A Note on the Effect of Rising Trade Exposure on the 2016 Presidential Election

[*Appendix to Autor, Dorn, Hanson, and Majlesi "Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure"*]

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1 Introduction

This research note examines whether the exposure of local labor markets to increased import competition from China effected voting in the U.S. presidential election in 2016. It relates the change in the county-level Republican two-party vote share between 2000 and 2016 to the growth in local labor markets' exposure to Chinese import penetration. We find a robust positive effect of rising import competition on Republican vote share gains. The magnitude of the Republican gains is non-trivial. A counterfactual study of closely contested states suggests that Michigan, Wisconsin, Pennsylvania and North Carolina would have elected the Democrat instead of the Republican candidate if, ceteris paribus, the growth in Chinese import penetration had been 50 percent lower than the actual growth during the period of analysis. The Democrat candidate would also have obtained a majority in the electoral college in this counterfactual scenario. These results add to previous research that documents negative impacts of import competition on employment and earnings in trade-exposed local labor markets (Autor, Dorn and Hanson, 2013; Acemoglu et al. 2016) and a decreased likelihood that moderate politicians win congressional elections in such locations (Autor, Dorn, Hanson and Majlesi, 2016).

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2 Measurement

We study the Republican two-party vote share, which corresponds to the number of Republican votes in a county, divided by the sum of Republican and Democrat votes. The outcome period of 2000 to 2016 spans the period of most rapid growth of import competition from China following China's accession to the WTO in 2001. The 2000 and 2016 elections were both closely contested, and did not feature an incumbent president. The vote count data are based on Dave Leip's Atlas of the U.S. Presidential Elections and are preliminary for the 2016 election (data version 0.25). We do not observe the 2016 votes for some or all of the counties in the states of Massachusetts, Maine, Mississippi and Illinois, and additionally omit Alaska and Hawaii where it is difficult to define local labor markets. Our final sample comprises 2,971 counties.

We match the election data at the county level to economic conditions in commuting zones (CZs), including the exposure of these local labor markets to import competition from China. The growth of Chinese import penetration is measured over the period 2002 to 2014. Our measure of the local labor market shock is the average change in Chinese import penetration in a CZ's industries, weighted by each industry's share in initial CZ employment:

$$\Delta IP^{cu}_{i\tau} = \sum_j \frac{L_{ijt}}{L_{it}} \Delta IP^{cu}_{j\tau}. \tag{1}$$

In this expression, $\Delta IP^{cu}_{j\tau} = \Delta M^{cu}_{j\tau}/(Y_{j0} + M_{j0} - X_{j0})$ is the growth of Chinese import penetration in the U.S. for industry j over period τ, defined to be the 2002-2014 change. It is computed as the growth in U.S. imports from China during the period 2002-2014, $\Delta M^{cu}_{j\tau}$, divided by initial absorption (U.S. industry shipments plus net imports, $Y_{j0} + M_{j0} - X_{j0}$) in the base period 1991, near the start of China's export boom. The fraction L_{ijt}/L_{it} is the share of industry j in CZ i's total employment, as measured in County Business Patterns data prior to the outcome period in the year 2000.

In equation (1), the difference in ΔIP^{cu}_{it} across commuting zones stems entirely from variation in local industry employment structure at the start of period t. This variation arises from two sources: differential concentration of employment in manufacturing versus non-manufacturing activities and specialization in import-intensive industries within local manufacturing. Importantly, differences in manufacturing employment shares are not the primary source of variation. In a bivariate regression, the start-of-period manufacturing employment share explains less than 40 percent of the variation in ΔIP^{cu}_{it}.

An identification challenge for the estimation is that realized U.S. imports from China in (1) may be correlated with industry import-demand shocks. In this case, OLS estimates of the relationship between increased imports from China and changes in U.S. manufacturing employment may understate the impact of the pure supply shock component of rising Chinese import competition, as both U.S. employment and imports may rise simultaneously in the face of unobserved positive shocks to U.S. product demand. To identify the causal effect of rising Chinese import exposure on local-level political outcomes, we employ an instrumental-variables strategy that accounts for the potential endogeneity of U.S. trade exposure. We exploit the fact that during our sample period, much of the growth in Chinese imports stems from the rising competitiveness of Chinese manufacturers, which is a supply shock from the perspective of U.S. producers. China's lowering of trade barriers (Bai, Krishna, and Ma, 2015), dismantling of the constraints associated with central planning (Naughton, 2007; Hsieh and Song, 2015), and accession to the WTO (Pierce and Schott, 2016) have contributed to a massive increase in the country's manufacturing capacity and a concomitant rise in the country's manufacturing exports (Hsieh and Ossa, 2015).

