Did Trade Liberalization with China Influence U.S. Elections?*

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Abstract

This paper examines the impact of trade liberalization on U.S. Congressional elections. We find that U.S. counties subject to greater competition from China via a change in U.S. trade policy exhibit relative increases in turnout, the share of votes cast for Democrats and the probability that the county is represented by a Democrat. Using a regression discontinuity analysis, we show that these changes are consistent with Democrats in office during the period examined being more likely to support legislation limiting import competition or favoring economic assistance. (JEL Codes: F13; F16; D72) (Keywords: China; Voting; Elections; Import Competition; Normal Trade Relations; World Trade Organization)

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1 Introduction

International trade has long been a contentious issue in U.S. elections, with the U.S. trade deficit with China emerging as a focus of particular attention in the 2000s. Recent research establishes a link between the sharp loss of U.S. manufacturing jobs during that period and a change in U.S. trade policy – the granting of Permanent Normal Trade Relations (PNTR) to China – which might affect voters' preferences via several channels, including unemployment, wages, profits and goods prices.[1]

This paper examines the relationship between increased import competition from China and voting in elections for the U.S. House of Representatives, as well as whether any change in voting is consistent with the legislative positions of those elected to Congress. In the first part of our analysis, we show that U.S. counties with greater exposure to PNTR's trade liberalization exhibit relative increases in the share of votes cast for Democrats and the probability that a Democrat represents the county from 2000 to 2010, as well as increases in voter turnout. The second part of our analysis documents a rationale for this change in voting by showing that Congressional Democrats during this period were more likely to support policies that place restrictions on imports and that provide economic assistance that might mitigate the impact of import competition.

We focus on voting in elections for the U.S. House of Representatives because House members serve two-year terms and are expected to maintain close personal contact with constituents. As a result, House members may be more responsive to the short-term demands of voters than elected officials with longer terms such as Senators or Presidents.[2]

We examine voting within *counties* rather than Congressional districts for two reasons. First, using counties as the unit of analysis allows us to reliably track outcomes before and after the redistricting that occurs between the 2000 and 2002 Congressional elections. This ability is important because it permits us to observe voting consistently before and after PNTR, and because 2000 to 2002 was a critical period in the decline of U.S. manufacturing employment. Indeed, that period accounts for nearly two thirds of the job loss that occurred between January 2000 and November 2007. A district-level analysis, by contrast, is necessarily limited to years before or after this key period. A second benefit of conducting the analysis at the county level is that we are able to observe demographic control variables at the same level as the voting data,

[1]Pierce and Schott (2016a) find that U.S. industries with greater exposure to PNTR experience larger increases in imports from China and greater declines in manufacturing employment after 2000. Autor et al. (2013) find that rising Chinese imports account for 25 to 50 percent of the manufacturing job loss across U.S. commuting zones between 2000 and 2007. Handley and Limao (2017) estimate that the granting of PNTR is equivalent to a 13 percent reduction in import tariffs.

[2]Karol (2012) finds that Senators and Presidents are more likely to support policies (like free trade) that are in the long-run interests of the country as a whole, even if they run counter to the short-run preferences of voters. Conconi et al. (2014) show that Senators are more likely to support trade liberalization than Representatives, but that the result does not hold for Senators facing elections within the next two years.

while also allowing for greater variation in measures of voting, exposure to PNTR, and demographic characteristics than would be possible for most Congressional districts. While election outcomes are determined at the district level – where population size is identical by design – county population sizes can vary substantially. As a result, we show that our results are robust to weighting by population.

Our difference-in-differences empirical strategy examines whether counties more exposed to the change in U.S. trade policy (first difference) experience differential changes in voting for Democrats after the policy is implemented (second difference). Across specifications that are either unweighted or weighted by counties' initial population, coefficient estimates suggest that moving a county from the 25th to the 75th percentile in terms of exposure to the change in U.S. trade policy is associated with a 1.3 to 1.4 percentage point increase in the share of votes cast for Democrats, representing a 2.6 to 3.6 percent increase relative to the across-county average share of votes for Democrats in the 2000 Congressional election, the closest Congressional election to the change in U.S. trade policy. Coefficient estimates from similar specifications indicate that the probability of a switch in representation for a county from a Republican to a Democrat Representative increases by 3 to 4 percentage points.

We allow for the potential influence of spillovers from nearby areas by controlling for changes in exposure to China experienced by neighboring counties that are part of the same labor market. Results from these specifications are qualitatively similar to the baseline specifications but somewhat larger in magnitude: moving a county from the 25th to the 75th percentile in terms of both own exposure to the policy change and neighboring counties' exposure is associated with a 4.2 percent increase in the share of votes won by the Democrat relative to the average in the year 2000 election, versus 3.6 percent in the baseline specification.

Additional evidence on voter turnout and on voting for other offices provides further support for a role for PNTR in U.S. election outcomes. First, we find that counties more exposed to PNTR exhibit larger increases in voter turnout after the policy change, relating to the political science literature on the effect of economic conditions on voter turnout (e.g. Schlozman and Verba 1979). Second, we find that the increase in the share of votes cast for Democrats associated with PNTR is also present for Presidential and gubernatorial elections, though this relationship is partially offset in the 2016 Presidential election.

We also show that the effect of trade liberalization on elections is transmitted, in part, through the labor market. Using a two-stage least squares specification, we estimate the effect of changes in the county-level unemployment rate on voting in House elections, using exposure to PNTR as an instrument for the unemployment rate. These two-stage least squares results indicate that higher instrumented unemployment rates are associated with increased electoral support for Democrats, consistent with the OLS results described above.

The second part of our analysis examines Representatives' votes on legislation during the 1990s and 2000s using a regression discontinuity identification strategy that compares the voting of Democrats and Republicans who win office by small margins.

The analysis indicates that Democrats during this period are more likely to take positions that restrict trade and that offer economic assistance that may benefit those adversely affected by import competition, providing a rationale for the change in voting documented in the first part of the paper. We find that the tendency for Democrats to support such legislation is stronger after implementation of PNTR.

Together, the results in the first and second parts of the paper suggest that voters who perceive themselves as being disadvantaged by trade are more likely to vote for politicians that might restrict imports or be in favor of redistributing gains from winners to losers. We also find evidence that these relationships provide intuition for the results of the 2016 U.S. Presidential election, in which the Republican nominee, Donald Trump, departed from traditional party views and expressed strong support for restricting U.S. imports from China and other lower-wage countries. Extending our results on Presidential elections to 2016, we find that while exposure to PNTR is associated with relatively high Democrat vote shares through 2012, the result is partially offset in 2016.

This paper relates to literatures on voting in both political science and economics, and also complements the large literature examining the impact of international trade on labor market outcomes.[3] In the voting literature, Feigenbaum and Hall (2015) examine the effect of Congressional-district-level economic shocks from Chinese imports – using the approach in Autor, Dorn and Hanson (2013) – on the roll-call behavior of legislators and electoral outcomes. They find that legislators from districts experiencing larger increases in Chinese import competition become more protectionist in their voting on trade-related bills, and that incumbents are able to insulate themselves from electoral competition via this voting behavior. Using a different identification strategy, Jensen, Quinn and Weymouth (2016) find that votes for presidential incumbents rise with expanding U.S. exports and fall with rising U.S. imports.

More recently, Autor et al. (2016) examine the relationship between increased Chinese import competition and partisan rankings of members of Congress. They find that Congressional district-county pairs exposed to larger gains in imports from China experience increases in the partisanship of Representatives representing those districts, with initially Democrat districts becoming somewhat more liberal, and initially Republican districts becoming substantially more conservative. In contrast to the results in this paper, Autor et al. (2016) find no relationship between higher exposure to Chinese import competition and party vote share. In addition to the differences associated with units of analysis (counties versus Congressional districts) and main explanatory

[3] A substantial body of research documents a negative relationship between import competition and U.S. manufacturing employment, e.g., Freeman and Katz (1991), Revenga (1992), Sachs and Shatz (1994) and Bernard et al. (2006). More recently, a series of papers link Chinese imports to employment outcomes in the United States and other developed or developing countries, e.g., Groizard, Ranjan and Rodriguez-Lopez (2012), Autor et al. (2013), Mion and Zhu (2013), Utar and Torres Ruiz (2013), Ebenstein et al. (2014) and Bloom et al. (2016). Increasingly active areas of research examine links between international trade and health (McManus and Schaur 2016, Lang et al. (2016) and Pierce and Schott 2016b), crime (Dix-Carneiro et al. 2017 and Che and Xu 2016), the provision of public goods (Feler and Senses 2016), marriage and fertility decisions (Autor, Dorn, and Hanson 2017), and media coverage (Lu, Shao, and Tao 2016).

variable (change in policy versus import growth), Autor et al. examine a shorter time period – 2002 to 2010 – than that employed in this paper (1992 to 2010).

Outside the United States, Dippel, Gold and Heblich (2015) examine data from German labor markets and find that higher imports from Eastern Europe and China are associated with an increase in the share of votes for far right parties.[4] And, in related research on immigration rather than trade, Mayda, Peri and Steingress (2016) find that the share of votes cast for Republicans in U.S. elections responds to the level of immigration, with the effect varying based on the share of naturalized migrants and non-citizen migrants in the population.

Finally, this paper also relates to a literature that examines the role of trade on legislators' voting activity. Conconi et al. (2012), for example, examine the impact of district-level trade competition on Representatives' votes to grant U.S. Presidents Fast Track Authority *vis a vis* the negotiation of trade agreements, and Conconi et al. (2015) examine the role of skilled labor abundance in Representatives' votes on trade and immigration bills. Blonigen and Figlio (1998) find that legislators' votes for bills related to trade protection are positively associated with direct foreign investment.

We proceed as follows. Section 2 provides an overview of the growth of U.S.-China trade. Section 3 describes our data sources. Sections 4 and 5 present our empirical results. Section 6 concludes.

2 China's Growth as a U.S. Trade Partner and Focus of Political Discourse

Over the past thirty-five years China has jumped from being an insignificant contributor to world GDP to the world's second-largest economy and largest trading state. In 2007 it became the United States' largest source of imports, accounting for 17 percent of all imports versus just 3 percent in 1990. Moreover, as illustrated in Figure 1, the pace of gains in U.S. imports from China accelerated after China's receipt of PNTR in 2000. U.S. exports to China also grew substantially over this period, but less rapidly, with the result that by 2007 the United States' trade deficit with China exceeded $250 billion U.S. dollars, or 1.7 percent of GDP, up from 0.3 percent of GDP in 1990.

As illustrated in Figure 2, the United States' growing imports from China coincide with a sharp, 18 percent decline in U.S. manufacturing employment from March 2001 to March 2007. Pierce and Schott (2016a) show that this decline was steeper in industries more exposed to the U.S. granting of permanent normal trade relations to China, while Autor et al. (2013) show that commuting zones with industries facing higher import competition from China experienced greater declines in manufacturing employment.

Broader measures of the the labor market exhibit similar breaks. Autor et al. (2013) show that workers in regions experiencing higher levels of import competition exhibit

[4]Scheve and Slaughter (2001) show that individuals' trade policy preferences are affected by skill level and homeownership status.

greater uptake of social welfare programs such as disability, and Pierce and Schott (2016b) show that counties more exposed to PNTR experience both relatively higher levels of unemployment and lower levels of labor force participation during the 2000s. These trends – potentially influential in driving voting preferences – are consistent with estimates of substantial adjustment costs for workers who switch industries or occupations in Artuc et al. (2010), Ebenstein et al. (2014), Caliendo et al. (2015) and Acemoglu et al. (2016).

Growth in the U.S. trade deficit with China has motivated U.S. legislators at various levels of government to propose restricting imports from China. As discussed in Pierce and Schott (2016a), Congress demonstrated substantial resistance to the renewal of normal trade relations for China during the 1990s. Moreover, members of the House of Representatives noted that the effects of trade liberalization with China might have different effects based on areas' industry composition. Representative Eva Clayton, a Democrat representing eastern North Carolina, asked in the lead-up to a vote on PNTR for China, "[m]ust Eastern North Carolina lose in order for the Research Triangle to Gain?"[5] After the granting of PNTR and China's entry into the WTO in 2001, Senators Charles Schumer and Lindsey Graham repeatedly introduced legislation in the U.S. Senate to impose tariffs on U.S. imports from China based on allegations that China manipulates its exchange rate relative to the U.S. dollar (Lichtblau 2011).

