SUPPLEMENTARY MATERIAL: Global Markets and Local Representation

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A Calculation of Import Competition Measurement

A.1 Imports from China vs. Total Imports

In part because imports from China ultimately account for only a portion of total U.S. imports, and in part because they are distributed unevenly across products and industries, imports from China also differ from total import pressures across products and industries.

We illustrate this point in Figure A1, which depicts import pressures across NAICS 4-digit industries for China in the top panel, for world-wide imports with China excluded in the middle panel, and for world-wide imports in the bottom panel. Within each panel, we calculate the import shares across industries, with darker colors indicating that an industry accounts for a larger share of total imports. As the figure indicates, the distribution of imports from China and from the world overlaps for a portion of industries, but the distribution also differs considerably for others. Some of the industries that account for the highest import shares among total imports are barely represented in imports from China (and vice versa).

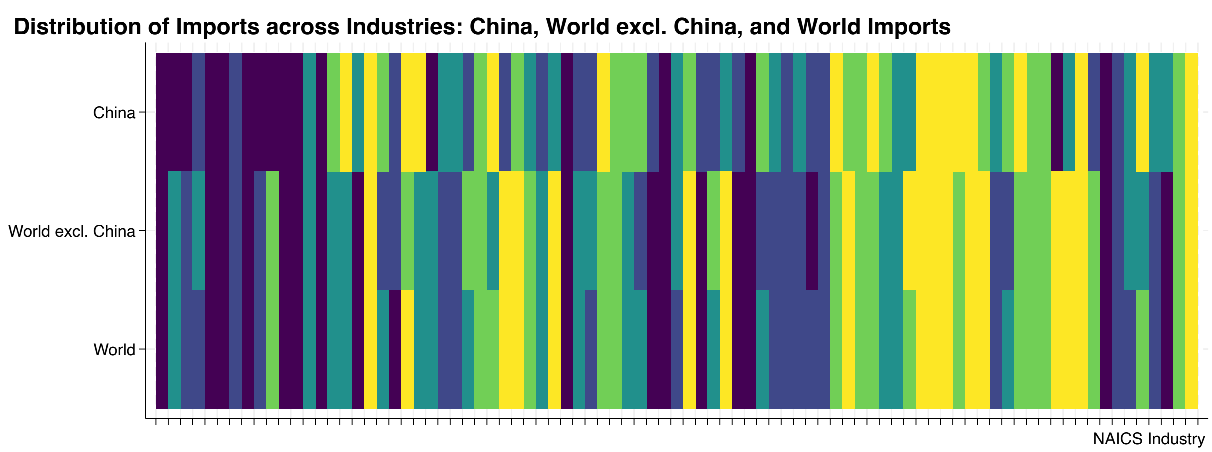

Figure A1 Distribution of imports across 4-digit NAICS industries for China (top panel), world excluding China (middle panel), and world (bottom panel). Darker shades represent a higher share of imports accounted for by a 4-digit NAICS industry.

A.2 County-industry Employment Data

Our primary employment data source is the annual County Business Patterns (CBP) data published by the U.S. Census Bureau, which reports employment figures for 6-digit NAICS industries on the level of U.S. counties. However, to maintain confidentiality, the source files often replace the exact county-industry employment counts with suppression flags indicating a employment range with upper and lower bounds based on the approximate size of industry establishments in the given county. To address this limitation, we use county-level employment data for 6-digit NAICS industries (revision 2012) provided by Eckert et al. (2020) with missing employment figures imputed using a linear programming method that leverages geographic and industry hierarchies within the CBP data.

To ensure consistency in geographic identifiers across data sets, we implement a data-cleaning function that standardizes Federal Information Processing Standards (FIPS) codes over time based on the notes from David Dorn.[1] We reconcile historical FIPS code changes for select counties. Specifically, it adjusts FIPS codes for Buchanan County, Virginia (51515 and 51019) and Shannon/Oglala Lakota County, South Dakota (46102 and 46113) to reflect official changes between Census periods and remove observations with FIPS codes corresponding to Alaska (02), Washington D.C. (11), and Hawaii (15). By harmonizing these identifiers, our approach facilitates longitudinal and cross-sectional analyses that rely on consistent geographic units.

To ensure consistency across time periods, we convert all industry-related data to the 2017 revision of NAICS. This standardization allows for accurate comparisons over time, as industry codes and definitions change between NAICS revisions. Official concordance tables provided by the U.S. Census Bureau are used to map older NAICS classifications to their 2017 counterparts ensuring alignment and comparability in our analysis.

We assign counties to corresponding modified commuting zone delineations using the concordance provided by Fowler et al. (2016). These modified commuting zones expand the original concept of commuting zones (CZ) initially developed by the USDA Economic Research Service. The initial CZ clustering process defined geographic areas that group together counties with strong economic and commuting ties, reflecting local labor markets more accurately than administrative boundaries. It was, however, constrained by the need to predefine regional subgroups due to technical limitations. In contrast, the approach by Fowler et al. (2016) overcome these constraints, enabling more flexible and refined labor market delineations.At the modified CZ-level, we then calculate the ratio of CZ-industry employment to total CZ-private sector employment, using employment-based weights derived from the share of the labor force in each county relative to the total labor force in the CZ. Precise labor force data — provided by the U.S. Bureau of Labor Statistics — serves as the basis for weighting in the calculation of county-industry employment.

Because our dependent variable, the local ties of legislators, is measured at the district-level, we convert county-employment variables to this geographic unit as well. To do so, we use population-based weights provided by Ferrara et al. (2024) whenever available. If these weights are missing, we resort to default area-based weights. Specifically, we rely on their M4-weights, which account for population distribution while distinguishing between urban and rural areas, excluding noninhabitable regions, and incorporating topographic suitability. This population-based approach is preferable to traditional area-based weighting, which assumes a uniform distribution of stock variables (Ferrara et al. 2024). Given the spatial clustering of industry employment, this assumption is unlikely to hold. However, a remaining limitation is that (manufacturing) employment may be even more spatially concentrated than population (Ferrara et al. 2024). The Congressional Districts in Hawaii and Alaska are excluded from the analysis because of missing county-Congressional District weights.

[1] See `https://www.ddorn.net/data/FIPS_County_Code_Changes.pdf`.

A.3 U.S. Import Data

Data on global imports to the U.S. at the 6-digit Harmonized System (HS) product level for the time frame of analysis is sourced from UN Comtrade. We include all imported goods, even if they are shipped through an intermediary country. HS codes ending in "X," which cannot be assigned to the 6-digit level, are excluded (31131X, 31135X, 31181X, 31515X, 33631X). All import values are reported in free on board prices.

To convert trade data from product to industry level, we match HS codes to the corresponding NAICS codes following Pierce and Schott (2009). When a product maps to multiple industries, we distribute its import value equally across the relevant industries. To ensure consistency with the employment data, we crosswalk these import data to the 2017 NAICS using the concordance from Eckert et al. (2020). All trade values are expressed in constant 2010 U.S. dollars. Finally, we calculate annual Congressional District-level import competition using the equation provided in the main text (see section 2). This measure integrates employment variables (industry employment, Congressional District employment, and Congressional District-industry employment) with the import data described in this section.

