
[18] For brevity, I only present results here using the *Sector Net Export Share* variable to proxy for the trade exposure of the respondent's industry, though I get qualitatively identical results if I use the *Sector Tariff* variable.

estimates, I see that support for new import limits are simply decreasing in education. There is not a non-linear relationship in trade policy preferences amongst the informed individuals in my sample that follows the pattern found by Bradford (2008) with respect to trade policy outcomes.

However, in column 3 of Table 5, I sample all individuals (informed and uninformed) and create a dependent variable that simply takes the value of "1" if an individual favors new import limits, and a "0" if they do not. This dependent variable includes both individuals who explicitly say they oppose new limits, as well as those that simply say they have not thought about trade protection enough to offer an opinion. Estimates using this sample show the same pattern across skills/education in stated preferences by voters, as Bradford (2008) finds for trade policy outcomes. The least skilled group (those with less than high school education) do not express their preference for new import limits any more than those with a college (or higher) degree, while the medium-skilled groups (high school education or some college) express preference for new import limits in rates that are about 9-10 percentage points higher than the other skill groups. These results suggest that while low-skill workers are more likely to want new import limits when they are informed about trade policy outcomes, since a disproportionately large share of them are not informed, they do explicitly favor trade protection any more than high-skill workers. To the extent that political representatives only respond to voiced opinions by their constituents, the low information acquisition by low-skill workers can explain the non-linear trade policy outcomes across skill levels documented by Bradford (2008).

4.5. Life-cycle effects: Retirement

A final aspect of my data that I explore is the effect of retirement. Standard political economy models do not consider life-cycle changes and retirement is a significant life-cycle

change which may affect both whether an individual acquires information on issues such as trade protection, and whether they favor or impose trade protection with the significant change in the source of their annual income. The ANES survey asks individuals of their retirement status allowing us to easily explore this issue.[19]

I first include a dummy variable indicating whether an individual is retired in the specification that examines the determinants of whether an individual has thought about trade protection (reported in Table 3). The coefficient on retirement status comes in negative, but is statistically insignificant in most specifications I examine. This suggests that there is only weak evidence, at best, that retirees are (or feel) less informed than current workers on the issue of trade policy.

I next turn to an examination of whether retired individuals who acquire information on trade policies are more or less likely to favor new import limits. As discussed in section 2, retirees experience a significant de-linking of their income source from their (former) occupation industry and workforce skills. Thus, I hypothesize an individual's skill and trade exposure of their (former) industry have a much weaker effect an individual's trade policy preferences once they are retired.

Importantly, the ANES survey gathers data on retirees' last occupation industry in which they were employed. This allows me to interact the skill and industry trade exposure variables with retirement status to examine the hypothesis that retirement will decrease support for trade protection from those previously exposed to harm from freer trade. Table 6 presents results when I add the *Retired* dummy variable, as well as its interactions with the skill and trade exposure variables, to the same specifications examining the determinants of support for new import limits

[19] The survey actually gathers information on whether individuals are fully retired or partially retired and still working part-time. I aggregate these two types into one "retired" category and my estimates are qualitatively

after controlling for sample selection (as reported in Table 4). The results provide support that retirement leads those that formerly supported new import limits to decrease that support. In every instance the sign of the coefficient of an interaction term is opposite of the associated skill or industry trade exposure variable, indicating that retirement mitigates these variables' effect on an individual's trade policy preference. Table 7 shows this more clearly by providing marginal effects of the skill and industry occupation variables separately for retired individuals and those not retired.[20] In virtually every case the effect of a skill or industry trade measure is statistically insignificant for a retired individual, while its independent effect (on all non-retired individuals in the sample) are generally statistically significant and of the same magnitude as those reported in Table 4.

In summary, the life-cycle change of retirement has a significant impact on expressed trade policy preferences. Skill and industry trade exposure variables are generally no longer significant in explaining their trade policy preferences. This life-cycle change effect on trade policy preferences is, of course, important for the United States and many other countries as their population ages.

5. Conclusion

This paper provides new empirical evidence for important features of trade policy preference formation that current models of political economy rarely, if ever, address. First, information acquisition by individuals on policy matters is potentially costly and the data suggest that many do not feel sufficiently informed to state an opinion on trade policy. These

identical to when one classifies retired individuals as only those fully retired.