Calls for such action generally increase during elections. Indeed, in a move the New York Times referred to as "election year politics over a loss of American jobs" (Sanger and Chan 2010), the House of Representatives in 2010 granted President Obama expanded authority to impose tariffs on a wide range of Chinese goods. Perhaps most notably, the 2016 Presidential campaign featured sharp dialogue relating to trade with China from both Republicans and Democrats. For example, Republican Donald Trump called for a 45 percent tariff on U.S. imports from China (Haberman 2016), while Democrat Bernie Sanders proposed "reversing trade policies like NAFTA, CAFTA and PNTR with China that have driven down wages and caused the loss of millions of jobs."[6]

3 Data

This section describes the data used to measure election outcomes, exposure to competition from China, and other trade-related variables that may affect election outcomes.

[5]See http://history.house.gov/People/Detail/11065.

[6]See (www.berniesanders.com/issues/income-and-wealth-inequality/). Media coverage during the 2016 Presidential primaries focused on the role of these trade positions in support for Trump and Sanders, e.g. Stromberg (2016). For additional examples, see Brower and Lerer (2012) for the 2012 election, and Collinson (2015) for the 2016 election cycle.

3.1 Summarizing and Measuring Exposure to PNTR

We make use of the structure of the U.S. tariff schedule to define a measure of each industry's – and in turn, each county's – exposure to PNTR. The U.S. tariff schedule has two basic sets of tariff rates: *NTR tariffs*, which average 4 percent across industries and are applied to goods imported from other members of the World Trade Organization (WTO); and *non-NTR tariffs*, which were set by the Smoot-Hawley Tariff Act of 1930 and are typically substantially higher than the corresponding NTR rates, averaging 37 percent across industries. While imports from non-market economies such as China are by default subject to the higher non-NTR rates, U.S. tariff law allows the President to grant these countries access to NTR rates on an annually renewable basis, subject to approval by Congress.

U.S. Presidents granted China such a waiver every year starting in 1980, but their annual approval by Congress became politically contentious and less certain following the Chinese government's crackdown on the Tiananmen Square protests in 1989. Re-approval remained controversial throughout the 1990s, especially during other flashpoints in U.S.-China relations including China's transfer of missile technology to Pakistan in 1993 and the Taiwan Straits Missile Crisis in 1996. Importantly, if annual renewal of the waiver had failed, U.S. tariffs on imports from China would have risen substantially from the temporary NTR levels to the generally much higher non-NTR rates.

The possibility of tariff increases each year served as a disincentive for firms considering sinking investments associated with increasing U.S. imports from China.[7] PNTR, which was passed by Congress in October 2000 and took effect upon China's entry to the WTO in December 2001, permanently locked in U.S. tariffs on imports from China at the low NTR rates, eliminating these disincentives.[8] As documented in Pierce and Schott (2016a), the industries and products most affected by the policy change experienced larger declines in U.S. manufacturing employment, as well as larger increases in imports from China – including related-party imports – and larger increases in exports to the United States by foreign-owned firms in China.[9]

We compute counties' exposure to PNTR in two steps. The first step is to calculate exposure for U.S. industries. We follow Pierce and Schott (2016a) in defining the industry-level impact of PNTR as the increase in U.S. tariffs on Chinese goods that would have occurred in the event of a failed annual renewal of China's NTR status

[7]Intuition for these incentives can be derived, in part, from the literature on investment under uncertainty (e.g., Pindyck 1993 and Bloom, Bond and Van Reenen 2007), which demonstrates that firms are more likely to undertake irreversible investments as the ambiguity surrounding their expected profit decreases. Handley (2014) introduces these insights to firms' decisions to export, and Handley and Limao (2017) examine the impact of a reduction of trade policy uncertainty on trade and welfare.

[8]The passage of PNTR followed the bilateral agreement in 1999 between the U.S. and China regarding China's eventual entry into the WTO.

[9]Heise et al. (2015) describe the effect of PNTR on the structure of supply chains, and Feng, Li and Swenson (Forthcoming) discuss the effect of PNTR on entry and exit patterns of Chinese exporters, as well as changes in export product characteristics.

prior to PNTR,

$$NTR\,Gap_j = Non\ NTR\,Rate_j - NTR\,Rate_j. \tag{1}$$

We refer to this difference as the NTR gap, and compute it for each four-digit SIC industry j using *ad valorem equivalent* tariff rates provided by Feenstra et al (2002) for 1999, the year before passage of PNTR. As illustrated in Figure 4, NTR gaps vary widely across industries, with a mean and standard deviation of 33 and 15 percentage points, respectively. As noted in Pierce and Schott (2016a), 79 percent of the variation in the NTR gap across industries is attributable to non-NTR rates, set 70 years prior to passage of PNTR. This feature of non-NTR rates effectively rules out reverse causality that would arise if *non-NTR rates* were set to protect industries with declining employment or surging imports. Furthermore, to the extent that *NTR rates* were raised to protect industries with declining employment prior to PNTR, these *higher* NTR rates would result in *lower* NTR gaps, biasing our results away from finding an effect of PNTR.[10]

We compute U.S. counties' exposure to PNTR as the employment-share-weighted average NTR gap across the sectors in which they are active,

$$NTR\,Gap_c = \sum\nolimits_j \left(\frac{L_{jcb}}{L_{cb}} NTR\,Gap_j \right), \tag{2}$$

where L_{jcb} is the base-year b employment of SIC industry j in county c and L_{cb} is the overall employment in county c in base year b. County-industry-year employment data are from the U.S. Census Bureau's County Business Patterns (CBP), and we use $b = 1990$ for the base year to mitigate any potential relationship between counties' industrial structure and the year 2000 change in U.S. trade policy.

NTR gaps can only be calculated for products subject to import tariffs, such as manufacturing, agriculture and mining products. NTR gaps for services, which are not subject to import tariffs are, by definition, zero. Given that services comprise a large share of employment, the distribution of *county*-level $NTR\ Gap_c$ is shifted leftwards relative to the distribution of manufacturing and other *industries* for which the $NTR\,Gap_j$ is defined: the mean and standard deviation of the county-level NTR gap are 7.3 and 6.5 percentage points, as displayed visually in Figure 4. The difference between the 25th and 75th percentiles is 8.3 (=10.6-2.3) percentage points.

We also compute counties' exposure to PNTR via the average NTR gap of surrounding counties in the same commuting zone – a geographic area roughly analogous to a local labor market – as outcomes for a particular county may also be affected by the exposure to PNTR of adjacent counties.[11] The correlation of own- and commuting-zone

[10] Cross-industry variation in the NTR rate explains less than 1 percent of variation in the NTR gap.

[11] We use the U.S. Census Bureau definition of commuting zones as of 1990 and the concordance of counties to commuting zones provided by Autor et al. (2013). The 3113 counties in our sample are distributed across 741 commuting zones, with the number of counties per commuting zone ranging from 1 to 19 (the Washington, D.C. area).

NTR gaps across counties, 0.58, is displayed visually in Figure 5.

3.2 Election Results and Demographics

Data on county-level election outcomes are from *Dave Leip's Atlas of U.S. Presidential Elections*.[12] These data track the number of votes received by Democratic and Republican candidates for Congress in each county in each election year, as well as the number of registered voters.[13]

Figure 3 reports the distribution of the Democrat vote share across counties over the sample period. As indicated in the figure, the average county experienced a decline in Democrat vote share during the 1990s and early 2000s, followed by a rebound in 2006 and 2008, and then a decline in 2010. The mean Democrat vote share in the 2000 Congressional election – the election closest to the granting of PNTR to China – is 40 percent, with a standard deviation of 23 percentage points.[14]

We match the voting data to county-level demographic data from the 1990 Decennial Census that have been found to be important correlates of voting behavior in the political science and economics literatures on voting.[15] These data are summarized in Table 1.

3.3 Other Controls for Exposure to Import Competition

Our analysis includes time-varying controls for counties' average NTR rate and their exposure to the phasing out of textile and clothing quotas under the global Multi-Fiber Arrangement (Khandelwal et al. 2013).

We compute counties' exposure to U.S. import tariffs and the MFA phase-outs as the employment-share weighted average of their tariff rates and exposure to MFA, i.e., as in equation 2. Following Brambilla et al. (2010) and Pierce and Schott (2016a), we measure the extent to which industry quotas were binding under the MFA as the import-weighted average fill rate of the textile and clothing products that were under quota in that industry, where fill rates are defined as the actual imports divided by

[12] For details on data collection, see www.uselectionatlas.org.

[13] County boundaries are substantially more stable than those of Congressional districts, whose borders change after each decennial census. During our sample period, there are only three changes: South Boston, VA (county code 51780) joined Halifax County (51083) on July 1, 1995; Dade County, FL (12025) was renamed as Miami-Dade FL (12086) on November 13, 1997; and Skagway-Yakutat-Angoon, AK (2231) was changed to Skagway-Hoonah-Angoon Census Area, AK (2232) on September 22, 1992, and then to Hoonah-Angoon Census Area, AK on June 20, 2007. In each case, we aggregate the noted counties for the entire sample period.

[14] Note that the 40 percent share of votes cast for Democrats in the 2000 House of Representatives elections is an average across counties. Overall, the Democratic candidate received 46,595,202 votes (46.8 percent of total) in the 2000 House of Representatives elections, while the Republican candidate received 46,738,619 votes (47.0 percent of total) and candidates from other parties received 6,125,773 votes (6.2 percent of total). See Federal Election Commission (2001).

[15] See, for example, Baldwin and Magee (2000), Conconi et al. (2012), Gilbert and Oladi (2012), Kriner and Reeves (2012), Wright (2012).

allowable imports under the the quota. Industries with higher average fill rates faced more binding quotas and are therefore more exposed to the end of the MFA. Products not covered by the MFA have a fill rate of zero.

4 Trade Liberalization with China and Voting in U.S. Congressional Elections

This section explores the link between the U.S. granting of PNTR to China in 2000 and voting in U.S. Congressional elections.

4.1 Identification Strategy

Our baseline estimation examines the link between exposure to PNTR and support for the Democratic candidate for the U.S. House of Representatives in county c in even election years t from 1992 to 2010, a period that straddles the year 2000 change in U.S. trade policy. We use a difference-in-differences (DID) specification that asks whether counties with higher NTR gaps (first difference) experience differential changes in voting after the change in U.S. trade policy (second difference),

$$\begin{aligned} Election\,Outcome_{ct} &= \theta Post\,PNTR_t \times NTR\,Gap_c \\ &\quad + Post\,PNTR_t \times \mathbf{X}_c'\boldsymbol{\gamma} + \mathbf{X}_{ct}'\boldsymbol{\beta} \\ &\quad + \boldsymbol{\delta_c} + \boldsymbol{\delta_t} + \alpha + \varepsilon_{ct}, \end{aligned} \tag{3}$$

The dependent variable is one of several election outcomes for county c in year t including the share of votes received by the Democrat, an indicator for whether a Democrat wins the election, and voter turnout. The first term on the right-hand side is the DID term of interest, an interaction of a post-PNTR (i.e., $t > 2000$) indicator with the (time-invariant) county-level NTR gap, as defined in the preceding section.

$\mathbf{X}_c$ represents a vector of initial period county demographic attributes taken from the 1990 Census that are found to be important in the economics and political science literatures on voting. These attributes are median household income, the shares of the population with a bachelor's and graduate degrees, the share of non-white population, the share of veterans and the share of voters over 65. Including interactions of these attributes with the $Post\,PNTR_t$ indicator allows the relationship between these demographic characteristics and voting outcomes to differ before and after passage of PNTR. $\mathbf{X}_{ct}$ represents a matrix of time-varying policy attributes including the average U.S. import tariff rate associated with each county's mix of industries as well as the county's exposure to the phasing out of the MFA. $\boldsymbol{\delta_c}$ and $\boldsymbol{\delta_t}$ represent county and year fixed effects. One advantage of this DID identification strategy is its ability to net out characteristics of counties that are time-invariant, while also controlling for aggregate shocks that affect all counties identically in a particular year, such as whether the election occurs during a presidential versus non-presidential election year.[16]

We consider both unweighted regressions (Tables 2 to 5), which are representative of the relationship for the average county, and regressions for which observations are weighted by counties' initial population (Table 6), making them representative of the average individual. While county sizes can vary substantially, the population-weighted results are indicative of – though not equivalent to – election outcomes at the district-level, as Congressional districts are all of equal population by design.