B Further Information and Robustness Tests

Table B1 List of Predictor Variables

Variable	Operationalization	Data Source
Main predictor		
Import pressure	manufacturing import competition per worker in a given Congressional District and election	Calculated by the authors (see section 2)
Moderators		
Local identity	region-specific mean of response scores to questions about local identification	Calculated based on Inglehart et al. (2014)
Local spillovers	upstream spillovers, weighted average across upstream industries within the Congressional District	Calculated by the authors
Congressional District controls		
% BA degree	Logged Population share with a Bachelor degree	Crosson and Kaslovsky (2025), original data from Foster-Molina (2017)
% Democratic vote	Logged Vote share of the democratic candidate in the most recent presidential election	for 2004 and 2008 Crosson and Kaslovsky (2025) and originally from Bonica (2023); for 2012 and 2016 Singer et al. (2021)
% White	Logged white population share	Crosson and Kaslovsky (2025), original data from Foster-Molina (2017)
Legislator controls		
Democrat	Dummy (1 if the legislator is a democrat, 0 otherwise)	Crosson and Kaslovsky (2025), originally from Volden and Wiseman (2014)
Incumbent	Dummy (1 if the legislator is an incumbent, 0 otherwise)	Calculated by the authors
State controls		
Land area	Logged land area of U.S. state	U.S. Census Bureau

We present several additional results, following the discussion in the main text.

Estimators and fixed effects. The main models including Congressional District fixed effects were estimated with penalized maximum likelihood, as developed in Firth (1993) and discussed for fixed effects models in Cook et al. (2020). In column 1 of Table B2, we instead present results from the commonly used conditional logit fixed effects estimator. The results remain robust to this change, even though the sample size decreases considerably as a consequence of the estimator dropping 'no-event units' from the sample. In column 2, as an alternative, we present results from a Mundlak-Chamberlain correlated random effects model, which models the fixed effects by including district-specific averages of the predictor variables as additional control variables (Mundlak 1978; Bell and Jones 2015; Wooldridge 2019). As in the standard fixed effects model, the coefficients on the time-varying predictor variables then represent the *within-effects*, analogously to the coefficients in a standard fixed effects model. Column 2 displays these within-effects. In this model, too, the results remain robust, with similarly sized and statistically significant effects of import pressures. Additionally, the results for the between-effects (not reported) indicate that these effects exist separately also in the cross-section, that is, across Congressional Districts.

In column 3, we further assess the cross-national nature of the effects by collapsing the data set to a pure cross-section, with one observation for each Congressional District, calculating average values of all variables. The outcome variable then is the share of election-years in which a Congressional District was represented by a candidate with local ties, and we estimate linear regression models. The results are robust to this change.

Finally, returning to the original panel data set, we include state fixed effects in column 4. In this specification, the coefficient on import pressure decreases in size and loses statistical significance. When decomposing within- and between-effects (not reported), following Bell and Jones (2015), we find large and statistically significant differences across Congressional Districts between states, but not across Congressional Districts within states.

Table B2 Estimators and Fixed Effects

	(1) Logit CD FE	(2) Mundlak Chamberlain	(3) OLS Collapsed	(4) Logit State FE
Import pressure	.14	.36	.087	.005
	(.055)	(.136)	(.030)	(.072)
% BA degree	-.421	-1.02	-.28	-.486
	(.227)	(.236)	(.055)	(.131)
% Democratic vote	-.078	.047	-.08	-.111
	(.195)	(.332)	(.118)	(.238)
% White	.078	.383	.041	.143
	(.485)	(.332)	(.088)	(.314)
Democrat	.008	.114	.011	.088
	(.154)	(.122)	(.07)	(.145)
Incumbent	.104	.131	.157	.068
	(.037)	(.084)	(.104)	(.043)
Land area			-.028	
			(.019)	
Number Obs.	2,146	3,341	444	2,146
Election year FE	✓	✓		✓
District FE	✓	✓		
State FE				✓

(1) Logit District FE, (2) Mundlak-Chamberlain correlated random effects probit, (3) OLS, (4) Logit State FE. Intercepts and fixed effects omitted. Column 2 only reports within-effects, between-effects are omitted. Coefficient estimates with standard errors, clustered by states, in parentheses.

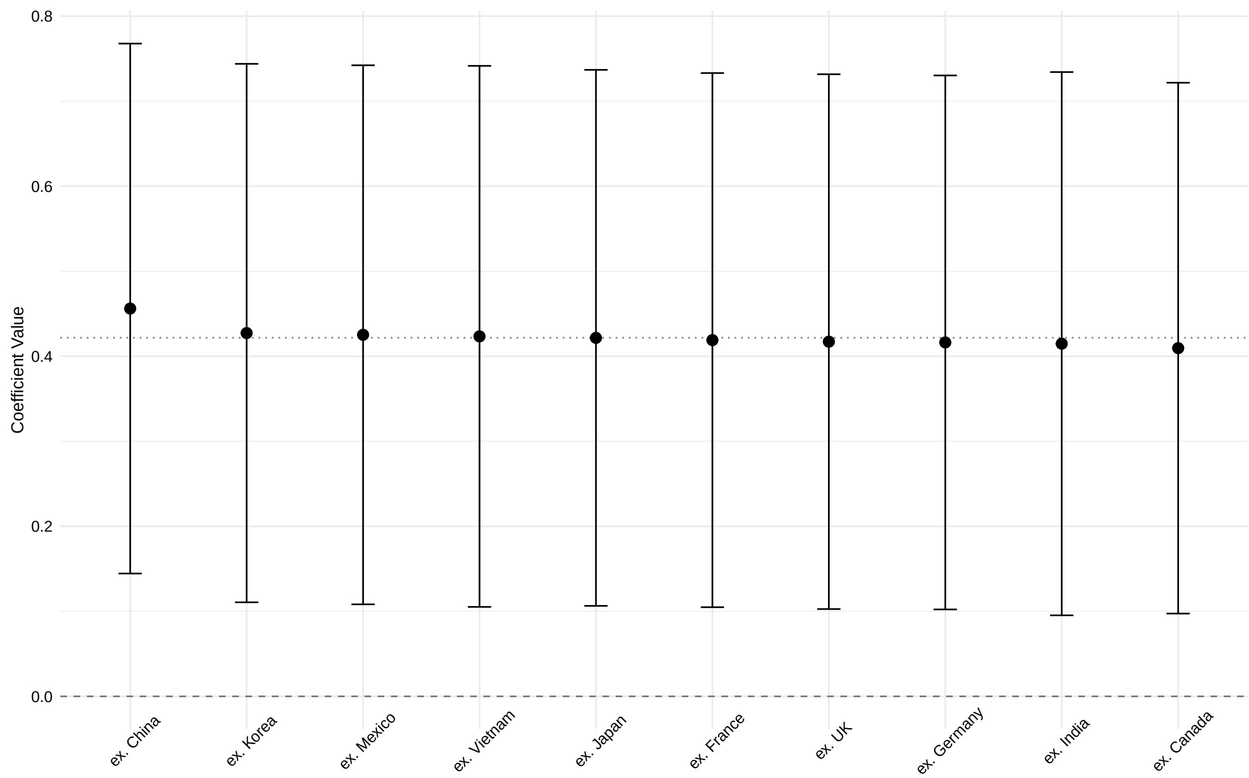

Figure B1 Coefficient plot displaying the effect of import pressures on local representation (and 95% confidence intervals), excluding the respective imports from ten large U.S. trade partner countries in the calculation (sorted by effect size). The dotted line refers to the effect size without excluding any country (see Table 1, column 2).