To identify the supply-driven component of Chinese imports, we instrument for growth in Chinese imports to the U.S. using the contemporaneous composition and growth of Chinese imports in eight other developed countries.[1] Specifically, we instrument the measured import-exposure variable ΔIP_{it}^{cu} with a non-U.S. exposure variable ΔIP_{it}^{co} that is constructed using data on industry-level growth of Chinese exports to other high-income markets:

$$\Delta IP_{it}^{co} = \sum_{j} \frac{L_{ijt-10}}{L_{uit-10}} \Delta IP_{j\tau}^{co}. \qquad (2)$$

This expression for non-U.S. exposure to Chinese imports differs from the expression in equation (1) in two respects. In place of computing industry-level import penetration with U.S. imports by industry ($\Delta M_{j\tau}^{cu}$), it uses realized imports from China by other high-income markets ($\Delta M_{j\tau}^{co}$), and it replaces all other variables with lagged values to mitigate any simultaneity bias.[2] As documented by Autor, Dorn and Hanson (2016), all eight comparison countries used for the instrumental variables analysis witnessed import growth from China in at least 343 of the 397 total set of manufacturing industries. Moreover, cross-country, cross-industry patterns of imports are strongly correlated between each of these countries and the U.S. That China made comparable gains in penetration by detailed sector across numerous countries in the same time interval suggests that China's falling prices, rising quality, and diminishing trade and tariff costs in these surging sectors are a central

[1]The eight other high-income countries are those that have comparable trade data covering the full sample period: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

[2]The start-of-period employment shares L_{ijt}/L_{it} are replaced by their 10 year lag, while initial absorption in the expression for industry-level import penetration is replaced by its 3 year lag.

cause of its manufacturing export growth.

Data on international trade for 2002 to 2014 are from the UN Comtrade Database, which gives bilateral imports for six-digit HS products.[3] To concord these data to four-digit SIC industries, we first apply the crosswalk in Pierce and Schott (2012), which assigns ten-digit HS products to four-digit SIC industries (at which level each HS product maps into a single SIC industry), and aggregate up to the level of six-digit HS products and four-digit SIC industries (at which level some HS products map into multiple SIC entries). To perform this aggregation, we use data on U.S. import values at the ten-digit HS level, averaged over 1995 to 2005.[4] All dollar amounts are inflated to dollar values in 2015 using the PCE deflator. Data on CZ employment by industry from the County Business Patterns for the years 1990 and 2000 are used to compute employment shares by industry in (1) and (2).

3 Results

Our estimating equation for this analysis is

$$\Delta Y_{jt} = \gamma_d + \beta_1 \Delta IP^{cu}_{jt} + Z'_{jt}\beta_2 + e_{jt}, \tag{3}$$

where the dependent variable ΔY_{jt} is the change in the Republican two-party vote share between 2000 and 2016 in county j. The main explanatory variable of interest is the contemporaneous change in import exposure ΔIP_{jt} in the commuting zone to which county j belongs. Equation (3) further includes a vector of control variables Z_{jt} measuring start-of-period economic conditions and demographic characteristics, either at the CZ or the county level. These include the share of manufacturing in CZ employment, the Autor and Dorn (2013) routine-task-intensity index and offshorability index for CZ occupations, county population shares for nine age and four racial groups, and the shares of the county population that are female, college educated, foreign born, and Hispanic, where each of these variables is measured in 2000.[5] All regressions are weighted by a county's total votes in the 2000 presidential election. Following our strategy outlined above, we estimate (3) using two-stage least squares, with the import-exposure variable instrumented by contemporaneous

[3] See http://comtrade.un.org/db/default.aspx.

[4] The crosswalk assigns HS codes to all but a small number of SIC industries. We therefore slightly aggregate the four-digit SIC industries so that each of the resulting 397 manufacturing industries matches to at least one trade code and none is immune by construction to trade competition.

[5] The manufacturing employment share is based on County Business Pattern data. The Autor-Dorn indices are based on occupational employment shares in the Census combined with task data from the Dictionary of Occupational Titles. All population composition variables are based on Census short-form tabulations.

changes in Chinese imports to other non-U.S. high-income countries as in (2).