Figure 6 plots the average Democrat vote share (left panel) and probability of Democrat victory (right panel) for two groups of counties: those with both own- and surrounding-county NTR gaps above, versus below, the median of these gaps across all counties. The vertical line in each figure represents the year in which PNTR was passed. As indicated in the figures, the Democrat vote share and probability of Democratic representation tend to be higher for high NTR gap counties in both the pre- and post-PNTR periods. Importantly, in each case, trends in outcomes prior to the change in U.S. policy are similar, consistent with the parallel trends assumption inherent in difference-in-differences analysis. Among those counties with NTR gaps above the median, there is movement towards relatively higher Democrat vote shares in 2002 and 2008 and higher probability of Democrat victory in 2008. Estimation of Equation 3 examines the extent to which there is a statistically significant shift toward higher Democrat vote shares and a higher probability of Democratic victory for more exposed counties in the post-PNTR period.

4.2 Exposure to PNTR and Elections for the U.S. House of Representatives

The first three columns of Table 2 summarize the results of estimating equation (3) via OLS for the years 1992 to 2010. Robust standard errors adjusted for clustering at the county level are reported below each estimate. As indicated in the first column of the table, we find no relationship between PNTR and the share of votes cast Democrats in a specification that includes only the DID term of interest and the fixed effects. However, once the time-invariant and time-varying county attributes found to be important in the voting literature are added as covariates (columns two and three), we estimate a positive and statistically significant coefficient for the DID term, indicating that higher exposure to PNTR is associated with a relative increase in the share of votes cast for Democrats. The DID point estimate shown in the third column, 0.175, implies that moving a county from the 25th to the 75th percentile NTR gap (from 2.35 to 10.59 percent) is associated with a 1.4 percentage point increase in the share of votes won by the Democratic candidate, or 3.6 percent of the average 40 percent share of the vote cast for Democrats in the 2000 Congressional election (as displayed in the final row of

[16]One disadvantage is that the long sample period renders it susceptible to biased standard errors associated with serial correlation (Bertrand, Duflo and Mullainathan 2004).

the table).

Columns four through six of Table 2 examine the relationship between PNTR and three other election outcomes: an indicator for whether the Democrat wins the county, an indicator for whether the election results in a switch to a Democrat representing the county, and an indicator for whether the election results in a switch to a Republican representing the county.[17] For the latter two regressions the sample is restricted to observations in which the prior office holder was a Republican, or Democrat, respectively.

As indicated in the table, we find a positive and statistically significant relationship between exposure to PNTR and the probability of both Democrat victory and a switch to a Democratic Representative. By contrast, we find a statistically significant relative decline in the probability of a switch to a Republican Representative. The point estimate for Democrat victory in column four, 0.209, indicates that an interquartile shift in a county's exposure to PNTR is associated with a 1.7 percentage point increase in the probability of victory, or 4.9 percent of the probability of victory in the year 2000. Similar exercises indicate an estimated increase in the probability of switching to Democrat of 1.8 percentage points, and an estimated decrease in the probability of switching to a Republican of -2.2 percentage points. These estimated changes represent approximately 42 and -49 percent of the average probabilities of such switches occurring in the year 2000 (approximately 4 and 5 percent, respectively). Coefficient estimates for the remaining covariates suggest that voters with a college degree are more likely to support Democrats after 2000, relative to before, while those over 65 are less likely to do so.

Taken together, the results in columns one through six indicate that counties more exposed to the change in policy exhibit relative increases in electoral support for Democrats. In Section 5 we explore potential explanations for this voting behavior by comparing the policy choices of Congressional Democrats on legislation related to international trade and economic assistance to those of their Republican counterparts.

The final column of Table 2 examines the relationship between exposure to PNTR and voter turnout, defined as the number of people voting in the election divided by the number of registered voters.[18] As reported in the table, we find that higher exposure to PNTR is associated with a statistically and economically significant increase in voter turnout. The coefficient estimate for the DID term indicates that a county moving from the 25th to the 75th percentile in terms of exposure is associated with a 0.90 percentage point increase in turnout, or 1.4 percent of the average turnout across counties in the year 2000 (65 percent).

[17] Because counties are reallocated to Congressional districts over time, we emphasize that this analysis does not directly examine victories in House elections, but rather examines the probability that a Representative from a particular party represents a county.

[18] Turnout is defined as the votes cast in U.S. House elections (for non-Presidential-election years) or the Presidential election (other years) divided by the total number of registered voters in the county. For the 60 county-year observations in which turnout exceeds 100 percent, we set it to that level. (Results are robust to their exclusion.) Turnout data are missing from *Dave Leip's Atlas of U.S. Presidential Elections* for all elections in 1994 and 1998.

To the extent that some voters perceive themselves as being injured by increased import competition in the more heavily-affected counties, this result is in line with a political science literature arguing that economic adversity can increase voter turnout (e.g. Schlozman and Verba 1979). This result differs from Dippel, Gold and Heblich's (2015) finding that higher imports have no relationship with election turnout in Germany. This difference may stem, in part, from U.S. voters directing votes toward a major party in response to trade competition, whereas Dippel, Gold and Heblich (2015) show that import competition in Germany is associated with an increase in votes for far-right parties.

4.3 Exposure to PNTR via Neighboring Counties Within Commuting Zones

In this section we examine whether voters in one county might be influenced by economic conditions in neighboring counties that are part of the same labor market. The specification we consider is similar to that considered in the previous section but it is augmented with an additional difference-in-differences term–an interaction of the post-PNTR indicator variable with the average NTR gap across other counties in the same commuting zone (z).

As illustrated in Table 3, the signs of the estimated coefficients for both the own and commuting zone DID terms are consistent with those in Section 4.2. That is, the DID coefficient estimates are positive for regressions of the Democrat vote share, the probability of Democrat victory, the probability of a switch towards a Democrat, and turnout, and negative for the probability of a switch towards a Republican. Estimates for the two DID terms are jointly statistically significant in all cases, as indicated by the F-test p-values reported in the third-to-last row of the table.

In terms of economic significance, the coefficient estimates in the first column suggest that an interquartile shift in a county's exposure to PNTR is associated with a 1.7 percentage point increase in the share of votes won by the Democrat candidate, representing 4.2 percent of the average share of the vote cast for Democrats in the year 2000. Point estimates in the third column indicate that the same interquartile shift in exposure to PNTR boosts the probability of Democrat victory by 5.8 percent compared to the average probability of victory across counties in the year 2000. For switching to a Democrat, switching to a Republican and turnout, the comparable percentages are 45, -91 and 1.4 percent, respectively. These magnitudes are larger than those reported in the baseline results in Section 4.2 indicating that counties' voting outcomes are also affected by spillovers from neighboring counties in the same labor market.

4.4 Exposure to PNTR and the Democrat Vote Share for Other Offices

In this section we examine the relationship between PNTR and the Democrat vote share for three other offices: President, U.S. Senate and Governor. Presidential and gubernatorial elections occur every four years, though gubernatorial elections do not occur in the same year for all states.[19] Senatorial elections occur every six years, with approximately one third of Senators up for election in any given election year. As with the results for the U.S. House of Representatives elections discussed earlier, the unit of analysis is the U.S. county.

Results are reported in Table 4. We find positive and statistically significant relationships between the change in U.S. trade policy and the share of votes won by Democrats in both Presidential and gubernatorial elections. The DID point estimates for President and governor suggest that moving a county from the 25th to the 75th percentile in terms of exposure to PNTR is associated with increases in the Democrat vote share of 0.37 and 1.3 percentage points, or 0.93 and 2.6 percent of the average share of votes won by Democrats for these offices across counties in the year 2000. The observed effects on Presidential and gubernatorial outcomes provide further evidence consistent with the role of PNTR's trade liberalization on elections. We also find a positive relationship between PNTR and the share of votes won by Democrats in Senatorial elections, but this relationship is not statistically significant at conventional levels, possibly due to the longer term served by Senators (Conconi et al. 2014).

During the 2016 Presidential election the Republican nominee, Donald Trump, departed from the traditional Republican position on trade by expressing strong support for protecting U.S. industries from import competition, especially from lower-wage countries such as Mexico and China. We examine whether this support affected the estimated relationship between voting for Democrats and exposure to PNTR in Table 5. The first column in this table reproduces results from the first column of Table 4. In the second column, we extend the analysis to the 2016 election using recently available data and include an additional covariate that interacts the DID term with a dummy variable for the 2016 election. The coefficient for this term is negative and statistically significant, indicating that the positive relationship between exposure to PNTR and support for Democrats is partially offset by a negative effect specific to the 2016 election. This negative offsetting effect is consistent with voters in areas subject to higher import competition offering greater support to the candidate favoring trade protection policies.

[19] As a result, observations for the Presidential and gubernatorial elections are only defined for years in which an election has taken place. The baseline sample period for Presidential elections ends with the 2008 election.

4.5 Weighting Counties by Population

The coefficient estimates reported in the previous three sections are based on unweighted regressions, and therefore are representative of the relationship between PNTR and voting behavior for the average county. In this section we re-estimate the relationship between exposure to PNTR and House of Representatives election outcomes with weighting by initial (1990) population, which provides estimates more representative of the average individual.

As indicated in Table 6, we continue to find positive and statistically significant relationships between PNTR and the share of votes won by Democrats, the likelihood of a switch to a Democrat Representative and turnout. We no longer find statistically significant relationships between counties' exposure to the change in U.S. trade policy and the likelihood of either Democrat victory or a switch to a Republican Representative.

The statistically significant coefficient estimates in the first, third and fifth columns indicate that moving a county from the 25th to the 75th percentile NTR gap increases the Democrat vote share, the probability of a switch to a Democrat Representative and turnout by 2.6, 34 and 2.7 percent relative to their levels in the year 2000. The first two of these magnitudes are somewhat lower than those implied by the estimates in Table 2 (3.6 percent and 42 percent, respectively), while the estimated effect for turnout is higher (1.4 percent in Table 2).

4.6 PNTR, Unemployment and Voting

A large literature in political science and economics that examines the impact of economic shocks on voting patterns suggests that good times reward incumbents while bad times reward challengers (Lewis-Beck and Stegmier 2000). In the context of trade flows, Jensen, Quinn and Weymouth (2016) show that higher export growth is associated with greater electoral support for Presidential incumbents, while higher import growth increases vote shares for challengers. By contrast, Wright (2012) suggests that higher unemployment rates are associated with greater voting for Democrats.

In this section we examine the relationship between voting in U.S. House of Representatives elections and the unemployment rate ($U - Rate_{ct}$) using counties' exposure to PNTR as an instrument for the unemployment rate,

$$\begin{aligned} DemVote_{ct} &= \theta U - Rate_{ct} \\ &\quad + Post\,PNTR_t \times \mathbf{X}_c'\boldsymbol{\gamma} + \mathbf{X}_{ct}'\boldsymbol{\beta} \\ &\quad + \boldsymbol{\delta_c} + \boldsymbol{\delta_t} + \alpha + \varepsilon_{ct}. \end{aligned} \tag{4}$$

County-level measures of the unemployment rate during our sample period are available from the U.S. Bureau of Labor Statistics' Local Area Unemployment (LAU) statistics program. All other variables are as defined above. We note that one potential drawback to this specification is that there may be channels other than unemployment through which exposure to PNTR affects voting. For example, voters might remain employed but face wage declines, or experience changes in other dimensions that affect voting such as health, crime or earnings variance.[20]

Results for House elections are presented in Table 7. The first column reproduces the baseline specification from Table 2 for the set of observations for which we observe county-level unemployment.[21] Next, we report OLS regressions of the unemployment rate on the DID term for the NTR gap and the Democrat vote share on the unemployment rate in Columns 2 and 3. As indicated in the table, we find a positive and statistically significant relationship for the former and a negative and statistically significant relationship for the latter. The precisely estimated relationship between the DID term and the unemployment rate demonstrates its explanatory power as an instrument.

Next, we report results of two-staged least squares results for the Democrat vote share, indicators for Democrat victory and switch to a Democrat Representative, and turnover in columns 4 to 7. Results for all outcomes indicate a positive and statistically significant relationship between the unemployment rate – instrumented with the NTR gap DID term – and electoral support for Democrats. Coefficient estimates indicate that an interquartile shift in the year 2000 unemployment rate (from 3.2 to 5.1 percent, or 1.9 percentage points) is associated with an increase in the Democrat vote share of 4.6 percent, and increases in the likelihood of Democrat victory, a switch to a Democrat, and turnout of 5.6, 8.0 and 3.6 percent, respectively. These results suggest that at least a portion of the relationship between PNTR and voting behavior is being transmitted via changes in the unemployment rate.