Import pressure. We investigate whether the effects are driven by imports from specific countries. We re-estimate the base model, in column 2 of Table 1, excluding one at a time imports from one of the ten largest U.S. trading partners in our computation of import competition. In Figure B1, we visualize the coefficient estimates on import pressures. The results show that the results are not sensitive to the exclusion of any specific country.

While we prefer the measure of import pressure in the main text, which captures persistent import pressures, we also calculate a measure of import *shocks* based on the change in imports relative to the base year 2002 and based on employment patterns in this base year. This measure closely follows other measures in the literature on trade shocks. Specifically, we calculate

$$ISW_{cd,t} = \sum_i \left(\frac{L_{cd,i,0}}{L_{cd,0}} \times \frac{M_{i,t} - M_{i,0}}{L_{i,0}} \right) \quad (1)$$

where we use *changes* in imports relative to a base year, 2002, and likewise rely on employment across industries and Congressional Districts in the base year. We replicate Table 1 from the main text in Table B3 when using this alternative measure. While our main measure captures import volumes based on the composition of local economies in a given year, this alternative measure captures changes in import volumes based on the composition of local economies at the beginning of our sample. The advantage of this latter formulation is that labor market re-allocations away from industries that experience high import penetration do not result in a lower value, which would incorrectly suggest weaker import pressures. The advantage of our main formulation is that it captures import pressures based on the current structure of the local economy, and that it captures more permanent import penetration because of persistently high import volumes, rather than a sudden shift in imports relative to the base year.

Table B3 Import shocks & Local Representation

	(1) No Controls	(2) Base Model	(3) District FE	(4) Status Anxiety	(5) Internal Migration
Import shock	.123	.324	.556	2.42	.297
	(.054)	(.13)	(.256)	(.966)	(.131)
× Share White				-.48	
				(.22)	
Δ Born in state					-.024
					(.017)
% BA degree		-1.22	-1.77	-1.22	-1.24
		(.223)	(.367)	(.216)	(.241)
% Democratic vote		-.46	-.919	-.526	-.464
		(.393)	(.463)	(.392)	(.445)
Democrat		.16	.119	.145	.23
		(.271)	(.335)	(.270)	(.275)
Incumbent		.19	.061	.208	.076
		(.118)	(.114)	(.110)	(.126)
Land area		-.092	-.232	-.115	-.084
		(.111)	(.175)	(.118)	(.105)
% White		.195	.465	4.27	.265
		(.436)	(.582)	(1.89)	(.451)
Observations	3,038	2,906	2,906	2,906	2,479
Election year FE		✓	✓	✓	✓
District FE			✓		

Logit models. Intercepts and fixed effects omitted. Coefficient estimates with standard errors, clustered on states, in parentheses.

Alternative measures of local ties. Table B4, for the baseline models in odd columns and the Congressional District fixed effects models in even columns, introduces several alternative outcome measures.

First, in columns 1 and 2 of Table B4, we consider the logged distance (in miles) between a representatives' birthplace and their district as an alternative outcome variable. The results point in the expected direction, with import pressures being associated with the election of candidates born closer to their districts but fail to reach statistical significance at the 5% level.

Second, in columns 3 and 4 of Table B4, we scale distance by land area of the state. This measure incorporates that a larger distance might be relatively less meaningful in larger states, and that in larger states a larger distance still allows a representative to be born in the same state. In contrast, in smaller states, a larger distance is more likely to imply that a representative is born outside the state. In these models, the results retain statistical significance at the 5% level.

Third, in columns 5 and 6 of Table B4, we recode the distance variable such that it is 0 for representatives born in-state. This variable blends our main outcome measure with distance. The results again retain statistical significance at the 5% level.

Finally, in columns 7 and 8 of Table B4, we replace the outcome variable with the Local Roots Index from Hunt (2022) and estimate linear regression models. The results retain statistical significance at the 5% level in the pooled model, but are no longer significant at the 5% once we include Congressional District fixed effects.

Table B4 Alternatives Measures of Local Ties

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Distance		Distance/Area		Distance/State		Local Roots	
	Base	CD FE	Base	CD FE	Base	CD FE	Base	CD FE
Import pressure	-.31	-.21	-.22	-.16	-.52	-.38	.25	.072
	(.232)	(.195)	(.104)	(.072)	(.220)	(.153)	(.113)	(.189)
% BA degree	2.19	1.57	.76	.49	1.82	1.42	-.90	-.49
	(.272)	(.892)	(.147)	(.341)	(.319)	(.743)	(.155)	(.214)
% Democratic vote	.31	.32	.38	.11	.96	.11	.024	-.14
	(.602)	(.593)	(.242)	(.259)	(.564)	(.637)	(.307)	(.327)
% White	-.97	-.89	-.15	-.32	-.31	-.41	.26	-.027
	(.583)	(1.390)	(.239)	(.711)	(.630)	(1.857)	(.287)	(.682)
Democrat	-.43	-.39	-.059	-.086	-.13	-.21	.18	.10
	(.345)	(.431)	(.143)	(.184)	(.384)	(.531)	(.162)	(.288)
Incumbent	-.40	-.24	-.18	-.12	-.34	-.24	.076	.10
	(.136)	(.082)	(.067)	(.043)	(.151)	(.097)	(.127)	(.058)
Land area	.70		-.030		.42		-.011	
	(.147)		(.074)		(.199)		(.084)	
Observations	3,341	3,341	3,341	3,341	3,341	3,341	2,849	2,849
Election year FE	✓	✓	✓	✓	✓	✓	✓	✓
District FE		✓		✓		✓		✓

Linear regression models. Coefficient estimates with standard errors, clustered by states, in parentheses.

Clustering. Across our specifications, we cluster standard errors at the level of states, as the highest-level clearly defined entities. This incorporates that import pressures plausibly are correlated across Congressional Districts and over time within states. In Table B5, we consider several alternative error structures, both for our baseline models and the fixed effects models: clustering at the level of Congressional Districts (column 1 and 2); at the level of Congressional Districts and election years, thus allowing additionally for arbitrary correlation across Congressional Districts within the same election year, using double-clustered standard errors (column 3 and 4); and at the level of states and election years, using again double-clustered standard errors (column 5 and 6). The results are robust across all specifications.