[20] Ai and Norton (2003) demonstrate that marginal effects for probit and logit models are often incorrectly calculated by statistical packages. I get qualitatively identical results if I simple run regressions on separate samples of retired and non-retired individuals. I get strong and statistically significant effects on skills and industry exposure

"uninformed" individuals are systematically those with less education and income, and I show that this can explain why trade policy outcomes may be non-linear in skills (with low-skill and high-skill have lower preferences for trade protection than medium-skill workers), even though freer trade may be progressively more harmful to one's income the lower skill one has. Second, I show that the life-cycle change surrounding retirement has significant impacts on individuals' stated trade policy preferences, lowering the likelihood that an individual will acquire information on trade policies, and fully mitigating any effects of skill or industry trade exposure effects on an individuals' preferences for trade protection. Thus, the evidence in this paper suggests that future political economy modeling of trade policy outcomes will need to incorporate these features to obtain realistic predictions of trade policy formation. Another contribution of the paper is to show that both an individual's skills and the trade exposure of their occupation industry matter, which contrasts with the Scheve and Slaughter (2001) study using these same ANES data, and which suggests that workers are neither freely mobile nor freely immobile in their ability to switch occupation industries.

for the non-retired individual sample, and coefficients much closer to zero and statistically insignificant on these variables for the sample of retired individuals.

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Figure 1: Net benefits of import protection and information acquisition by individuals' skills.