5 Party Affiliation and Legislator Voting Behavior

The previous section establishes that voters in counties facing larger increases in competition from China experience relative increases in their likelihood of voting for Democratic candidates. One explanation for this result is that workers displaced by Chinese imports sought to elect officials that would either protect U.S. workers from international trade or soften the effect of this competition by promoting economic assistance programs. This section investigates this potential explanation by examining whether Congressional Democrats in the U.S. House of Representatives during the 1990s and 2000s were more likely to vote for legislation along these lines than were House Republicans. We use a regression discontinuity approach to examine whether Republicans' and Democrats' votes differ on trade-related and economic assistance-related bills. We begin by discussing the classification of bills as being either for or against free trade

[20]Pierce and Schott (2016b), for example, find that counties with greater exposure to PNTR exhibit increases in mortality due to suicide and accidental poisoning. Autor, Dorn and Hanson (2017) find that U.S. regions with rising imports from China exhibit changes in marriage and fertility patterns, while Che and Xu (2016) and Feler and Senses (2016) show that they also experience elevated crime.

[21]Unemployment rate data for some counties are not available in the LAU.

or economic assistance and then describe our identification strategy before presenting the results.

5.1 Classification of "Trade" and "Economic Assistance" Bills

House members' votes from 1993 to 2011 (from the start of the 103^{rd} to part of the 112^{th} Congresses) are obtained from the website www.govtrack.us. Data on the set of bills considered by the House during this period are from the Rohde/PIPC House Roll Call Database, maintained and generously provided by David Rohde of Duke University. We adopt Rohde's classifications of bills related to trade and economic assistance programs, and then classify bills as pro- versus anti-free trade and pro- versus anti-economic assistance using ranking data from the National Journal. We describe each of these steps in turn.

5.1.1 Trade Bills

The Rohde/PIPC House Roll Call Database assigns each bill a code summarizing its content.[22] We follow Rohde in considering bills to be trade-related if they fall under the heading "Economy - Foreign Trade."[23] We classify trade-related bills as pro- versus anti-free trade based on the National Journal's rankings of the "economic liberalness" of the bills' sponsors.[24] A ranking of $r\epsilon(0, 100)$ indicates that the sponsor is more "liberal" in their voting on economic legislative matters than r percent of House members. Bills whose primary sponsor's ranking exceeds 50 are coded as anti-free-trade. The remaining bills are coded as pro-free-trade. This objective approach to classifying bills has two advantages, First, it is based on publicly available information and is easily replicable. Second, it relies on a ranking system that is based exclusively on a principle component analysis of members' votes on economic issues. We note, however, that the results discussed below are also robust to the authors' qualitative classification of bills as either pro- or anti-free trade.

5.1.2 Economic Assistance Bills

We consider bills to be related to economic assistance if they fall into the following categories of the Rohde database: "jobs" (code 810 of the database), "welfare benefits/social services" (code 811), "job training" (code 816), "nutrition programs" (code

[22] The complete list of codes can be found at http://sites.duke.edu/pipc/data/.

[23] That heading includes the following categories: "Japanese trade" (540), "Federal trade commission" (542), "unfair trading practices" (543), "export controls" (544), "compensation to U.S. business and workers" (545), "Export-Import Bank" (546), "tariff negotiations" (547), "import quotas-tariffs" (548), and "miscellaneous" (549). We follow Rohde's convention of including the sub-category "Federal trade commission" in this category, though the is primarily responsible for consumer protection, rather than international trade. There is only one bill that falls under this sub-category.

[24] Further detail on these rankings is available at http://www.nationaljournal.com/2013-vote-ratings/how-the-vote-ratings-are-calculated-20140206.

831), "family assistance" (code 832), "homeless" (code 835), "unemployment assistance" (code 962), and "minimum wage" (code 966). As above, we use the National Journal rankings to classify bills as pro- versus anti- economic assistance according to whether the bills' sponsors' economic liberalness rankings are above or below 50.

5.2 Identification Strategy

We examine the relationship between House members' votes on trade and economic assistance bills and their party affiliation using the following specification,

$$y_{dh} = \alpha + \beta Democrat_{dh} + \mathbf{X}'_{\mathbf{dh}}\theta + \delta_{\mathbf{s}} + \delta_{\mathbf{h}} + \varepsilon_{dh}, \tag{5}$$

where d and h denote Congressional districts and the particular two-year Congress during which Representatives serve.[25] The dependent variable y_{dh} represents the share of pro-free trade or pro-economic assistance bills supported by a particular representative during a particular Congress. The dummy variable $Democrat_{dh}$ takes the value 1 if the Representative is a Democrat and zero otherwise. $\mathbf{X_{dh}}$ represents a matrix of district-Congress attributes, including the demographic characteristics of the district and personal attributes of the Representative.[26] $\delta_{\mathbf{s}}$ and $\delta_{\mathbf{h}}$ represent state and Congress fixed effects, and ε_{dh} is the error term. As noted in the introduction, Congressional district boundaries change substantially over the sample period as a result of redistricting. We are therefore unable to include district fixed effects in equation 5.

In this specification, identification of β requires that Representatives' party affiliation be uncorrelated with the error term. As there may be several reasons why this assumption is violated, we follow Lee (2008) in identifying the causal effect of party affiliation on voting behavior using a regression discontinuity (RD) approach.[27] Specifically, we make use of the principle that the probability of a Democrat winning a congressional election disproportionately increases at the point where they receive a larger share of votes than the Republican competitor.

Formally, define the assignment variable

$$Margin_{dh} \equiv VoteShare_{dh}^{Democratic} - VoteShare_{dh}^{Republican}$$

as the difference in voting share between the Democratic and Republican candidates in Congressional district d for election to Congress h. As illustrated in Figure 7, the probability of a Democratic candidate winning an election conditional on the margin of victory has a discontinuity at the cutoff 0. That is, this probability is substantially near 1 for values of $Margin_{dh}$ (abbreviated to m, hereafter) just above zero compared with

[25] For example, $h = 110$ represents the 110th Congress, which met from January 3, 2007 to January 3, 2009.

[26] Data on House members' age, gender, party affiliation and other characteristics used in the second part of our analysis are obtained from Wikipedia.

[27] Lee et. al (2004) use RD to investigate the effect of party affiliation on legislators' right-vs-left voting scores.

values of m just below zero.[28] Hahn et al. (2001) show that when $E\left[\varepsilon_{dh}|Margin_{dh}=m\right]$ is continuous in m at the cutoff 0, β in equation (5) can be identified as

$$\hat{\beta}_{RD}=\frac{\lim_{m\downarrow 0}E\left[y_{dh}|Margin_{dh}=m\right]-\lim_{m\uparrow 0}E\left[y_{dh}|Margin_{dh}=m\right]}{\lim_{m\downarrow 0}E\left[Democrat_{dh}|Margin_{dh}=m\right]-\lim_{m\uparrow 0}E\left[Democrat_{dh}|Margin_{dh}=m\right]}. \tag{6}$$

Lee and Lemieux (2010) show that $\hat{\beta}_{RD}$ is essentially an instrumental variable estimator. Specifically, the first stage of the instrumental variable estimation is

$$Democrat_{dh}=\gamma I\left\{Margin_{dh}\geq 0\right\}+g\left(Margin_{dh}\right)+\mu_{dh},$$

while the second stage is

$$y_{dh}=\alpha+\beta Democrat_{dh}+f\left(Margin_{dh}\right)+\varepsilon_{dh},$$

where $I\{.\}$ is an indicator function that takes a value of 1 if the argument in brackets is true and 0 if it is false, and where $g(.)$ and $f(.)$ are flexible functions of the assignment variable that control for the direct effect of the strength of the Democratic versus Republican parties on the outcome variable y_{dh}. Lee and Lemieux (2010) suggest both nonparametric and parametric approaches to estimate $\hat{\beta}_{RD}$. We pursue both approaches, with details provided in Section B of the appendix.

The identifying assumption of our RD estimation – that $E\left[\varepsilon_{dh}|Margin_{dh}=m\right]$ is continuous in m at the cutoff 0 – implies that the election outcome at the cutoff point is determined by random factors, i.e., no party or candidate can fully manipulate the election.[29] To provide quantitative support for this assumption, we perform two checks suggested by Lee and Lemieux (2010). First, if there were full manipulation at the cutoff point 0, the distribution of district characteristics on the two sides of the cutoff point would be different, and a mixture of district-level discontinuous densities would imply that the aggregate distribution of assignment variable is discontinuous at the cutoff point. We check the density distribution of the assignment variable using the method developed by McCrary (2008). As shown in Figure A.1 of the online appendix, we do not find any discontinuity in the density distribution of the assignment variable at the cutoff point 0, and hence fail to reject the hypothesis that our identifying assumption is satisfied.

[28]Note that there are cases in which a third party won the election even though the Democratic candidate received more (less) votes than the Republican party. As a result, $\Pr\left[Democratic_{d,t}=1|Margin_{d,t}=m\right]\neq 1$ when $m>0$.

[29]Using RD to investigate the incumbent advantage, Lee (2008) argues:

> "It is plausible that the exact vote count in large elections, while influenced by political actors in a non-random way, is also partially determined by chance beyond any actor's control. Even on the day of an election, there is inherent uncertainty about the precise and final vote count. In light of this uncertainty, the local independence result predicts that the districts where a party's candidate just barely won an election—and hence barely became the incumbent—are likely to be comparable in all other ways to districts where the party's candidate just barely lost the election."

The second check directly examines characteristics of Congressional districts in the neighborhood of the cutoff point. If there were full manipulation at the cutoff, districts on the margin would not be balanced and these pre-determined district characteristics would show discontinuities in their distribution at the cutoff point. Figures A.2 to A.10, reported in the appendix reveal that none of the distributions of district attributes used in our analysis exhibit discontinuities at the cutoff 0, indicating that our hypothesis of a valid RD setting cannot be rejected.

5.3 Results

We start with a visual presentation of the relationship between Democrats' margin of victory, $Margin_{dh}$, and subsequent votes on trade and economic assistance bills by the district's Representative, y_{dh}, across the 103^{rd} (January 1993 through January 1995) to the 112^{th} (January 2011 to January 2013) Congresses. Figures 8 and 9 show that the share of districts' pro-free trade votes drops discontinuously at the cutoff point $Margin_{dh} = 0$, where the Democrat earns a larger share of votes than the Republican, while their share of pro-economic assistance votes rises discontinuously at this cutoff. Given that the chance of winning the election jumps discontinuously at the same point (see Figure 7), these outcomes reveal that Democratic Representatives during this period were more likely to take anti-free trade positions and pro-economic assistance positions than their Republican colleagues. Our regression analysis estimates these differences where the margin of Democrat victory equals zero.

Formal estimation results for the effect of party affiliation on Representatives' voting for pro-free trade and pro-economic assistance bills, $\hat{\beta}^{RD}$, are reported in Tables 8, for pro-trade legislation and 9 for pro-economic assistance legislation. The first column of each table reports results using OLS, while columns two and three report results for the non-parametric and parametric RD estimations, respectively. As noted in the tables, estimates are negative and statistically significant in all three columns for pro-free trade bills, and positive and statistically significant in all three columns for pro-economic assistance bills, consistent with Figures 8 and 9. The results in Tables 8 and 9 are also robust to variation in the bandwidth of our nonparametric estimation as well as alternative polynomial expansions.[30]

In terms of economic significance, the 2SLS coefficient estimates reported in the third column of each table indicate that a Democratic affiliation is associated with a 15 percent reduction in the share of votes for pro-free trade legislation and a 33 percent increase in the share of votes for pro-economic assistance bills, relative to Republican affiliation. These results therefore provide a rationale for the voting results reported in Section 4.

Moreover, comparison of legislators' votes over time indicates even sharper differences between parties after the change in U.S. trade policy. Table 10 compares results for the final specifications reported in Tables 8 and 9 for the pre- versus post-PNTR

[30] See Section B of the appendix for further discussion.

time periods. As indicated in the table, we find that for both types of legislation, Democrats are less likely to support pro-free trade and more likely to support pro-economic assistance legislation in Congresses after 2000 versus before.

In sum, the results of this section indicate that Democratic Representatives during the period we examine were more likely to oppose expansion of trade and more likely to support economic assistance that might, for example, mitigate the effects of trade liberalization on those employed in import-competing industries. These results provide a rationale for our earlier finding that voters in counties subject to larger increases in competition from China increase the share of votes cast for Democrats.

6 Conclusion

This paper examines the effect of increased import competition from China on U.S. political outcomes. Our primary measure of exposure to competition from China comes from the U.S. granting of Permanent Normal Trade Relations to China, and we examine its effect in a difference-in-differences specification.