Table B5 Alternative standard errors

	(1)	(2)	(3)	(4)	(5)	(6)
	CD		CD & Year		State & Year	
	Base	CD FE	Base	CD FE	Base	CD FE
Import pressure	.422	.802	.422	.802	.422	.802
	(.123)	(.19)	(.113)	(.176)	(.151)	(.227)
% BA degree	-1.201	-1.786	-1.201	-1.786	-1.201	-1.786
	(.238)	(.37)	(.212)	(.339)	(.183)	(.328)
% Democratic vote	-.491	-1.134	-.491	-1.134	-.491	-1.134
	(.378)	(.537)	(.336)	(.531)	(.326)	(.44)
Democrat	.136	.144	.136	.144	.136	.144
	(.207)	(.26)	(.199)	(.265)	(.241)	(.334)
Incumbent	.183	.108	.183	.108	.183	.108
	(.089)	(.1)	(.157)	(.139)	(.159)	(.137)
Land area	-.126	-.313	-.126	-.313	-.126	-.313
	(.091)	(.166)	(.081)	(.155)	(.104)	(.173)
% White	.145	.293	.145	.293	.145	.293
	(.351)	(.485)	(.317)	(.448)	(.401)	(.55)
Observations	3,341	3,341	3,341	3,341	3,341	3,341
Election year FE	✓	✓	✓	✓	✓	✓
District FE		✓		✓		✓

Logit models. Intercepts and fixed effects omitted. Coefficient estimates and standard errors, clustered on Congressional District (column 1 and 2), on Congressional District and Election Year (column 3 and 4), on State and Election Year (column 5 and 6).

Miscellaneous. Figure B2 displays the marginal effect of pre-existing local identification, with import pressure as moderating variable, based on Table 2, Column 2 in the main text.

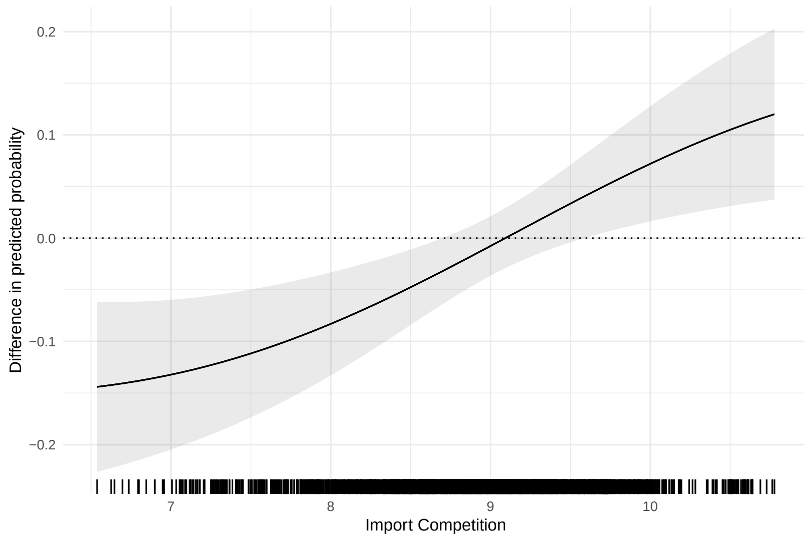

Figure B2 Marginal effect of pre-existing local identification on local ties of legislators, moderated by import pressure. Vertical axis: marginal effect of moving from the 25th to the 75th percentile of pre-existing local identification. Horizontal axis: Import pressure. Rug plot indicates the distribution of import pressure in the estimation sample.

Figure B3 displays the marginal effect of import pressure, with the (logged) percent of white residents as moderator, based on the results in Table 1, column 4, in the main text. One possible explanation for these results might be ceiling effects, which might occur if a high share of white residents is associated with a high probability of electing representatives with local ties. However, further inspection suggests that ceiling effects are not explaining the results for the interaction: the predicted probability of electing a candidate with local ties ranges from 59.4% to 64.4% when moving across the full range of % white in our sample (averaging across observations and observed values for all other variables). Compared to a sample average of 64.2%, this suggests that ceiling effects around % white are not a concern.

In Table B6, we show that the results do not differ significantly for competitive districts, defining competitive districts with a margin of victory of 10% in column 1 and of 5% in column 2.

In Table B7, we consider heterogeneity in the effects along state size. In column 1, we interact import pressure with (logged) state size. We find modest support for heterogeneous effects: in larger states, the effects decline, though the interaction term is not statistically significant at conventional levels. When omitting the two largest states, Texas and California, the statistical significance of the effect declines further (column 2). When considering these two states specifically, the effects of import pressures are larger in Texas (column 3) and smaller in California (column 4), compared to other states, highlighting heterogeneity *among* large states.

In Table B8, we re-consider the role of partisanship. First, we split the sample by partisanship, estimating the models separately for those districts represented by a democrat and those not represented by a democrat (columns 1 and 2). Most variables have similar

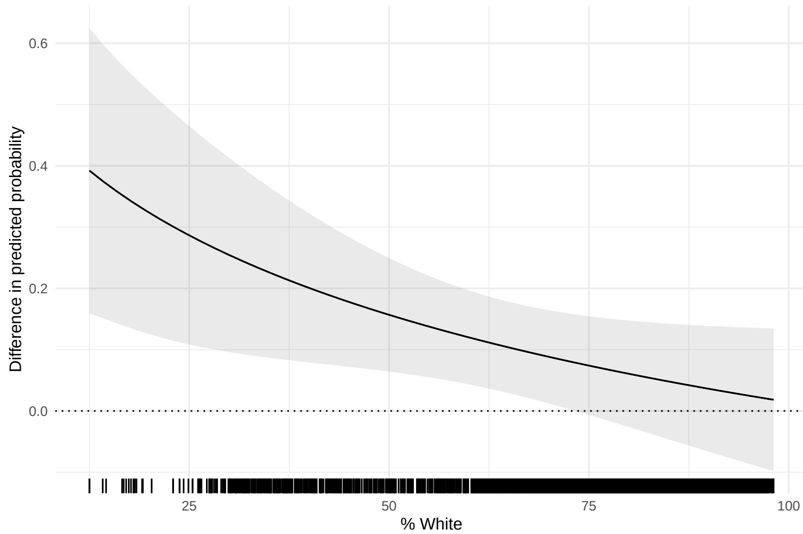

Figure B3 Marginal effect of import pressures, moderated by logged percent of white residents. Vertical axis: marginal effect of moving from the 25th to the 75th percentile of import pressure. Rug plot indicates the distribution of logged percent white residents in the estimation sample.

coefficients in size and statistical significance, including our main predictor, import pressure,which is significant at the 5% and 10% level respectively. In columns 3, we return to our full sample, but recode some of the variables: for districts represented by a Republican, we replace the share of the population with a bachelor's degree with the share of the population without a bachelor's degree, we replace the two-party vote share of the Democratic party in the last presidential election with the two-party vote share of the Republican party, and we replace the Share of White population with the share of non-White population. The results are robust to this specification.