In Table 1, we report estimates for equation (3), in which the dependent variable is the change in the Republican two-party vote share between 2000 and 2016 in a county. The first two columns contain initial OLS and 2SLS estimates, respectively, with no additional control variables included in the estimation. In column (1), the OLS coefficient is positive but imprecisely estimated. When import penetration is instrumented in column (2) using our strategy outlined above, the estimate increases in magnitude and becomes statistically significant. The fact that the 2SLS point estimate exceeds its OLS counterpart is consistent with findings in Autor, Dorn, and Hanson (2013) showing that the exogenous component of rising China import penetration generates more negative local labor market impacts than the endogenous trade measure, because the latter also comprises domestic demand shocks that can lead to both greater imports and greater demand for local outputs. The column (2) point estimate of 2.81 indicates that for two counties, one at the 25^{th} percentile of the increase in trade exposure (a 2002-2014 increase of 0.58 percentage points in import penetration) and another at the 75^{th} percentile of the increase in trade exposure (a 2002-2014 increase of 1.35 percentage points in import penetration), the Republican two-party vote share between 2000 and 2016 is predicted to increase by an additional 2.2 ($2.81 \times [1.35 - 0.58]$) percentage points in the more exposed county. Relative to the mean change in the Republican two-party vote share between 2000 and 2016 of -0.6 percentage points, this magnitude is non-trivial.

We include as additional regressors in column (3) industry and occupation controls that are measured at the CZ level and comprise the share of manufacturing in total employment (from the 2000 County Business Patterns data), and the routine employment share and offshorability among occupations (based on Autor and Dorn (2013) and derived from 2000 Census data). We control for the start-of-period manufacturing share within CZs so as to focus on variation in exposure to trade stemming from differences in industry mix within local manufacturing sectors. Additionally, in column (4), we add demographic controls that comprise the percentage of a county's population in nine age and four racial groups, as well as the population shares that are female, college-educated, foreign-born, and Hispanic. Finally, adding Census division dummies in column (5) allows for differing trends in the Republican two-party vote share across the nine geographical Census divisions. In this case, our identification comes from within-division, cross-county variation in trade exposure and voting outcomes. The addition of these control variables only modestly affects the point estimates for import penetration. In alternative regression models where the outcome is the level of the 2016 Republican two-party vote share (with the 2000 vote share included as a control), we obtain similar results.

Table 1: **Exposure to Chinese Import Competition and Presidential Elections, 2016 vs. 2000. Dependent Variable: Change in Percentage of Two-Party Vote Obtained by the Republican Candidate, 2016 (Trump) vs. 2000 (Bush)**

	(1)	(2)	(3)	(4)	(5)
Δ CZ Import Penetration	1.12	2.81 *	3.68 **	2.36 **	2.09 *
	(1.01)	(1.38)	(1.42)	(0.86)	(0.86)
Estimation	OLS	2SLS	2SLS	2SLS	2SLS
Control Variables					
2000 Ind/Occ Controls			yes	yes	yes
2000 Demography Controls				yes	yes
Census Division Dummies					yes

Notes: N=2,971 counties. The mean Republican two-party vote percentage in our sample in 2000 is 49.33 (s.e. 18.07), and its mean change between 2000 and 2016 is -0.62 (s.e. 9.96). CZ import penetration increased by an average of 1.03 (s.e. 0.69) from 2002 to 2014. The county-level voting data is preliminary and excludes all or parts of the states of MA, ME, MS, IL, AK and HI. The republican two-party vote share corresponds to republican votes divided by the sum of republican and democrat votes. The growth of Chinese import penetration is measured over the period 2002 to 2014. The 2SLS models in columns 2-5 instrument for the change in Chinese import penetration in the US using the change in other developed countries' imports from China. Industry and occupation controls in column 3 are measured at the CZ level and comprise the share of manufacturing in total employment (from the 2000 County Business Patterns data), as well as routine share and offshorability among occupations (based on Autor and Dorn (2013) and derived from 2000 Census data). Demographic controls in column 4 comprise the percentage of a county's population in 9 age and 4 racial groups, as well as the population shares that are female, college-educated, foreign-born, and Hispanic. Census division dummies in column 5 allow for different time trends across the 9 geographical Census divisions. Observations are weighted by a counties' total votes in the 2000 presidential election. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

4 Counterfactual Exercise

In this section, we conduct a counterfactual exercise to explore how the composition of votes in a number of closely contested states would have differed had Chinese import penetration grown less than it actually did. The computation of the counterfactual is based on the coefficient estimate in column (5) of Table 1, which indicates that Republican gain in the two-party vote share of 2.09 percentage point for a one percentage point greater growth of average Chinese import penetration in a CZ. For each county, we compute the fraction of two-party votes that would have been obtained by the Democrat instead of the Republican candidate if the trade shock had been $X\%$ smaller as the product of $2.09 \times X\% \times \Delta IP^{cu}_{jt}$, that is, the point estimate of the causal effect of the trade shock on the vote share, the size of each county's measured trade shock, and the scaling factor $X\%$. We next multiply this product with the number of two-party votes in a county in order to obtain the number of additional votes that the Democrat candidate would have obtained in the counterfactual scenario. We finally aggregate these county-level votes to state totals.