We find that U.S. counties more exposed to increased competition from China experience relative increases in the share of votes cast for Democrats in Congressional elections, along with increases in the probability that a Democrat represents a county and the probability of a county switching from a Republican to a Democrat Representative. The results are also economically significant – we find that moving a county from the 25th to the 75th percentile of exposure to PNTR increases the Democrat vote share in Congressional elections by 1.4 percentage points, or a 3.6 percent increase relative to the average share of votes won by Democrats in the 2000 Congressional election. Moreover, we find that the effect of the increase in import competition on voting is slightly larger once we account for the exposure of other counties in the same labor market, and that increased import competition is associated with higher voter turnout and a higher share of votes cast for Democrats in gubernatorial and Presidential elections, though the relationship is partially offset in the 2016 Presidential election.

The second half of our analysis investigates potential links between these voting outcomes and the legislative votes of members of Congress. We use a regression discontinuity approach to examine differences between Democrats' and Republicans' voting on bills related to trade and economic assistance programs. We find that Democrats during the period we examine are more likely to support policies that limit import competition and that provide economic assistance that may benefit workers adversely affected by trade competition, providing an explanation for the voting behavior documented in the first part of our paper.

Our results suggest that voters who perceive themselves as being disadvantaged by trade are more likely to vote for politicians that might restrict imports or promote economic assistance. A potentially fruitful avenue for further research is to investigate a link between PNTR and the success of Republican and Democrat candidates proposing to alter trade agreements during the 2016 Presidential primaries.

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County Attribute	Obs	Mean	SD	Min	Max
Median Household Income	3,138	31.28	8.63	11.21	77.35
Percent Bachelor	3,138	9.03	4.22	0.00	40.30
Percent Graduate	3,138	4.48	2.74	0.00	29.70
Percent Non-White	3,138	12.85	15.85	0.00	94.90
Percent Veteran	3,138	14.79	2.77	4.20	29.00
Percent 65+	3,138	14.86	4.46	0.70	37.70

Notes: Table reports summary statistics of county attributes as of 1990. Meidan household income is in thousands of dollars. Source: U.S. Census Bureau, 1990 Decennial Census.

Table 1: County Attributes in 1990

VARIABLES	$Demovote_{ct}$	$Demovote_{ct}$	$Demovote_{ct}$	Dem Win_{ct}	$S2Dem_{ct}$	$S2Rep_{ct}$	$Turnout_{ct}$
Post x NTR Gap_c	-0.034	0.139***	0.175***	0.209**	0.219**	-0.272*	0.108***
	0.037	0.042	0.047	0.104	0.09	0.157	0.022
Post x Median HHI in 1990_c		0.022	0.02	-0.208*	-0.111	0.718***	-0.321***
		0.042	0.042	0.106	0.083	0.145	0.021
Post x Percent Bachelors in 1990_c		0.689***	0.694***	1.955***	0.402*	-2.275***	0.671***
		0.099	0.099	0.253	0.222	0.382	0.048
Post x Percent Graduate in 1990_c		0.073	0.072	-0.017	0.613*	0.318	-0.483***
		0.128	0.128	0.321	0.336	0.396	0.07
Post x Percent Non-White in 1990_c		-0.019	-0.018	-0.049	0.124**	-0.034	-0.023**
		0.021	0.021	0.043	0.054	0.047	0.009
Post x Percent Over 65 in 1990_c		-0.192**	-0.191**	-0.473***	0.054	0.758***	-0.173***
		0.075	0.075	0.165	0.123	0.251	0.035
Post x Percent Veteran in 1990_c		0.093	0.093	-0.074	-0.049	-0.117	0.435***
		0.096	0.096	0.223	0.184	0.321	0.048
NTR_{ct}			102.098	161.644	-426.093**	-165.798	104.513***
			64.596	168.454	199.253	329.328	31.65
MFA Exposure $(China)_{ct}$			0.123	1.242*	-0.095	-3.050***	0.092
			0.262	0.69	0.685	1.103	0.116
MFA Exposure $(ROW)_{ct}$			-0.386	-3.180**	0.06	7.331***	-0.144
			0.591	1.532	1.5	2.452	0.262
Observations	31,106	31,106	31,106	**31,106**	16,889	11,105	22,970
R-squared	0.632	0.638	0.638	0.577	0.378	0.464	0.817
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Period	1992(2)2010	1992(2)2010	1992(2)2010	1992(2)2010	1994(2)2010	1994(2)2010	1994(2)2010
Drops	none	none	none	none	Lag D Win	Lag R Win	none
FE	c,t	c,t	c,t	c,t	c,t	c,t	c,t
Clustering	c	c	c	c	c	c	c
Mean Dependent Variable in 2000	40	40	40	35	4	5	65

Notes: Table reports difference-in-differences (DID) OLS regression results for dependent variables (noted in column heading) in county c in year t, including the share of votes cast for Democrats (columns 1-3) as well as dummy variables for whether the Democrat wins (column 4), whether there is a switch to a Democrat (column 5), whether there is a switch to a Republican (column 6), and turnout (column 7). Sample period is even years from 1992 to 2010. Turnout data are missing for 1994 and 1998. The first covariate is the DID term of interest, an interaction of a post-PNTR dummy with the county-level NTR gap. The next six covariates interact a post-PNTR dummy variable with county demographic attributes as of 1990. The remaining covariates account for the weighted average import tariff imposed on the county's industrial structure as well as the elimination of quantitative restrictions on apparel and clothing imports from China and rest of world (ROW). Standard errors adjusted for clustering at the county level are reported below coefficients. *, ** and *** signify statistical significance at the 10, 5 and 1 percent level.

Table 2: PNTR and County-Level Voting for Democrats (Baseline Results)

VARIABLES	Demovote	Dem Win	S2Dem	S2Rep	Turnout
Post x NTR Gap$_c$	0.123**	0.149	0.186*	-0.035	0.103***
	0.056	0.124	0.112	0.173	0.025
Post x NTR Gap$_{cz}$	0.127*	0.149	0.071	-0.703***	0.011
	0.066	0.150	0.122	0.220	0.030
Post x Median HHI in 1990$_c$	0.019	-0.209**	-0.111	0.734***	-0.322***
	0.042	0.106	0.083	0.145	0.021
Post x Percent Bachelors in 1990$_c$	0.722***	1.988***	0.417*	-2.422***	0.674***
	0.099	0.256	0.223	0.384	0.049
Post x Percent Graduate in 1990$_c$	0.030	-0.066	0.584*	0.501	-0.486***
	0.129	0.326	0.339	0.399	0.071
Post x Percent Non-White in 1990$_c$	-0.018	-0.050	0.124**	-0.023	-0.023**
	0.021	0.043	0.054	0.047	0.009
Post x Percent Over 65 in 1990$_c$	-0.198***	-0.481***	0.052	0.845***	-0.174***
	0.075	0.165	0.123	0.253	0.035
Post x Percent Veteran in 1990$_c$	0.108	-0.057	-0.042	-0.217	0.437***
	0.096	0.223	0.184	0.320	0.048
NTR$_{ct}$	98.480	157.406	-430.756**	-164.728	104.211***
	64.600	168.312	199.155	327.039	31.639
MFA Exposure (China)$_{ct}$	0.112	1.229*	-0.100	-3.072***	0.090
	0.262	0.692	0.685	1.100	0.116
MFA Exposure (ROW)$_{ct}$	-0.360	-3.150**	0.071	7.341***	-0.140
	0.593	1.535	1.501	2.449	0.262
Observations	31,106	**31,106**	16,889	11,105	22,970
R-squared	0.64	0.58	0.38	0.47	0.82
Estimation	OLS	OLS	OLS	OLS	OLS
Period	1992(2)2010	1992(2)2010	1992(2)2010	1992(2)2010	1992(2)2010
Drops	none	none	Lag D Win	Lag R Win	none
F-Test p-value	0.00	0.05	0.03	0.00	0.00
FE	c,t	c,t	c,t	c,t	c,t
Clustering	c	c	c	c	c
Mean Dependent Variable in 2000	40	35	4	5	65

Notes: Table reports difference-in-differences (DID) OLS regression results for dependent variable (noted in column heading) in county c in year t, including the share of votes cast for Democrats (column 1) as well as dummy variables for whether the Democrat wins (column 2), whether there is a switch to a Democrat (column 3), whether there is a switch to a Republican (column 4), and turnout (column 5). Sample period is even years from 1992 to 2010. Turnout data are missing for 1994 and 1998. The first covariate is an interaction of a post-PNTR dummy with the county-level NTR gap, and the second covariate is an interaction of the post-PNTR dummy with the average NTR gap of the remaining counties within county c's commuting zone. The next six covariates interact a post-PNTR dummy variable with county demographic attributes as of 1990. The second covariate is an interaction of post-PNTR dummy with the average NTR gap for all other counties in the county's commuting zone (z), as defined by the U.S. Census. The remaining covariates account for the weighted average import tariff imposed on the county's industrial structure as well as the elimination of quantitative restrictions on apparel and clothing imports from China and rest of world (ROW). Standard errors adjusted for clustering at the county level are reported below coefficients. *, ** and *** signify statistical significance at the 10, 5 and 1 percent level.

Table 3: PNTR and County-Level Voting for Democrats (Own- and Commuting Zone Exposure)

	Democrat Vote Share		
VARIABLES	President	Senator	Governor
Post x NTR Gap$_c$	0.045**	0.013	0.152***
	0.018	0.031	0.049
Post x Median HHI in 1990$_c$	0.131***	0.073**	-0.115***
	0.018	0.032	0.044
Post x Percent Bachelors in 1990$_c$	0.729***	0.275***	-0.097
	0.045	0.072	0.108
Post x Percent Graduate in 1990$_c$	0.032	0.189*	0.788***
	0.059	0.105	0.155
Post x Percent Non-White in 1990$_c$	0.045***	-0.063***	-0.066***
	0.008	0.012	0.018
Post x Percent Over 65 in 1990$_c$	0.037	0.046	-0.230***
	0.031	0.048	0.074
Post x Percent Veteran in 1990$_c$	0.266***	0.312***	0.205**
	0.043	0.065	0.097
NTR$_{ct}$	21.861	30.255	-54.442
	27.202	51.046	78.739
MFA Exposure (China)$_{ct}$	0.373***	0.384*	-0.592*
	0.142	0.226	0.308
MFA Exposure (ROW)$_{ct}$	-1.532***	-1.086**	0.603
	0.319	0.5	0.694
Observations	**15,519**	21,101	13,596
R-squared	0.90	0.60	0.57
Estimation	OLS	OLS	OLS
Period	1992(4)2008	1992(2)2010	1992(2)2010
Drops	none	none	none
FE	c,t	c,t	c,t
Clustering	c	c	c
Mean Dependent Variable in 2000	40	43	49

Notes: Table reports difference-in-differences (DID) OLS regression results for Democrat vote share in county c in year t for the noted elections. Sample period is even years from 1992 to 2010. Presidential and gubernatorial elections occur every four years, but the latter do not occur on the same year for all states. Senatorial elections occur every six years, with approximately one-third of senators up for election in any given election year. The first covariate is the DID term of interest, an interaction of a post-PNTR dummy with counties' weighted average NTR gap. The next six covariates interact a post-PNTR dummy variable with county demographic attributes. The remaining covariates account for the weighted average import tariff imposed on the county's industrial structure as well as the elimination of quantitative restrictions on apparel and clothing imports from China and rest of world (ROW). Standard errors adjusted for clustering at the county level are reported below coefficients. *, ** and *** signify statistical significance at the 10, 5 and 1 percent level.