Next, we consider two issues that are particularly prevalent for the fixed effects specifications. First, our spatial units of analysis, Congressional Districts, change with redistricting periods. The redistricting changes the contours of some of the units, such that a 'fixed effect' becomes potentially difficult to interpret. In Table B9, we estimate both the pooled and the Congressional District fixed effects models separately for the two redistricting periods in our sample. The results show a significant positive effect of import pressure during both periods.

Second, in Table B10, we drop the elections in 2008 and 2010 from the sample, because they coincide with the financial crisis and replicate Table 1 from the main text.

Table B6 Competitive Districts

	(1) Comp. CD (+/- 10%)	(2) Comp. CD (+/- 5%)
Import pressure	.414	.408
	(.161)	(.157)
× Competitive CD (+/- 10%)	.013	
	(.097)	
× Competitive CD (+/- 5%)		.065
		(.164)
Competitive CD (+/- 10%)	-.34	
	(.843)	
Competitive CD (+/- 5%)		-.877
		(1.448)
% BA degree	-1.179	-1.184
	(.202)	(.203)
% Democratic vote	-.423	-.458
	(.362)	(.368)
Democrat	.133	.162
	(.252)	(.253)
Incumbent	.109	.086
	(.107)	(.108)
Land area	-.118	-.119
	(.114)	(.113)
% White	.272	.248
	(.438)	(.436)
Observations	3,318	3,318
Election year FE	✓	✓

Logit models. Intercepts and fixed effects omitted. Coefficient estimates with standard errors, clustered on states, in parentheses.

Table B7 Heterogeneity by State Size

	(1) Land area	(2) Drop TX, CA	(3) Interact TX	(4) Interact CA
Import pressure	1.00	1.00	.41	.53
	(.517)	(.752)	(.159)	(.171)
× Land area	-.14	-.14		
	(.117)	(.198)		
× TX			.28	
			(.138)	
× CA				-.34
				(.164)
Area	1.16	1.02	-.24	-.060
	(1.022)	(1.769)	(.079)	(.117)
% BA degree	-1.17	-1.28	-1.24	-1.16
	(.202)	(.298)	(.209)	(.203)
% Democratic vote	-.47	-.46	-.32	-.43
	(.374)	(.456)	(.398)	(.384)
% White	.075	.074	.20	.053
	(.470)	(.523)	(.447)	(.477)
Democrat	.11	.29	.10	.14
	(.254)	(.252)	(.258)	(.252)
Incumbent	.18	.17	.14	.16
	(.100)	(.109)	(.095)	(.099)
TX			-1.60	
			(1.265)	
CA				2.76
				(1.439)
Observations	3,341	2,667	3,341	3,341
Election year FE	✓	✓	✓	✓

Logit models. Intercepts and fixed effects omitted. Coefficient estimates and standard errors, clustered on states.

Table B8 Import Pressure & Local Representation

	(1) Democrat subsample	(2) Republican subsample	(3) Recoded controls
Import pressure	.486	.349	.342
	(.203)	(.211)	(.186)
% BA degree	-1.58	-1.08	-.853
	(.412)	(.299)	(.335)
% Democratic vote	-.485	-.099	
	(.66)	(.563)	
% Own party			-.015
			(.47)
Incumbent	.171	.22	.162
	(.124)	(.124)	(.092)
Land area	-.316	.151	-.09
	(.114)	(.14)	(.113)
Democrat			-1.27
			(.61)
% White	.353	-.702	-.177
	(.526)	(.802)	(.202)
Observations	1,606	1,735	3,341
Election year FE	✓	✓	✓

Logit models. Intercepts and fixed effects omitted. Coefficient estimates with standard errors, clustered on states, in parentheses.

Table B9 Import Pressure & Local Representation: Separate Models for Redistricting Periods

	(1)	(2)	(3)	(4)
	2002-2010		2012-2016	
	Base Model	District FE	Base Model	District FE
Import pressure	.392	.498	.472	.559
	(.205)	(.272)	(.152)	(.184)
% BA degree	-1.144	-1.38	-1.294	-1.394
	(.262)	(.363)	(.204)	(.253)
% Democratic vote	-.735	-1.217	-.218	-.357
	(.538)	(.605)	(.359)	(.404)
Democrat	.221	.266	-.034	-.03
	(.262)	(.289)	(.324)	(.351)
Incumbent	.28	.206	.069	-.052
	(.11)	(.133)	(.149)	(.163)
Land area	-.12	-.215	-.145	-.16
	(.106)	(.126)	(.136)	(.151)
% White	.24	.305	-.085	-.079
	(.532)	(.607)	(.406)	(.431)
Observations.	2065	2065	1276	1276
Election year FE	✓	✓	✓	✓
District FE		✓		✓

Logit models. Intercepts and fixed effects omitted. Coefficient estimates with standard errors, clustered on states, in parentheses.

Table B10 Import Pressure & Local Representation: Exclude 2008 and 2010

	(1) No Controls	(2) Base Model	(3) District FE	(4) Status Anxiety	(5) Economic Decline	(6) Internal Migration
Import pressure	.24	.467	.849	4.491		.405
	(.176)	(.164)	(.240)	(2.079)		(.168)
× % White				-0.953		
				(0.497)		
Δ GDP					-.04	
					(.021)	
Δ Born in state						-.021
						(.015)
% BA degree		-1.231	-1.828	-1.220	-1.096	-1.198
		(.187)	(.323)	(0.18)	(.187)	(.22)
% Democratic vote		-.91	-.881	-0.496	-.229	-.54
		(.343)	(.444)	(0.343)	(.368)	(.407)
Democrat		.056	0	0.059	.084	.181
		(.255)	(.347)	(0.253)	(.271)	(.255)
Incumbent		.063	.031	0.0717	.051	.08
		(.097)	(.108)	(0.091)	(.105)	(.111)
Land area		-.144	-.313	-0.185	-.072	-.124
		(.12)	(.19)	(0.131)	(.122)	(.103)
% White		.116	.295	8.555	.19	.175
		(.426)	(.583)	(4.406)	(.472)	(.453)
Observations	2630	2501	2501	2501	2494	2891
Election year FE		✓	✓	✓	✓	✓
District FE			✓			

Logit models. Intercepts and fixed effects omitted. Coefficient estimates with standard errors, clustered on states, in parentheses.

Mechanism: local identity. Prior work suggests a link between global market pressure and local identity, albeit often only indirectly (e.g., Mayda and Rodrik 2005; Inglis and Donnelly 2011; Le Galès 2021). To assess such a link directly, we draw on the Nationscape survey (Tausanovitch and Vavreck 2021), a large-scale survey that (1) includes a question about local identification and (2) contains geo-coded information on a respondent's Congressional District. The survey was conducted in multiple waves before and after the 2020 election, and thus after our sample period. This allows us to assess whether import pressures during our sample period are associated with subsequently higher levels of local identification in individual-level survey data.