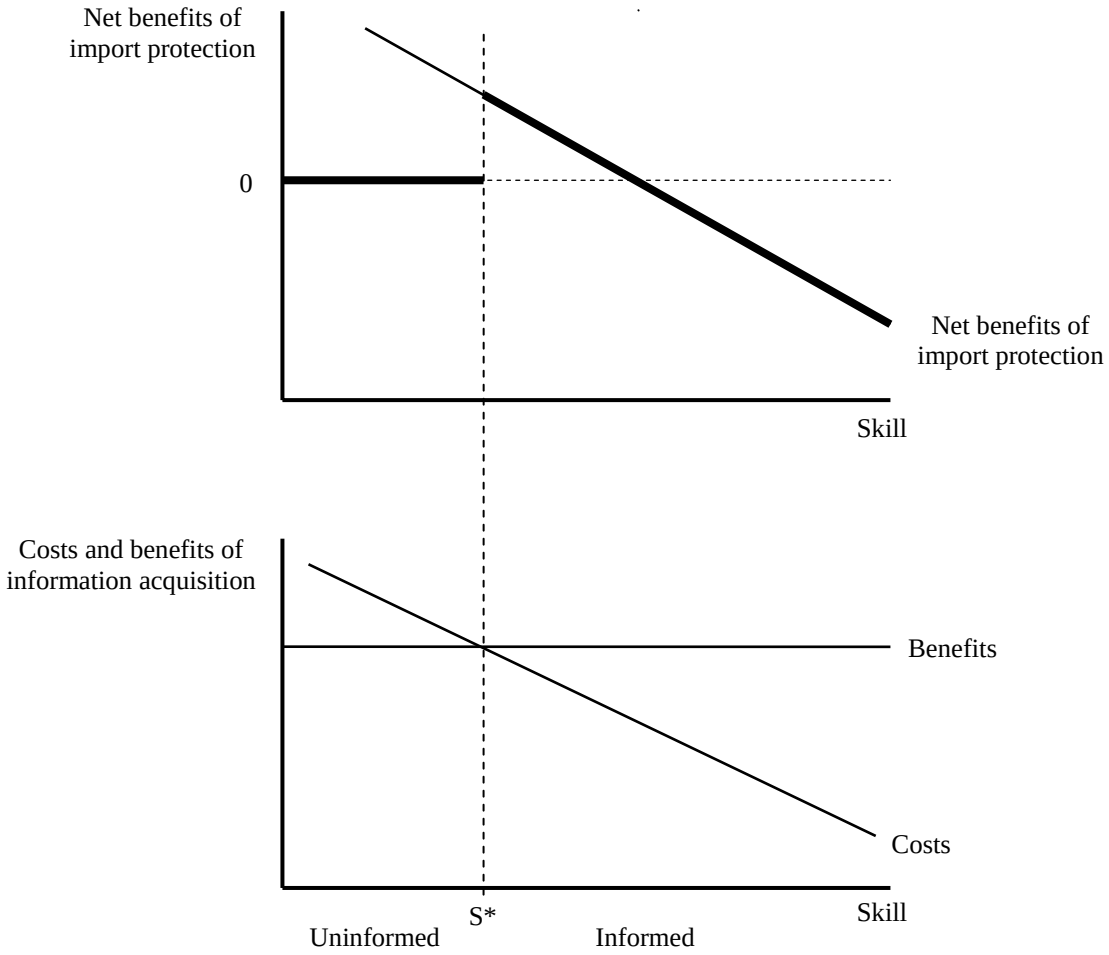

Table 1: Descriptive Statistics

Variable	Obser-vations	Mean	Standard Deviation	Min	Max
Dependent variables					
Thought about import limits?	10143	0.711	0.453	0.000	1.000
Want new import limits (conditional on thought)	6963	0.579	0.494	0.000	1.000
Want new import limits (all individuals)	9892	0.408	0.491	0.000	1.000
Independent variables in trade protection preference regression					
Relative Occupation Wage	8344	1.110	0.339	0.362	1.599
Education Years	9454	12.903	2.802	1.000	17.000
Sector Tariff	8299	0.008	0.025	0.000	0.266
Sector Net Export Share	8090	-0.011	0.221	-15.642	0.534
County Exposure	9887	0.063	0.064	0.000	0.450
County Exposure × House	9564	0.041	0.061	0.000	0.444
Additional independent variables in thought regression and as controls in trade vote regression					
Age (in years)	9636	45.472	17.572	17.000	99.000
Female	9644	0.553	0.497	0.000	1.000
African American	10143	0.150	0.358	0.000	1.000
Asian	10143	0.063	0.243	0.000	1.000
Hispanic	10143	0.117	0.321	0.000	1.000
Native American	10143	0.087	0.281	0.000	1.000
Democrat	9644	0.371	0.483	0.000	1.000
Republican	9644	0.287	0.453	0.000	1.000
Union Membership in Household	9644	0.178	0.383	0.000	1.000
Household Income - Lowest 25th Percentile	9644	0.225	0.418	0.000	1.000
Household Income - 25th-50th Percentile	9644	0.245	0.430	0.000	1.000
Household Income - 50th-75th Percentile	9644	0.224	0.417	0.000	1.000
Voted in Last Election	9644	0.612	0.487	0.000	1.000
Retired	9644	0.155	0.362	0.000	1.000

Table 2: Re-estimating Scheve and Slaughter: Support for Import Protection for 1992 and Full Sample of Years (Marginal Effects)

	1992 Sample Only				Full Sample of Years			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Relative Occupation Wage	-0.133***	-0.128***			-0.171***	-0.172***		
	(0.035)	(0.036)			(0.020)	(0.020)		
Education Years			-0.044***	-0.042***			-0.038***	-0.038***
			(0.005)	(0.005)			(0.003)	(0.003)
Sector Tariff	0.471		-0.081		0.973***		0.447	
	(0.661)		(0.687)		(0.323)		(0.322)	
Sector Net Export Share		-0.057		0.025		-0.214***		-0.147**
		(0.129)		(0.132)		(0.068)		(0.067)
County Exposure	-0.096	-0.053	-0.392	-0.353	0.148	0.181	0.065	0.076
	(0.321)	(0.032)	(0.352)	(0.350)	(0.159)	(0.159)	(0.162)	(0.162)
County Exposure × House	0.911***	0.987***	1.200***	1.253***	0.293*	0.306*	0.342**	0.354**
	(0.330)	(0.333)	(0.356)	(0.358)	(0.166)	(0.167)	(0.169)	(0.170)
Year dummies	No	No	No	No	Yes	Yes	Yes	Yes
Pseudo R^2	0.014	0.015	0.050	0.049	0.045	0.046	0.064	0.065
Chi-squared Statistic	27.77	27.85	91.48	88.09	324.89	322.32	460.54	457.60
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1504	1476	1417	1390	5480	5342	5409	5270

Notes: The table presents marginal effects (not coefficient estimates) of the regressors with standard errors in parentheses. Statistical significance at the 10, 5 and 1 percent levels are denoted by *, **, and ***, respectively. Columns 1 through 4 correspond to models 9, 10, 13, and 14, respectively, in Table 5 of Scheve and Slaughter (2001)