Table 4: Exposure to PNTR and Democrat Votes for Other Offices

VARIABLES	Democrat Vote Share President	 President
Post x NTR Gap_c	0.045**	0.065***
	0.018	0.022
Post x NTR Gap_c x (Year==2016)		-0.029*
		0.015
Post x Median HHI in 1990_c	0.131***	0.193***
	0.018	0.021
Post x Percent Bachelors in 1990_c	0.729***	0.935***
	0.045	0.051
Post x Percent Graduate in 1990_c	0.032	0.029
	0.059	0.067
Post x Percent Non-White in 1990_c	0.045***	0.136***
	0.008	0.009
Post x Percent Over 65 in 1990_c	0.037	0.017
	0.031	0.034
Post x Percent Veteran in 1990_c	0.266***	0.272***
	0.043	0.047
NTR_{ct}	21.861	24.992
	27.202	32.294
MFA Exposure $(China)_{ct}$	0.373***	0.448***
	0.142	0.147
MFA Exposure $(ROW)_{ct}$	-1.532***	-1.525***
	0.319	0.334
Observations	**15,519**	21,727
R-squared	0.90	0.89
Estimation	OLS	OLS
Period	1992(4)2008	1992(4)2016
Drops	none	none
FE	c,t	c,t
Clustering	c	c
Mean Dependent Variable in 2000	40	49

Notes: Table reports difference-in-differences (DID) OLS regression results for Democrat vote share in county c in year t for presidential elections during noted sample periods. Presidential elections occur every four years. The first covariate is the DID term of interest, an interaction of a post-PNTR dummy with the county-level NTR gap. The second covariate interacts this variable with a dummy variable for 2016 to pick out a potential "Trump" effect. The next six covariates interact a post-PNTR dummy variable with county demographic attributes for the year 1990. The remaining covariates account for the weighted average import tariff based on the county's industrial structure as well as the elimination of quantitative restrictions on apparel and clothing imports from China and rest of world (ROW). Standard errors adjusted for clustering at the county level are reported below coefficients. *, ** and *** signify statistical significance at the 10, 5 and 1 percent level.

Table 5: The Trump Effect

VARIABLES	Demovote	Dem Win	S2Dem	S2Rep	Turnout
Post x NTR Gap$_c$	0.152**	0.072	0.325*	0.259	0.217***
	0.067	0.209	0.184	0.271	0.048
Post x Median HHI in 1990$_c$	0.244***	0.313	-0.062	0.162	-0.153***
	0.05	0.211	0.174	0.197	0.034
Post x Percent Bachelors in 1990$_c$	0.192	0.609	0.396	-0.771	0.386***
	0.133	0.628	0.555	0.571	0.106
Post x Percent Graduate in 1990$_c$	0.381*	1.218	1.677**	-0.294	-0.172
	0.197	0.744	0.656	0.587	0.141
Post x Percent Non-White in 1990$_c$	0.085***	0.066	0.302**	-0.217**	0.025
	0.023	0.068	0.124	0.085	0.021
Post x Percent Over 65 in 1990$_c$	0.415***	-0.093	0.327	0.066	-0.276***
	0.122	0.331	0.297	0.501	0.094
Post x Percent Veteran in 1990$_c$	-0.148	0.336	-0.518	-1.171**	0.510***
	0.169	0.517	0.598	0.584	0.138
NTR$_{ct}$	145.577	243.3	327.446	-69.399	61.541
	96.457	258.516	403.866	566.98	78.671
MFA Exposure (China)$_{ct}$	0.253	1.673*	-0.243	-4.063***	0.077
	0.301	0.876	0.769	1.533	0.182
MFA Exposure (ROW)$_{ct}$	-1.025	-5.369***	-0.685	10.203***	-0.282
	0.684	1.92	1.71	3.384	0.399
Observations	31,106	**31,106**	16,889	11,105	22,970
R-squared	0.737	0.669	0.436	0.518	0.86
Estimation	OLS	OLS	OLS	OLS	OLS
Period	1992(2)2010	1992(2)2010	1992(2)2010	1992(2)2010	1992(2)2010
Drops	none	none	Lag D Win	Lag R Win	none
FE	c,t	c,t	c,t	c,t	c,t
Clustering	c	c	c	c	c
Weighting	Population	Population	Population	Population	Population
Mean Dependent Variable in 2000	49	51	8	4	66

Notes: Table reports difference-in-differences (DID) OLS population-weighted regression results for dependent variables (noted in column heading) in county c in year t, including the share of votes cast for Democrats (column 1) as well as dummy variables for whether the Democrat wins (column 2), whether there is a switch to a Democrat (column 3), whether there is a switch to a Republican (column 4), and turnout (column 5). Sample period is even years from 1992 to 2010. Turnout data are missing for 1994 and 1998. The first covariate is the DID term of interest, an interaction of a post-PNTR dummy with the county-level NTR gap. The next six covariates interact a post-PNTR dummy variable with county demographic attributes as of 1990. The remaining covariates account for the weighted average import tariff imposed on the county's industrial structure as well as the elimination of quantitative restrictions on apparel and clothing imports from China and rest of world (ROW). Standard errors adjusted for clustering at the county level are reported below coefficients. *, ** and *** signify statistical significance at the 10, 5 and 1 percent level.

Table 6: PNTR and County-Level Voting for Democrats (Weighted Regression)

				Two-Stage Least Squares (2SLS)			
	Demovote_{ct}	Demovote_{ct}	U-Rate_{ct}	Demovote_{ct}	Dem Win_{ct}	S2Dem_{ct}	Turnout_{ct}
Post x NTR Gap_c	0.168***		0.061***				
	0.048		0.007				
U-Rate_{ct}		-0.142*		2.429***	2.928*	4.203**	1.897***
		0.082		0.725	1.55	1.664	0.337
Post x Median HHI in 1990_c	0.001	0.04	0.056***	-0.134**	-0.371**	-0.389***	-0.383***
	0.043	0.042	0.006	0.068	0.157	0.142	0.032
Post x Percent Bachelors in 1990_c	0.616***	0.498***	0.073***	0.437***	1.514***	0.305	0.512***
	0.102	0.095	0.012	0.101	0.244	0.228	0.048
Post x Percent Graduate in 1990_c	0.092	0.125	-0.019	0.139	0.043	0.688*	-0.408***
	0.131	0.131	0.015	0.138	0.325	0.363	0.072
Post x Percent Non-White in 1990_c	-0.036	-0.037	-0.013***	-0.004	-0.056	0.208***	-0.003
	0.023	0.023	0.002	0.025	0.047	0.064	0.01
Post x Percent Over 65 in 1990_c	-0.199***	-0.193**	0.092***	-0.423***	-0.745***	-0.203	-0.340***
	0.076	0.075	0.009	0.103	0.223	0.174	0.045
Post x Percent Veteran in 1990_c	0.133	0.054	-0.066***	0.293**	0.248	0.355	0.510***
	0.099	0.097	0.014	0.124	0.273	0.28	0.057
NTR_{ct}	99.317	22.555		55.024	104.26	-504.968***	66.258*
	63.924	62.741		66.029	166.939	189.286	35.15
MFA Exposure $(\text{China})_{ct}$	0.157	0.249		0.302	1.247	-0.054	0.035
	0.285	0.285		0.317	0.773	0.836	0.107
MFA Exposure $(\text{ROW})_{ct}$	-0.329	-0.36		-0.575	-2.79	0.103	0.006
	0.641	0.642		0.716	1.704	1.828	0.244
Observations	27,974	27,974	27,974	**27,974**	27,974	15,155	19,890
R-squared	0.649	0.649	0.776	0.628	0.59	0.369	0.8
Estimation	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS
Instrument for U-Rate	.	.	.	PostxNTR Gap_c	PostxNTR Gap_c	PostxNTR Gap_c	PostxNTR Gap_c
First-Stage F Test	.	.	.	113	113	113	82
Period	1992(2)2010	1992(2)2010	1992(2)2010	1992(2)2010	1992(2)2010	1994(2)2010	1992(2)2010
FE	c,t	c,t	c,t	c,t	c,t	c,t	c,t
Clustering	c	c	c	c	c	c	c
Weighting	Population	Population	Population	Population	Population	Population	Population
Mean Dependent Variable in 2000	49	49	4	49	51	8	66

Notes: Table reports results of OLS (columns 1-3) and 2SLS (columns 4-7) regressions. Demovote is the Democrat vote share in county c in year t. U-Rate is the unemployment rate (in percent) in county c in year t. Dem Win is an indicator variable for whether votes for the Democrat candidate exceed those for the Republican candidate. S2Dem is an indicator variable for whether there is a switch from Republican to Democrat representation. Turnout is the share of registered voters who cast votes in the election. Sample period is even years from 1992 to 2010. Turnout data are missing for 1994 and 1998. The first covariate is an interaction of a post-PNTR dummy with county-level NTR gap. The next six covariates interact a post-PNTR dummy variable with county demographic attributes as of 1990. The remaining covariates account for the weighted average import tariff imposed on the county's industrial structure as well as the elimination of quantitative restrictions on apparel and clothing imports from China and rest of world (ROW). Standard errors adjusted for clustering at the county level are reported below coefficients. *, ** and *** signify statistical significance at the 10, 5 and 1 percent level.

Table 7: Voting for Democrats and the Unemployment Rate (2SLS)

	Pro-Trade Vote Share		
	[1]	[2]	[3]
Democrat	-0.173***	-0.179***	-0.149***
	0.007	0.033	0.030
Observations	4,294	4,296	4,296
R2	0.59	.	0.15
Covariates	Yes	No	No
Fixed Effects	State, Congress	.	State, Congress
Bandwidth	.	100%	.
Estimation Technique	Linear	Non-Parametric	Polynomial 3

Notes: Table summarizes the results of Representative-year level regression discontinuity regressions of the share of pro-trade votes on an indicator for whether the representative is a Democrat. Covariates include the district-year level demographic attributes and Representative-year level attributes described in Section 5 of the text. Coefficient estimates for these covariates are suppressed. Polynomial 3 refers to inclusion of third-order polynomials as instruments. Robust standard errors are reported below coefficients. *, ** and *** signify statistical significance at the 10, 5 and 1 percent level.

Table 8: Effect of Democrat Affiliation on Districts' Voting for Pro-Trade Bills

	Pro-Economic Assistance Vote Share		
	[1]	[2]	[3]
Democrat	0.435***	0.324***	0.325***
	0.009	0.027	0.0358
Observations	4,292	4,294	4,294
R2	0.61	.	0.36
Covariates	Yes	No	No
Fixed Effects	State, Congress	.	State, Congress
Bandwidth	.	100%	.
Estimation Technique	Linear	Non-Parametric	Polynomial 3

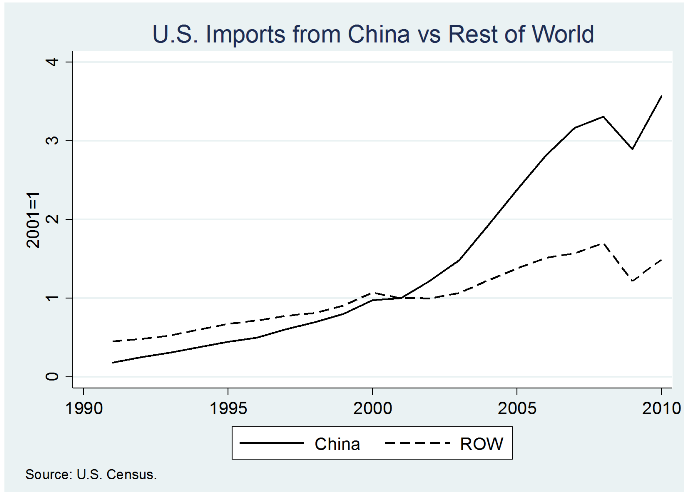
Notes: Table summarizes the results of Representative-year level regression discontinuity regressions of the share of pro-economic assistance votes on an indicator for whether the representative is a Democrat. Covariates include the district-year level demographic attributes and Representative-year level attributes described in Section 5 of the text. Coefficient stimates for these covariates are suppressed. Polynomial 3 refers to inclusion of third-order polynomials as instruments. Robust standard errors are reported below coefficients. *, ** and *** signify statistical significance at the 10, 5 and 1 percent level.

Table 9: Effect of Democrat Affiliation on Districts' Voting for Pro-Economic Assistance Bills

	Pro-Trade Vote Share		Pro-Economic Assistance Vote Share	
	1992-2000	2002-2010	1992-2000	2002-2010
Democrat	-0.051	-0.304***	0.277***	0.395***
	0.033	0.050	0.045	0.055
Observations	2,138	2,158	2,137	2,157
R2	0.05	0.26	0.19	0.57
Covariates	No	No	No	No
Fixed Effects	State, Congress	State, Congress	State, Congress	State, Congress
Bandwidth	.	.	.	.
Estimation Technique	Polynomial 3	Polynomial 3	Polynomial 3	Polynomial 3

Notes: Table summarizes the results of Representative-year-level non-parametric regression discontinuity estimations of the share of pro-trade or pro-economic assistance votes on an indicator for whether the representative is a Democrat. Covariates include the district-year-level demographic attributes and Representative-year-level attributes described in Section 5 of the text (coefficient estimates not displayed). Polynomial 3 refers to inclusion of third-order polynomials as instruments. Robust standard errors are reported below coefficients. *, ** and *** signify statistical significance at the 10, 5 and 1 percent level.