Specifically, the survey includes a question asking respondents "How important are each of the following to your identity?", and then asks a subset of respondents this question about "Your local community." Answer options includes "Very important", "Somewhat important", "Not too important", and "Not at all important." 42,945 respondents answered the question. For all of these respondents, we also have data on the Congressional District in which they reside. The Nationscape survey itself is representative of the U.S. adult population, with corresponding survey weights supplied with the survey. The sample matches official government data on many key characteristics, comparable to commercial high-quality surveys (Holliday et al. 2021).

In Table B11, we present several results. In columns 1 and 2, we present results from linear regression models, treating the outcome variable as continuous and scaling it such that higher values indicate stronger local identity (we obtain similar results when instead estimating ordered logit models). In columns 3 and 4, we present results from logit models, dichotomizing the outcome variable such that the answers "Very important" and "Somewhat important" are considered as expressions of strong local identity, and the remaining options as weak local identity.

We rely on similar model specification as before, with standard errors clustered on states. We use import pressure in each Congressional District in 2016, the last in our sample, as key predictor. For the control variables, we use the same control variables before, but replace district-level socio-economic control variables with individual-level variables, given that we predict individual-level attitudes: we replace the Democratic party vote share with whether a respondent voted for the Democratic party in the last election; the share of white residents with whether a respondent identifies as white; and the share of residents with at least a bachelor's degree with a respondent's education level. We omit the representative-level variables (incumbency and party), given that we do not predict attributes of representatives; we retain the control variable for land area, given that local identity might depend on geographic reach. These latter two decisions do not affect the following results.

In columns 1 and 3, we re-estimate our standard baseline model. While the coefficient estimates have the expected signs, they are not statistically significant at conventional levels. This changes once we include three standard individual-level controls, logged age, gender of a respondent, and the region of a respondent, which are important predictors of individual's place identity and corresponds to the main control variables also included in Munis (2021). With these control variables included, in columns 2 and 4, we obtain a statistically significant coefficient on import pressures.

Table B11 Import Pressure & Local Identity: Survey

	(1)	(2)	(3)	(4)
	Continuous		Binary	
	Base Model	Individual Controls	Base Model	Individual Controls
Import pressure	.008	.027	.038	.076
	(.011)	(.009)	(.028)	(.025)
Democratic vote	.11	.086	.31	.24
	(.015)	(.015)	(.059)	(.063)
White	-.049	-.063	-.074	-.12
	(.013)	(.013)	(.048)	(.043)
BA degree	.0014	-.010	.13	.087
	(.015)	(.015)	(.046)	(.049)
Land area	-.008	-.007	-.017	-.004
	(.010)	(.009)	(.019)	(.020)
Age		.13		.42
		(.024)		(.067)
Male		-.038		-.10
		(.018)		(.047)
Number Obs.	41,237	41,237	41,237	41,237
Region FE		✓		✓

Columns 1 and 2: Linear regression models. Columns 3 and 4: Logit models. Intercepts and fixed effects omitted. Coefficient estimates with standard errors, clustered on states, in parentheses. Survey weights included.

Mechanism: candidate selection. To separate out voter choice on election day from candidate selection through the primary process, we collect new data on the local ties of the losing major-party candidates in each Congressional District. In contrast to those that won Congressional elections, for whom data on the place of birth are available in a central location from the Biographical Directory of the U.S. Congress (Crosson and Kaslovsky 2025), no similar repository exists for those candidates that lost races. We therefore collected these data manually from publicly available information, including websites providing election information, local newspapers, and campaign statements. We focused on the most recent election in our data set, 2016, and limited ourselves to major-party candidates, because the extent of missing information was considerably higher among third-party candidates. We were able to locate the place of birth of the major-party losing candidate for over 80% of Congressional Districts. Together with the winning candidates, we thus have data on whether a candidate was born in-state for over 90% of major-party candidates running in 2016. For earlier elections, initial explorations suggested that the success rate would have been considerably lower, and the amount of missing information accordingly higher. We therefore refrained from expanding this search to other years.

We first verify that the association between import pressures and the local ties of representative remains when limiting the sample to just the year 2016, using the same model specification as before (with the exception of the election fixed effects, because we only have a single year of data now). These results capture our overall baseline association, which reflects both candidate selection and voter choice on election day.

In Table B12, we report several patterns that suggest that decisions in the primary process account for part of the overall association. In column 1, we show that in districts with higher import pressures, candidates with local ties are more likely to appear on the ballot. We replace the outcome variable with a binary variable indicating whether at least one major-party candidate was born in-state. Otherwise, we retain the same model specification as before. The results show that import pressures increase the chances that a candidate with local ties appears on the ballot. We obtain similar results when instead using a data set at the candidate-level, with one observation for each major-party candidate in each Congressional District (not reported).

In column 2, we limit the sample to Congressional Districts with uncontested primaries (using data on the number of candidates running in primaries from the Brookings Primaries Project, Kamarck et al. 2017). That the association remains in this sample suggests that strategic entry by local candidates – and non-entry by non-local candidates – accounts for some of the associations we report. In column 3, we limit the sample instead to Congressional Districts with contested primaries, and show that the pattern remains there as well.

In column 4, we limit the sample to districts with incumbents without local ties. We code the outcome variable as 1 when at least one candidate with local ties runs, and as 0 otherwise. The positive coefficient on import pressures remains, further offering evidence of a specific form of strategic candidate entry: local candidates are more likely to enter races where non-local incumbents encounter import pressures.

Finally, in column 5, we replace the outcome variable with the number of major-party candidates running in primaries, and estimate negative binomial count models. The results indicate that import pressures do not result in a larger number of candidates running in primaries, and thus are not associated with more competitive and contested primaries in general. Instead, together with the previous results, import pressures change the pool of candidates competing in Congressional Districts toward candidates with local ties, and voters select those with local ties at higher rates into office.

Table B12 Candidate Selection

	(1)	(2)	(3)	(4)	(5)
Import pressure	.62	.64	.54	.46	-.046
	(.152)	(.227)	(.230)	(.231)	(.074)
% BA degree	-1.74	-1.57	-2.48	-1.22	.013
	(.417)	(.563)	(.965)	(.758)	(.098)
% Democratic vote	.33	1.55	-1.21	1.16	-.23
	(.595)	(.857)	(.748)	(1.199)	(.172)
% White	-.069	.51	-.025	-.48	-.23
	(.547)	(1.000)	(.863)	(.998)	(.174)
Democrat	-.37	-.89	.64	-.80	-.013
	(.369)	(.424)	(.612)	(.541)	(.091)
Incumbent	.27	.029	.98	-1.05	-.59
	(.242)	(.322)	(.547)	(.393)	(.073)
Land area	.029	.060	.12	.22	-.001
	(.156)	(.148)	(.367)	(.144)	(.052)
Number Obs.	381	229	147	138	433

Columns 1-4: Logit models. Column 5: Negative binomial model. Intercepts and fixed effects omitted. Coefficient estimates with standard errors, clustered on states, in parentheses.