Table 3: What Factors Explain Whether People Have Thought about Import Restrictions, Discussed Politics in the Last Week or Read the Newspaper in the Last Week? (Marginal Effects)

Variables	Thought about import restrictions	Discussed politics in last week	Read newspaper in last week
Information Cost Variables			
Education Years	0.026***	0.035***	0.021***
	(0.002)	(0.002)	(0.002)
Household Income - Lowest 25th Percentile	-0.070***	-0.013	-0.046***
	(0.015)	(0.016)	(0.013)
Household Income - 25th-50th Percentile	-0.045***	-0.019	-0.015
	(0.014)	(0.015)	(0.012)
Household Income - 50th-75th Percentile	0.001	0.021	-0.025**
	(0.014)	(0.015)	(0.012)
Demographic Variables			
Age (in years)	0.002***	-0.002***	0.002***
	(0.000)	(0.000)	(0.000)
Female	-0.170***	-0.051***	-0.052***
	(0.009)	(0.011)	(0.008)
African American	-0.082***	-0.002	0.013
	(0.017)	(0.018)	(0.013)
Asian	-0.010	-0.061	-0.031
	(0.042)	(0.045)	(0.036)
Hispanic	-0.050**	-0.075***	0.001
	(0.019)	(0.021)	(0.015)
Native American	0.029	0.040	-0.035*
	(0.023)	(0.026)	(0.021)
Democrat	-0.002	0.003	0.021**
	(0.010)	(0.012)	(0.009)
Republican	0.018	0.026**	0.018**
	(0.011)	(0.012)	(0.009)
Union Membership in Household	0.024**	0.006	0.019*
	(0.013)	(0.014)	(0.011)
Voted in Last Election	0.059***	0.289***	0.082***
	(0.011)	(0.011)	(0.009)
Year Dummies	Yes	Yes	Yes
Pseudo R^2	0.094	0.120	0.085
Chi-squared Statistic	1086.39	1523.81	801.97
(p-value)	(0.000)	(0.000)	(0.000)
Observations	9448	9413	9411

Notes: Reported results are marginal effects (not coefficient estimates) of the regressors, where a one-unit change indicates the percentage point change in the dependent variable.

72.7% of individuals in the sample report they have thought about import restrictions, 61.4% have discussed politics with family or friends in the past week, and 82.4% have read the newspaper in the past week. Standard errors are in parentheses. Statistical significance at the 10, 5 and 1 percent levels are denoted by *, **, and ***, respectively.

Table 4: Trade Policy Preferences for Greater Import Protection after Controlling for Sample Selection? (Marginal Effects)

Variable	(1)	(2)	(3)	(4)
Relative Occupation Wage	-0.059**	-0.056***		
	(0.023)	(0.023)		
Education Years			-0.009***	-0.009***
			(0.001)	(0.001)
Sector Tariff	0.598*		0.545*	
	(0.310)		(0.308)	
Sector Net Export Share		-0.144**		-0.136**
		(0.064)		(0.064)
County Exposure	0.020	0.047	0.055	0.080
	(0.156)	(0.155)	(0.100)	(0.158)
County Exposure × House	0.369**	0.365**	0.384**	0.385**
	(0.167)	(0.166)	(0.169)	(0.169)
Year Dummies	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Chi-squared Statistic	446.48	452.86	466.20	470.56
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	8245	8108	8288	8149

Notes: The table presents marginal effects (not coefficient estimates) of the regressors with standard errors in parentheses. Statistical significance at the 10, 5 and 1 percent levels are denoted by *, **, and ***, respectively.

Table 5: Nonlinear Relationship Between Skills and Trade Policy Preferences? The Importance of Modeling Information (Marginal Effects)

	Various dependent variable definitions		
Variables	**Want new import limits? (Only those that have thought about it)**	**Want new import limits? (Full sample conditioning on whether one has thought about it)**	**Want new import limits? (Full sample not conditioning on whether one has thought about it)**
Education – Less Than High School	0.194***	0.199***	0.005
	(0.022)	(0.012)	(0.023)
Education – High School	0.207***	0.193***	0.097***
	(0.019)	(0.012)	(0.019)
Education – Some College	0.137***	0.131***	0.091***
	(0.020)	(0.011)	(0.020)
Education – College Degree	0.005	0.031**	-0.004
	(0.024)	(0.014)	(0.023)
Sector Net Export Share	-0.128*	-0.080*	-0.054
	(0.068)	(0.043)	(0.046)
County Exposure	0.102	0.053	-0.047
	(0.166)	(0.100)	(0.135)
County Exposure × House	0.302*	0.215*	0.366**
	(0.177)	(0.110)	(0.143)
Year Dummies	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Chi-squared Statistic	618.75	861.71	566.59
(p-value)	(0.000)	(0.000)	(0.000)
Observations	5380	8149	7657