Table 10: Pro-Free Trade and Pro-Economic Assistance Voting Before and After PNTR



Notes: Figure displays indexes of U.S. nominal imports from China and from the rest of the world (ROW) for the years 1992 to 2010. The base year for the indexes is 2000. Source: U.S. Census Bureau.

Figure 1: U.S. Imports from China and Rest of World (ROW)

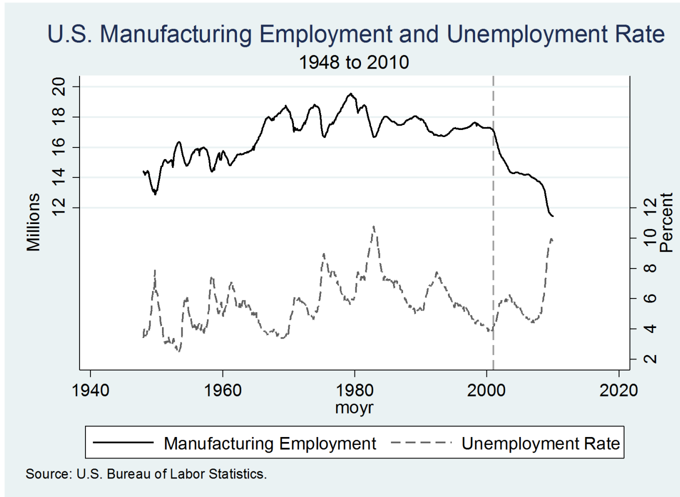
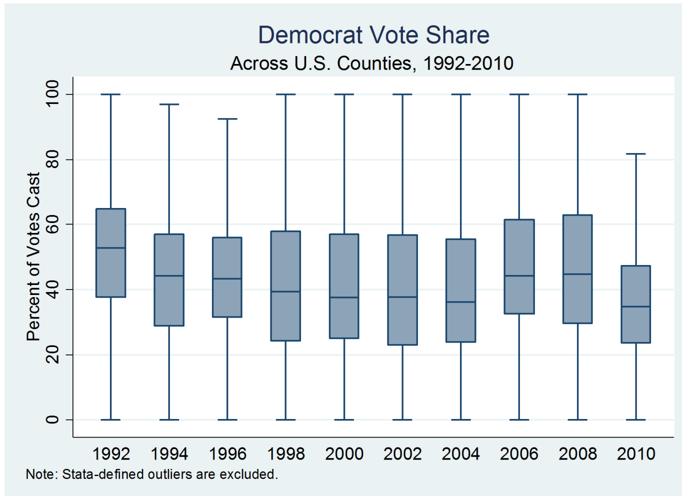
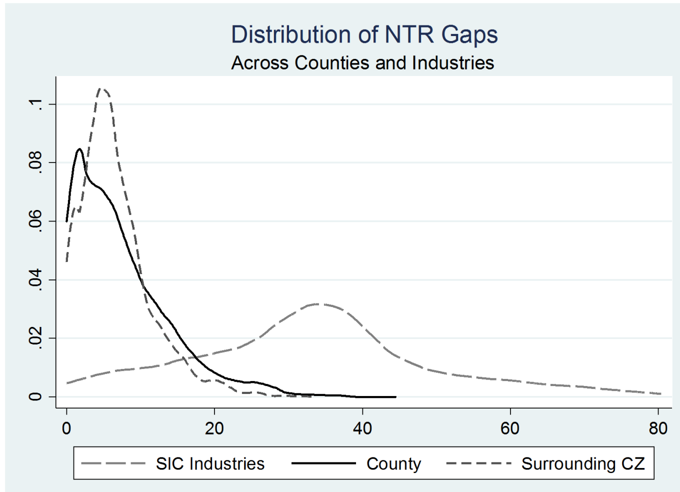


Figure 2: Post-War U.S. Manufacturing Employment



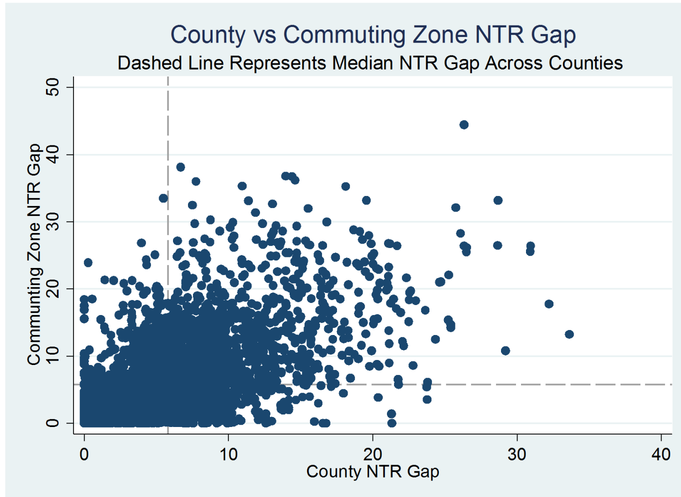
Notes: Figure summarizes the mean and inter-quartile range of the share of votes won by Democrats across U.S. counties in elections to the U.S. House of Representatives, by year. The mean, standard deviation, median and interquartile range for 2000, the election closest to the passage of PNTR, are 40, 23, 38 and 25 to 57 percent .

Figure 3: Distribution of Democrat Vote Share



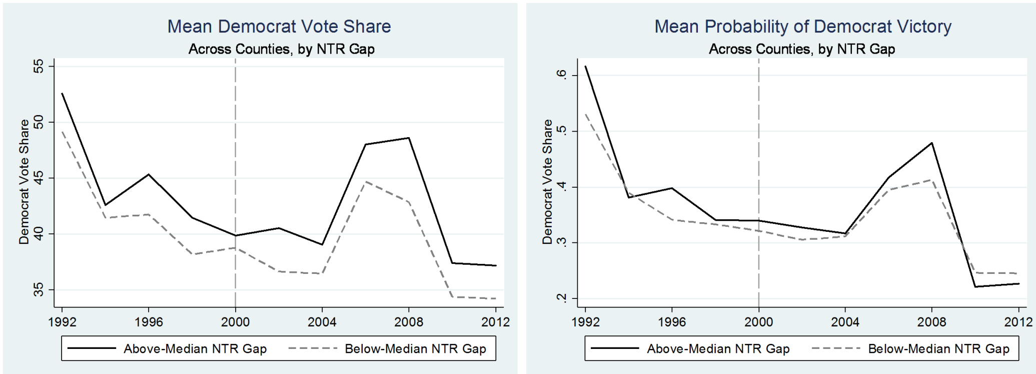
Notes: Figure displays distributions of the industry-level and county-level NTR gaps, measured in percentage points.

Figure 4: Distribution of NTR Gap Across Industries and Counties



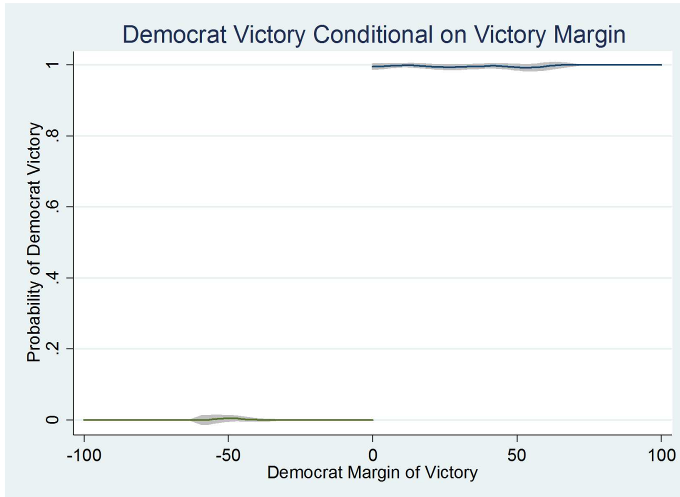
Notes: Figure compares counties' NTR gap to the average NTR gap of the other counties in their commuting zone. Dashed lines indicate the median county-level NTR gap, which is 5.8 percent.

Figure 5: Correlation of Own-County and Commuting Zone Exposure



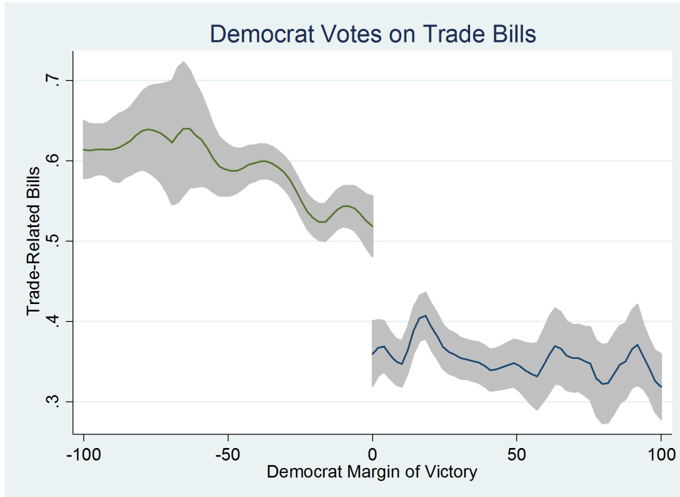
Notes: Left panel average Democrat vote share across counties according to whether their own NTR gap and the average of their surrounding counties are both above or below the median of these gaps across all counties. Right panel is the same with respect to the average probability of Democrat victory.

Figure 6: Simple DID View of the Shift Towards Democrats



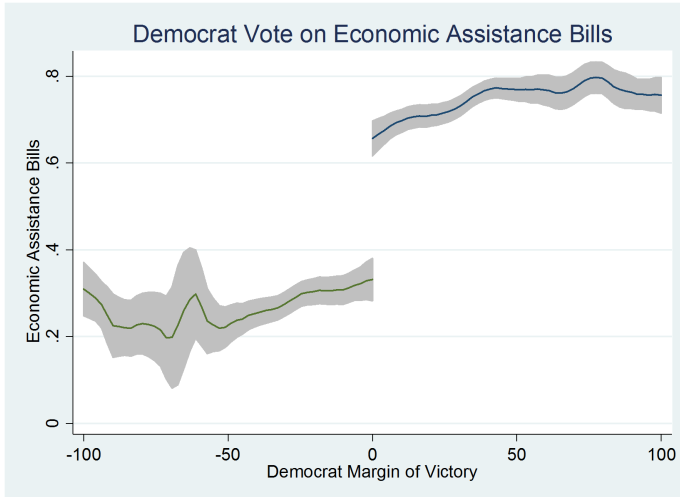
Notes: Unit of analysis is a district-year pair across the years 1992 to 2010. The horizontal axis is the difference between the Democrat and Republican vote margin. The vertical axis is a dummy variable indicating whether the district is represented by a Democrat. Note that because a district could be controlled by a third party, positive margin does not perfectly predict Democrat representation. Shading represents the 95 percent confidence interval.

Figure 7: Regression Discontinuity Intuition



Notes: Unit of analysis is a district-year pair across the years 1992 to 2010. Figure displays the discontinuity of the share of pro-trade votes (vertical axis) versus the Democrat vote share margin of victory (horizontal axis). A triangular kernel is used for local linear regressions. Shading represents the 95 percent confidence interval.

Figure 8: Democrat Votes On Trade Bills



Notes: Unit of analysis is a district-year pair across the years 1992 to 2010. Figure displays the discontinuity of the share of pro-redistribution votes (vertical axis) versus the Democrat vote share margin of victory (horizontal axis). A triangular kernel is used for local linear regressions. Shading represents the 95 percent confidence interval.

Figure 9: Democrat Votes On Economic Assistance Bills

Appendix

This appendix contains additional empirical results referenced in the main text.

A Legislator Voting Behavior

Figure A.1 displays the McCrary (2008) test of whether there is a discontinuity in the density of Democrats' winning margin over Republicans. The estimate of the discontinuity is 0.003 with a standard error of 0.125, indicating that there is not a statistically significant discontinuity. Figures A.2 to A.10 examine the distributions of each of the district-level attributes included in the legislative voting regressions in Section 5, plotted against the Democrat margin of victory. As discussed there, none of these distributions exhibit discontinuities at the cutoff point at which the Democrat margin of victory is 0.

B Approaches for Estimating Regression Discontinuity Coefficient

The nonparametric approach is a "local linear" estimation that uses observations within a window of width w on both sides of the cutoff point and assumes that $g(.)$ and $f(.)$ are linear, with potentially different slopes on the two sides of the cutoff point. We implement this approach using the procedure developed by Imbens and Kalyanaraman (2014) to calculate the optimal bandwidth w^*, and estimate analytical standard errors using the procedure developed in Porter (2003). In robustness checks, we examine whether our estimates are sensitive to different bandwidths, e.g., halving and doubling w^*, as in Lee and Lemieux (2010). As indicated in Table A.1, we obtain similar results in both cases for both sets of bills.