Table 2 presents the results of this counterfactual analysis. Column (1) shows the actual vote margin in favor of the Republican candidate in the 2016 election for a set of closely contested states. The three subsequent columns show counterfactual outcomes had the growth in Chinese import penetration in the U.S. had been 10%, 20%, or 50% smaller.

Table 2: **Counterfactual Outcomes in Closely Contested States**

	Vote Margin in Favor of Republican Candidate							
			Chinese Import Growth					
	Actual Outcome		10% Smaller		25% Smaller		50% Smaller	
Georgia	215,380	(5.28%)	201,003	(4.93%)	179,437	(4.40%)	143,494	(3.52%)
Arizona	84,904	(4.12%)	78,305	(3.80%)	68,406	(3.32%)	51,907	(2.52%)
North Carolina	177,009	(3.78%)	135,992	(2.90%)	74,467	(1.59%)	-28,075	(-0.60%)
Florida	119,489	(1.27%)	97,615	(1.04%)	64,805	(0.69%)	10,121	(0.11%)
Pennsylvania	73,224	(1.24%)	50,242	(0.85%)	15,769	(0.27%)	-41,686	(-0.71%)
Wisconsin	24,081	(0.81%)	8,995	(0.30%)	-13,633	(-0.46%)	-51,347	(-1.73%)
Michigan	13,107	(0.27%)	-6,493	(-0.13%)	-35,892	(-0.74%)	-84,891	(-1.75%)
New Hampshire	-2,687	(-0.37%)	-7,706	(-1.06%)	-15,233	(-2.10%)	-27,780	(-3.83%)
Minnesota	-43,783	(-1.49%)	-55,111	(-1.88%)	-72,103	(-2.45%)	-100,422	(-3.42%)
Electoral Votes Trump	306		290		280		245	
Electoral Votes Clinton	232		248		258		293	

Notes: The computation of the counterfactual is based on the estimate that a growth of import penetration by one percentage point reduces the Republican share of the two-party vote by 2.09 percentage points. Numbers in parentheses indicate the vote margin in favor of the Republican candidate as a percentage of the total vote.

Since we find that local labor market exposure to import competition from China increased the vote share for the Republican candidate, the counterfactual analyses for lower import growth correspondingly indicates more favorable results for the Democrat presidential candidate. The results in Table 2 show that the Democrat candidate would have won the states of Michigan and Wisconsin in counterfactual scenario with a 25% smaller trade shock, and additionally the states of Pennsylvania and North Carolina had the trade shock been 50% smaller than observed. In the latter scenario, the Democrat candidate would also have won the electoral college.

We stress that this exercise corresponds to a ceteris paribus scenario where the China shock affects the U.S. presidential general election exclusively through its effect on the Republican two-party vote share. This counterfactual is of course extremely restrictive. As documented by Autor, Dorn, Hanson and Majlesi (2016), the China shock directly contributed to the rapidly shifting ideological composition of the House of Representatives in the decade leading up to the Presidential election, and it is likely that those representatives' legislative and campaign activities subsequently contributed to the general election outcome in 2016. Moreover, it is conceivable that a different candidate would have been the victor of the 2016 Republican presidential primary election were it not for the China shock, as argued by reporters for the *New York Times* (Schwartz and Bui, 2016) and the *Wall Street Journal* (Davis and Hilsenrath, 2016).[6] While these observations make clear that our counterfactual exercise does not correspond to a realistic alternative scenario, they simultaneously offer little reason to believe that this exercise *overstates* the impact of the China shock on the outcome of the 2016 U.S. Presidential election.

5 Concluding Remarks

This note relates the change in the county-level Republican two-party vote share between 2000 and 2016 presidential elections to the growth in Chinese import penetration. We find that rising import competition was a robust positive contributor to Republican vote gains. A counterfactual exercise indicates that the Democrat candidate would have won the states of Michigan, Wisconsin, Pennsylvania and North Carolina—resulting in a majority of votes in the electoral college—if the growth of import competition from China had only been half as large as actually observed. Our analysis is based on preliminary vote counts for the 2016 election, and the quantitative results are thus subject to change until the official vote counts for the election are finalized.

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