We next consider whether these patterns from the primary process only account for part of the overall association between import pressures and the success of local candidates. First, the association is stronger than what is explained by decisions in the primary process. In column 1 of Table B13, we replicate our baseline model, but include a variable that incorporates whether the primary process already determined the local ties of the representative or whether voters are left with a choice over the local ties of their representative on the election day ballot. The association between import pressures and the local ties of representatives remains when accounting for the primary outcome.

Next, we limit the sample to races between local and non-local candidates. This sample almost certainly induces some sample selection bias that is correlated with import pressures: the above results suggest that local candidates are more likely to appear on the ballot where import pressures are higher, suggesting that the remaining non-local candidates are not representative of the pool of non-local candidates (and likely outperform on some dimensions); additionally, by construction districts that ultimately elected a representative with local ties are under-represented in this sample (because in these districts the losing candidate must have been one without local ties, limiting the set of districts that are included in the sample).

Keeping those caveats in mind, the association between import pressures and the local ties of candidates remains in head-to-head contests between local and non-local candidates.

Column 2 shows that the association remains positive, but fails to reach statistical significance at conventional levels, when including all races between local and non-local candidates. The association returns to statistical significance when focusing on races where voters faced an actual choice in head-to-head contests between local and non-local candidates: column 3 reports results for competitive districts (those won with a margin of victory of less than 10 percentage points), column 4 for districts with open seats (those with no incumbent running), where the *p*-value is just over .05 despite a small sample.

Table B13 Accounting for candidate selection

	(1) Primary outcome	(2) Local vs. Non-Local all	(3) close	(4) open
Import pressure	.55	.32	1.39	.99
	(.169)	(.299)	(.474)	(.520)
Primary outcome	.44			
	(.188)			
% BA degree	-1.31	-.79	-1.82	-3.54
	(.330)	(.529)	(2.352)	(2.370)
% Democratic vote	-.18	.96	1.03	6.40
	(.470)	(1.045)	(2.675)	(3.387)
% White	-.21	.31	-1.79	-.33
	(.512)	(.838)	(2.811)	(1.822)
Democrat	-.31	-.78	-1.87	-4.50
	(.382)	(.622)	(.815)	(1.399)
Incumbent	.69	.69	.45	
	(.236)	(.406)	(.676)	
Land area	-.14	-.31	-.020	.72
	(.167)	(.265)	(.513)	(.806)
Number Obs.	432	145	63	33

Logit models. Intercepts and fixed effects omitted. Coefficient estimates with standard errors, clustered on states, in parentheses.

Trade policy. To rule out that representatives with local ties are less effective at securing trade protection, and thus have more trade exposure in their district, we calculate the average tariff rate for each Congressional District. To do so, we first obtain data on the average applied tariff rate at the Harmonised System six-digit level from the World Integrated Trade Solution Database. The average applied tariff rate takes into account the sourcing of imports and differences in tariff rates across trade partners. We then translate the tariffs to the NAICS industry format, before merging with them the composition of employment across industries in each Congressional Districts, using the same data and procedure as before to calculate trade exposure. We therefore arrive at the average tariff rate per worker in each Congressional District, analogously to the average import pressure. The variable ranges from .3% to almost 64%, with a mean of 9.5%. A simple t-test suggests that representatives with local ties are associated with slightly *higher* tariff rates in their districts, as shown in Table B14. The difference in the average tariff rate is less than 1.5 percentage points, and therefore relatively small. After accounting for year and district-specific differences, the difference declines in size to become negligible and loses statistical significance (with a p-value of .481). Similar patterns emerge when using the logged tariff rate or the tariff rate two years ahead. Overall, these results suggest few reasons to suspect a type of reverse causality in which legislators with local ties are less effective at securing trade protection and thus more exposed to import pressure.

Table B14 Local Ties and District-Specific Tariffs

	Tariffs		Log Tariffs		Tariffs $t+2$	
	(1)	(2)	(3)	(4)	(5)	(6)
With local ties	10.0		2.14		9.22	
Without local ties	8.63		1.94		8.04	
Difference	1.41	.193	.206	.031	1.18	.237
	(.557)	(.254)	(.090)	(.03)	(.509)	(.15)
Number Obs.	3,510	3,510	3,510	3,510	3,058	3,058
Election year FE		✓		✓		✓
District FE		✓		✓		✓

Average tariffs in districts with representatives with and without local ties, and difference together with standard error clustered by state. Odd columns adjust for year and district fixed effects.

Additional controls. In Table B15, we consider several additional control variables: the (logged) median income in the Congressional District; the (logged) percent of the foreign-born residents in a Congressional District; and whether a representative is a woman. The results, presented in Table B15, are robust to the inclusion of these variables both for the pooled and the fixed effects specifications.

Table B15 Additional Controls

	(1)	(2)	(3)	(4)	(5)	(6)
	Median Income		Foreign-born		Woman	
Import pressure	.425	.796	.423	.799	.456	.843
	(.156)	(.234)	(.158)	(.239)	(.157)	(.24)
% BA degree	-.942	-1.469	-1.103	-1.725	-1.159	-1.724
	(.36)	(.48)	(.208)	(.308)	(.216)	(.356)
% Democratic vote	-.49	-1.153	-.438	-1.109	-.382	-1.021
	(.37)	(.434)	(.333)	(.415)	(.362)	(.443)
Democrat	.126	.126	.147	.149	.196	.214
	(.26)	(.348)	(.254)	(.341)	(.249)	(.339)
Incumbent	.18	.104	.178	.105	.16	.094
	(.099)	(.093)	(.097)	(.093)	(.1)	(.096)
Land area	-.129	-.324	-.108	-.301	-.095	-.268
	(.109)	(.184)	(.11)	(.183)	(.104)	(.179)
% White	.18	.333	.069	.255	.142	.283
	(.447)	(.597)	(.518)	(.659)	(.467)	(.635)
Median income	-.438	-.556				
	(.667)	(.987)				
% Foreign			-.101	-.065		
			(.139)	(.195)		
Female					-.637	-.71
					(.25)	(.34)
Observations.	3,341	3,341	3,341	3,341	3,341	3,341
Election year FE	✓	✓	✓	✓	✓	✓
District FE		✓		✓		✓

Logit models. Intercepts and fixed effects omitted. Coefficient estimates with standard errors, clustered on states, in parentheses.

Local identity: additional models. Our measure of pre-existing local identity is measured at a higher level of aggregation than our measure of import pressure. Heisig and Schaeffer (2019) suggest that such a multi-level structure in interaction models may induce deflated standard errors and p-values, and recommend estimating multi-level models with random slopes. In column 1 of Table B16, we replicate our model interacting import pressures with local identity, estimating a multi-level model that allows for random slopes for import pressures. The results are robust to this modification.

Table B17 compares regions where pre-existing local identification is low (in the lower quartile) and high (in the upper quartile). We find that these do not differ significantly in terms of education levels, land area, the Democratic party vote share (though here the p-value is .054), and the share of white residents (regardless of whether or not we log these variables). However, Congressional Districts do differ across pre-existing local identification on some dimensions beyond our baseline set of control variables. Most notably, median incomes are significantly lower where local identification is higher. The results are robust to adjusting for these differences in income in regression models, as we report in column 2 of Table B16.