Parametric estimation, by contrast, uses all of the observations over the domain of the assignment variable and assumes high-order polynomial functions of $g(.)$ and $f(.)$. In the main text, we implement this approach using third-order polynomial functions with potentially different coefficients on the two sides of the cutoff point. Following Lee and Card (2008), we calculate standard errors clustered at the assignment variable level. Here, we report results using second- and fourth-order polynomials to examine the sensitivity of our estimates to using third order polynomials. As indicated in Table A.2, we obtain similar results in both cases.

Appendix Tables and Figures

	Pro-Trade Vote Share		
	[1]	[2]	[3]
Democrat	-0.173***	-0.179***	-0.149***
	0.007	0.033	0.030
Observations	4,294	4,296	4,296
R2	0.59	.	0.15
Covariates	Yes	No	No
Fixed Effects	State, Congress	.	State, Congress
Bandwidth	.	100%	.
Estimation Technique	Linear	Non-Parametric	Polynomial 3

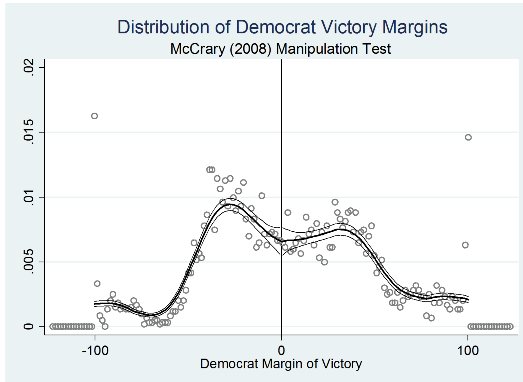
Notes: Table summarizes the results of Representative-year level regression discontinuity regressions of the share of pro-trade votes on an indicator for whether the representative is a Democrat. Covariates include the district-year level demographic attributes and Representative-year level attributes described in Section 5 of the text. Coefficient estimates for these covariates are suppressed. Polynomial 3 refers to inclusion of third-order polynomials as instruments. Robust standard errors are reported below coefficients. *, ** and *** signify statistical significance at the 10, 5 and 1 percent level.

Table A.1: RD Results: Alternate Bandwidths

	Pro-Trade Vote Share		
	[1]	[2]	[3]
Democrat	-0.173***	-0.179***	-0.149***
	0.007	0.033	0.030
Observations	4,294	4,296	4,296
R2	0.59	.	0.15
Covariates	Yes	No	No
Fixed Effects	State, Congress	.	State, Congress
Bandwidth	.	100%	.
Estimation Technique	Linear	Non-Parametric	Polynomial 3

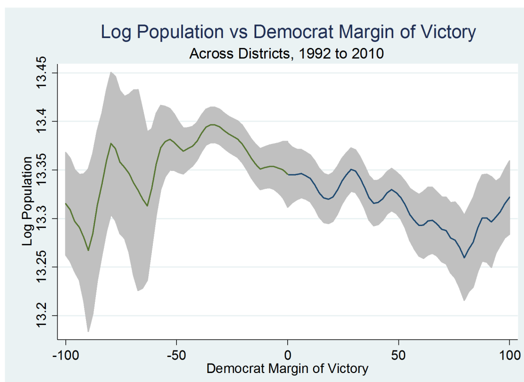
Notes: Table summarizes the results of Representative-year level regression discontinuity regressions of the share of pro-trade votes on an indicator for whether the representative is a Democrat. Covariates include the district-year level demographic attributes and Representative-year level attributes described in Section 5 of the text. Coefficient estimates for these covariates are suppressed. Polynomial 3 refers to inclusion of third-order polynomials as instruments. Robust standard errors are reported below coefficients. *, ** and *** signify statistical significance at the 10, 5 and 1 percent level.

Table A.2: RD Results: Alternate Polynomial Functions



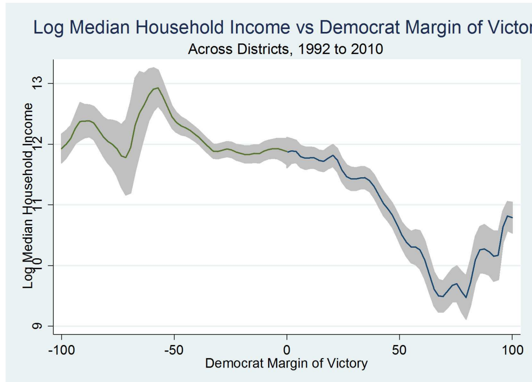
Notes: Figure displays the McCrary (2008) test of whether there is a discontinuity in the density of Democrats' winning margin over Republicans. This test rejects manipulation because the discontinuity estimate (i.e., the gap between counties in the treatment versus control group around the margin of zero) is -0.003 with a standard error of 0.125.

Figure A.1: RD Identifying Assumption Density Test



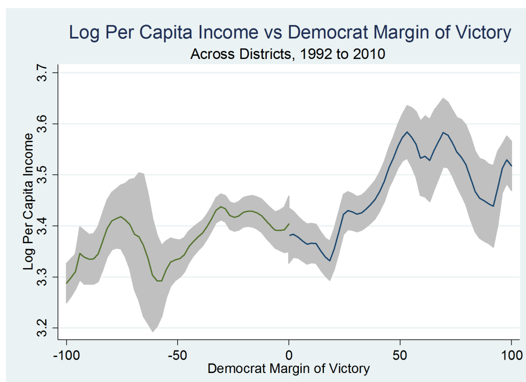
Notes: Unit of analysis is a district-year pair across the years 1992 to 2010. Figure displays the log of district population (vertical axis) versus the Democrat vote share margin of victory (horizontal axis). A triangular kernel is used for local linear regressions. Shading represents the 95 percent confidence interval.

Figure A.2: RD Identifying Assumption: Population



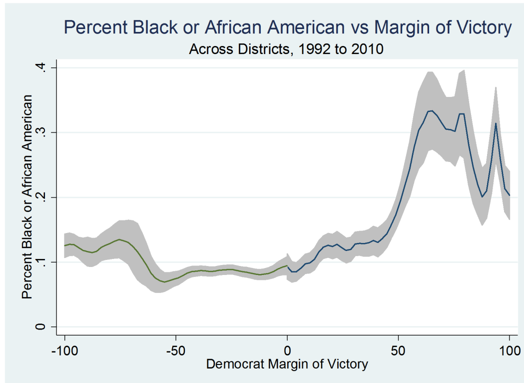
Notes: Unit of analysis is a district-year pair across the years 1992 to 2010. Figure displays the log of median household income (vertical axis) versus the Democrat vote share margin of victory (horizontal axis). A triangular kernel is used for local linear regressions. Shading represents the 95 percent confidence interval.

Figure A.3: RD Identifying Assumption: Household Income



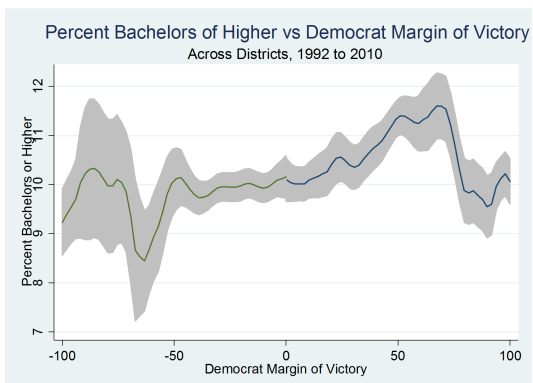
Notes: Unit of analysis is a district-year pair across the years 1992 to 2010. Figure displays the log of per capita income (vertical axis) versus the Democrat vote share margin of victory (horizontal axis). A triangular kernel is used for local linear regressions. Shading represents the 95 percent confidence interval.

Figure A.4: RD Identifying Assumption: Per Capita Income



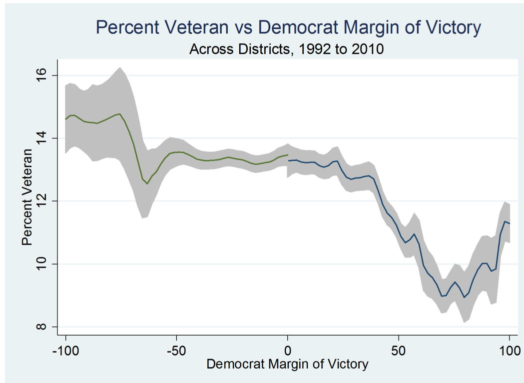
Notes: Unit of analysis is a district-year pair across the years 1992 to 2010. Figure displays the share of population that is black or African American (vertical axis) versus the Democrat vote share margin of victory (horizontal axis). A triangular kernel is used for local linear regressions. Shading represents the 95 percent confidence interval.

Figure A.5: RD Identifying Assumption: Black or African American Population Share



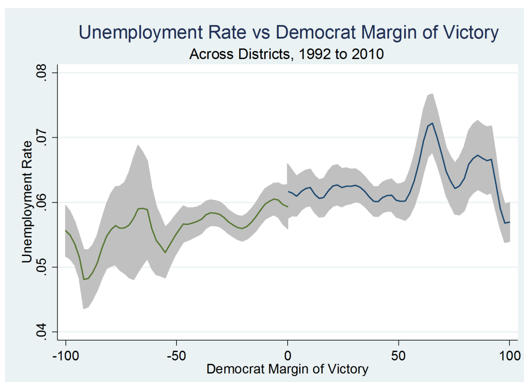
Notes: Unit of analysis is a district-year pair across the years 1992 to 2010. Figure displays the share of population with at least a bachelors degree (vertical axis) versus the Democrat vote share margin of victory (horizontal axis). A triangular kernel is used for local linear regressions. Shading represents the 95 percent confidence interval.

Figure A.6: RD Identifying Assumption: College or Above Share



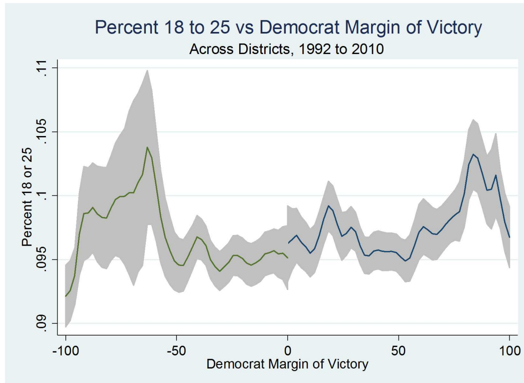
Notes: Unit of analysis is a district-year pair across the years 1992 to 2010. Figure displays the share of population that are veterans (vertical axis) versus the Democrat vote share margin of victory (horizontal axis). A triangular kernel is used for local linear regressions. Shading represents the 95 percent confidence interval.

Figure A.7: RD Identifying Assumption: Veteran Share



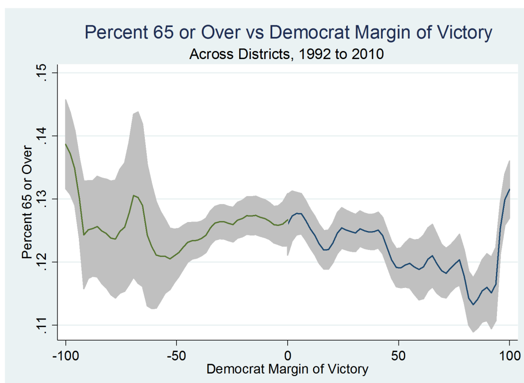
Notes: Unit of analysis is a district-year pair across the years 1992 to 2010. Figure displays the unemployment rate (vertical axis) versus the Democrat vote share margin of victory (horizontal axis). A triangular kernel is used for local linear regressions. Shading represents the 95 percent confidence interval.

Figure A.8: RD Identifying Assumption: Unemployment Rate



Notes: Unit of analysis is a district-year pair across the years 1992 to 2010. Figure displays the share of population aged 18 to 25 (vertical axis) versus the Democrat vote share margin of victory (horizontal axis). A triangular kernel is used for local linear regressions. Shading represents the 95 percent confidence interval.

Figure A.9: RD Identifying Assumption: 18 to 25 Share



Notes: Unit of analysis is a district-year pair across the years 1992 to 2010. Figure displays the share of population aged 65 or over (vertical axis) versus the Democrat vote share margin of victory (horizontal axis). A triangular kernel is used for local linear regressions. Shading represents the 95 percent confidence interval.

Figure A.10: RD Identifying Assumption: Over 65 Share