Notes: The table presents marginal effects (not coefficient estimates) of the regressors with standard errors in parentheses. Statistical significance at the 10, 5 and 1 percent levels are denoted by *, **, and ***, respectively.

Table 6: The Role of Retirement in Stated Support for Import Protection (Marginal Effects)

Variable	(1)	(2)	(3)	(4)
Relative Occupation Wage	-0.062**	-0.062**		
	(0.024)	(0.024)		
Education Years			-0.010***	-0.011***
			(0.002)	(0.002)
Sector Tariff	1.126***		1.076***	
	(0.368)		(0.364)	
Sector Net Export Share		-0.164**		-0.145*
		(0.076)		(0.076)
County Exposure	-0.018	-0.045	0.026	0.070
	(0.157)	(0.155)	(0.157)	(0.161)
County Exposure × House	0.382**	0.369**	0.389**	0.426**
	(0.167)	(0.166)	(0.167)	(0.172)
Retired	0.024	-0.010	-0.121	-0.217***
	(0.068)	(0.066)	(0.074)	(0.065)
Retired × Relative Occupation Wage	0.021	0.034		
	(0.068)	(0.053)		
Retired × Education Years			0.011*	0.015***
			(0.006)	(0.005)
Retired × Sector Tariff	-2.185***		-1.996***	
	(0.696)		(0.708)	
Retired × Sector Net Export Share		0.073		0.042
		(0.134)		(0.132)
Year Dummies	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Chi-squared Statistic	456.28	453.79	483.78	472.55
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	8245	8108	8288	7509

Notes: The table presents marginal effects (not coefficient estimates) of the regressors with standard errors in parentheses.Statistical significance at the 10, 5 and 1 percent levels are denoted by *, **, and ***, respectively.

Table 7: Differences Between Retired Individuals and Those Not Retired with Respect to the Effects of Skill and Occupation Industry on Support for Import Protection. (Marginal Effects)

	Not Retired	Retired
Column 1, Table 6		
Relative Occupation Wages	-0.062**	-0.041
	(pval=0.01)	(pval=0.43)
Sector Tariff	1.126***	-1.059*
	(pval=0.00)	(pval=0.07)
Column 2, Table 6		
Relative Occupation Wages	-0.062**	-0.028
	(pval=0.01)	(pval=0.58)
Sector Net Export Share	-0.164**	-0.090
	(pval=0.03)	(pval=0.42)
Column 3, Table 6		
Education Years	-0.010***	0.001
	(pval=0.00)	(pval=0.85)
Sector Tariffs	1.076**	-0.920
	(pval=0.00)	(pval=0.13)
Column 4, Table 6		
Education Years	-0.011***	0.005
	(pval=0.00)	(pval=0.36)
Sector Net Export Share	-0.146*	-0.103
	(pval=0.06)	(pval=0.36)

Notes: Reported results are marginal effects (not coefficient estimates) of the regressors and come from Table 6 specifications as noted. The "pval" reported in parentheses is the probability value of a chi-squared statistic that the marginal effect is statistically different from zero. Statistical significance at the 10, 5 and 1 percent levels are denoted by *, **, and ***, respectively.

Data Appendix

Many of the variables used in this study come directly from questions in the ANES survey, including our dependent variables, as well as the following regressors: *Education Years*, *House*, *Age*, *Female*, *African American*, *Asian*, *Hispanic*, *Native American*, *Democrat*, *Republican*, *Union Membership*, and *Retired*. The income variables I use come from household income questions which had respondents report where the 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 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 their Quarterly Census of Employment and Wages. This is identical to the procedure used by Scheve and Slaughter (2001). However, because we have multiple years in the sample, I normalize these 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 (2001) 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 (2001), 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 (2001) 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. Ship-

ment 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 measures of county exposure to trade, primarily *County Exposure* in this paper, follows Scheve and Slaughter's (2001) 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.