Finally, in column 3, we replace the survey-based measure of local identity with the (logged) share of the population born in-state. With this measure, the coefficient on the interaction term flips sign, with a p-value of .051. Two explanations might account for this finding.

First, in areas with a lower share of residents born in-state, a larger share of residents are born not just out-of-state, but abroad. Among the local population, the presence of foreign-born residents might reinforce the salience of local identity in response to import pressures. When interacting import pressures with the share of foreign-born residents, we obtain a positive coefficient, supporting this interpretation.

Second, the share of those born in-state reflects an accumulation of past economic fortunes: areas with a large share of residents born in-state tend to be areas that have long been struggling economically, and import pressures might be only a small part of broader (and deeper) economic problems. Where import pressures hit areas with a predominantly local population, we therefore might observe more muted effects. What supports this interpretation is that the interaction term drastically decreases in size and loses statistical significance when including district fixed effects (whereas the interaction with local identification remains robust).

Table B16 Local Identity: Additional Models

	(1)	(2)	(3)
Import pressure	-6.011	-10.106	4.273
	(2.22)	(3.419)	(2.143)
×Local identity	3.312	5.647	
	(1.2)	(1.847)	
×% Born in state			-1.037
			(0.532)
Local identity	-29.423	-51.555	
	(10.752)	(16.761)	
% Born in state			10.993
			(4.553)
% BA degree	-1.062	-0.973	-0.638
	(0.152)	(0.332)	(0.248)
% Democratic Vote	-0.469	-0.543	-0.192
	(0.296)	(0.401)	(0.322)
% White	-0.018	-0.1	0.005
	(0.246)	(0.517)	(0.47)
Democrat	0.236	0.14	0.141
	(0.138)	(0.274)	(0.264)
Incumbent	0.212	0.232	0.032
	(0.112)	(0.135)	(0.094)
Land area	-0.12	-0.121	-0.048
	(0.128)	(0.117)	(0.103)
Median income		-0.357	
		(0.612)	
Number Obs.	2528	2528	2902
Election year FE	✓	✓	✓

Logit models. Intercepts and fixed effects omitted. Coefficient estimates with standard errors, clustered on states, in parentheses. Column 1 is random effects logit model with random slope for import pressures, following Heisig and Schaeffer (2019).

Table B17 District Attributes and Local Identification

	local identification low	high	t-statistic
% BA degree	24.8	25.4	t = .32 (p = .752)
% White	72.0	73.8	t = .63 (p= .531)
% Democratic vote	0.52	0.46	t = -2.0 (p = .054)
Land area	104.4	87.9	t = -.76 (p = .456)
Median income	66065	58288	t = -2.3 (p = .033)
Unemployment rate	7.35	7.02	t = -.58 (p = .570)
Δ GDP	1.87	1.99	t = .27 (p = .793)

Congressional Districts with low levels of local identification (lower quartile) and high levels of local identification (upper quartile). *t*-statistics and *p*-values robust to heteroskedasticity and clustering by states.

Spillovers: additional models. Our assessment of spillovers uses a disaggregated data set at the level of the district-industry-election year. We rely on this disaggregated data set to assess our specific hypothesis that import pressures have larger effects when they occur on key industries in the local economy, such that they create spillovers upstream. Here, we pursue an alternative modeling strategy, calculating spillovers at the level of the Congressional District.

To do so, we calculate trade-induced spillovers as before, at the industry-district-year level, as the jobs in supplying industries upstream affected by an industry's trade pressures. We then aggregate those *trade-induced spillovers* to the district-year level and included these spillovers as predictor in the model. This variable captures the average indirect import pressure per worker in each Congressional District, analogously to our measure of direct import pressures. The results, presented in column 1 of Table B18, show that these aggregated spillovers have a positive and statistically significant effect on the election of candidates with local ties.

The disaggregated data set includes a large number of observations, which may deflate standard errors. Our main models were estimated with standard errors clustered on the Congressional District, accounting for arbitrary correlation within districts over time and across industries. We consider several alternative error structures. First, we double-cluster standard errors by state and industry, to additionally allow for arbitrary correlation within industries over time and across states. This specification reflects the two-way nature of the data set. Second, we consider standard errors clustered at the industry-state level, which defines clusters more narrowly as being specific to the industry and state simultaneously. Third, we cluster standard errors at the level of Congressional Districts. Fourth, we use bootstrapped standard errors. Fifth, we estimate weighted models, using the number of industries in each Congressional District-election year as weights, to account for the uneven number of observations in each Congressional District. The results, reported in columns 2-6 of Table B18, are robust to these modifications.

Table B18 Spillovers: Alternative Specifications

	(1) Aggreg. spillover	(2) State & NAICS	(3) State-NAICS	(4) CD	(5) Boot-strap	(6) Weight
Import pressure		0.072	0.072	0.072	0.067	0.078
		(0.013)	(0.029)	(0.026)	(0.02)	(0.025)
×Local spillovers		0.007	0.007	0.007	0.007	0.008
		(0.001)	(0.003)	(0.003)	0.002	(0.003)
Indirect import pressure	0.339					
	(0.119)					
Local spillovers		-0.006	-0.006	-0.006	0.004	-0.004
		(0.011)	(0.009)	(0.011)	0.013	(0.014)
% BA degree	-1.157	-1.109	-1.109	-1.109	-0.791	-1.202
	(0.213)	(0.178)	(0.013)	(0.242)	(0.131)	(0.206)
% Democratic vote	-0.338	-0.352	-0.352	-0.352	-0.281	-0.45
	(0.35)	(0.359)	(0.024)	(0.384)	(0.301)	(0.374)
% White	0.255	0.099	0.099	0.099	0.144	0.159
	(0.435)	(0.498)	(0.031)	(0.365)	(0.419)	(0.446)
Democrat	0.154	0.052	0.052	0.052	0.089	0.135
	(0.258)	(0.259)	(0.016)	(0.209)	(0.222)	(0.251)
Incumbent	0.164	0.177	0.177	0.177	0.143	0.196
	(0.099)	(0.106)	(0.007)	(0.091)	(0.093)	(0.102)
Land area	-0.128	-0.143	-0.143	-0.143	-0.109	-0.118
	(0.107)	(0.101)	(0.006)	(0.093)	(0.100)	(0.11)
Other imports		0.328	0.328	0.328	0.145	0.401
		(0.148)	(0.01)	(0.12)	(0.124)	(0.156)
Number Obs.	3341	709 150	709 150	709 150	709 150	709 150
Election year FE	✓	✓	✓	✓	✓	✓

Logit models. Intercepts and fixed effects omitted. Coefficient estimates and standard errors, clustered on states (column 1), on states and industry (column 2), on state-industry (column 3), on districts (column 4), bootstrapped (column 5), on states and weighted by number of observations (column 6).

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