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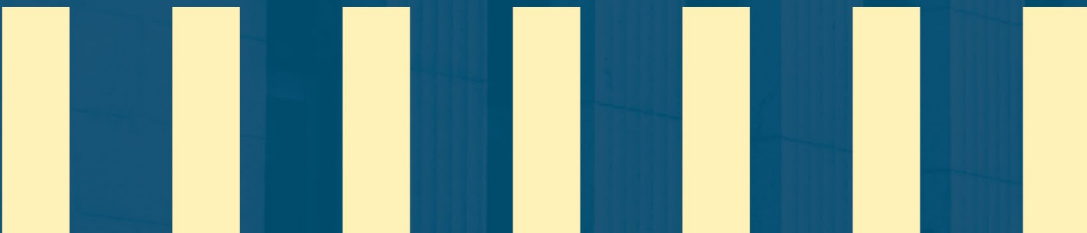
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Abstract

This paper studies the impact of offshoring by US firms on voting patterns in the US. Using county-level voting data combined with industry-level offshoring data from 2000 to 2020, we ask whether an increase in employment at foreign affiliates of US multinational firms in vertically oriented industries is associated with an increase in the vote share for the incumbent party candidate in Presidential, House, and Senate elections. We find that offshoring leads to a significant increase in the incumbent vote share for counties with higher shares of college educated workers, and a significant decrease for counties with higher shares of workers in the manufacturing sector and in occupations that are more easily relocated abroad. These results are consistent with the labor market literature on offshoring and our own findings, which show that offshoring has heterogeneous effects on workers' employment based on skill and occupational tasks. This suggests that voters respond to the economic effects of offshoring by rewarding or punishing incumbent party candidates.

JEL Codes: F23, F60, D72

Key Words: Offshoring, Political Economy, Voting, Multinational Firms, FDI.

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1 Introduction

Offshoring is a highly contentious topic in the US. Candidates from both major political parties often criticize firms that move jobs abroad. While running for president in 2020, Democrat Joe Biden proposed an “offshoring penalty surtax” on profits for goods and services produced abroad by US firms. Republican Donald Trump mentioned offshoring repeatedly, both as president and while running for office, including a 2016 tweet claiming that “Any business that leaves our country for another country... and then thinks it will sell its product back into the US without retribution or consequence, is WRONG!” And in 2004, Democratic presidential candidate John Kerry famously described the leaders of offshoring firms as “Benedict Arnold CEOs”. However, economic research suggests that the effects of offshoring aren’t so black and white. A growing literature has shown that offshoring can have both positive and negative effects depending on worker skills, tasks, offshoring destination, type of firm, and type of offshoring, with the net impact often being zero or a small positive effect.¹ Thus the likely impact of offshoring by US firms on US voting patterns is unclear. If voters believe the rhetoric of politicians like those mentioned above, or if they belong to a group that is harmed by offshoring, then an increase in offshoring will likely hurt candidates who were in office when the offshoring occurred. However, if the positive economic effects of offshoring outweigh the negative effects in a certain location or for a certain group, then those voters are likely to reward incumbents. Therefore the net effect of offshoring on voting patterns is an empirical question, which we seek to answer in this paper. To our knowledge, ours is the first paper to study the impact of offshoring on US voting patterns.

We combine data on offshoring by US multinational firms from the US Bureau of Economic Analysis (BEA) with county-level voting data from CQ Press Library and the US Election Atlas² for 2000 to 2020. Because offshoring data are not available at the local labor-market level, we construct a local measure offshoring exposure by combining information on offshoring at the industry-level with data on the industry composition of employment at the commuting zone (CZ) level in 2000, then apply this measure to each county within the CZ. We use employment in 2000 because it is the first year of our sample, and is thus more likely to be exogenous to future offshoring patterns. Using industry-level offshoring for the entire US to construct our local level exposure measure also helps with our identification strategy, as it is more likely to be exogenous to county-level voting outcomes. This shift share approach has been widely used in the literature, including by Topalova (2010), Autor et al. (2013), and Kovak et al. (2021). We perform a number of pre-trend analyses, which suggest that the shift share measure is indeed exogenous in our context. We also include an

¹See Oldenski (2021) for a summary of the literature.

²uselectionatlas.org

IV approach, instrumenting for offshoring by US firms using offshoring by firms in other OECD countries.

Our main measure of offshoring is the number of workers US multinational firms employ at their affiliates in countries outside of the US in vertically oriented industries. To do this, we divide industries based on the extent to which their offshoring is “vertical” or “horizontal”, where vertical offshoring refers to firms that produce abroad in order to sell back to the US and horizontal offshoring refers to sales to the host market or other countries.³ Our focus is on vertical offshoring because it is of greatest concern to most voters and candidates and may be more likely to substitute for US production and employment. In the Appendix we show that our results hold when we include all foreign affiliate employment, including both horizontal and vertical, though the results are stronger for vertical offshoring. Due to data limitations, we are only able to observe offshoring that occurs within firms, not between US firms and their arms-length foreign suppliers.

We focus on the vote share earned by the incumbent party candidate, rather than the Republican or Democrat vote share, for two reasons.⁴ First, as illustrated by the examples given above, candidates from both major parties have been critical of offshoring. Second, a vast body of political science research has concluded that voter behavior can generally be explained by a very simple model: when times are good, voters reward the incumbent, but when times are bad, they vote for the challenger. This pattern has been shown to hold in a variety of contexts regardless of which party happens to be the incumbent at the time.⁵

Our results show that whether the relationship between offshoring and the incumbent party vote share in a county is positive or negative depends on the characteristics of the workforce in that county. When offshoring by US firms increases in an industry, voters in counties with a larger share of initial employment in that industry increase their support for the incumbent in the next election *if* those counties have a relatively high share of college educated workers. The opposite is true for counties with a relatively large share of non-college educated workers. These results hold for House, Senate, and Presidential elections. We also find that the relationship between offshoring exposure and the incumbent party vote share is negative for counties with a larger share of occupations that can more easily be relocated abroad and for counties with a larger manufacturing employment

³The classification of industries by vertical versus horizontal orientation was constructed using firm-level data and was conducted at the Bureau of Economic Analysis (BEA), US Department of Commerce, under arrangements that maintain legal confidentiality requirements. The views expressed are those of the authors and do not reflect official positions of the US Department of Commerce. The industry-level offshoring measure was constructed using publicly available BEA data.

⁴For readers who are interested in the impacts of offshoring on the vote shares of the two major US political parties, these results are reported in Appendix B.

⁵See, for example, Aytac (2018), Jensen et al. (2017), Murillo and Visconti (2017), Ebeid and Rodden (2006), Markus (1988), Tufte (1975), and Kramer (1971).

share. These impacts tend to cancel out in aggregate, pointing to the importance of considering heterogeneous worker characteristics when studying the effect of offshoring on voting patterns in the US.

Our analysis is informed by the literature on the labor market effects of offshoring. From a theoretical point of view, two opposing forces are at work. The first is a substitution effect in which US workers are replaced by workers in the offshore country. The second is a scale effect in which the gains from offshoring allow US firms to expand and hire more workers in all locations, including the US. Kovak et al. (2021) use bilateral tax treaties as an instrument for offshoring and show that the positive scale effect outweighs the negative substitution effect. In particular, they find that offshoring by US MNEs has a modest net positive effect on US employment within the offshoring firm, and a smaller but still positive net effect on US employment at the industry and local labor market level. Other empirical papers, including Wright (2014), Criscuolo and Garicano (2010), and Desai et al. (2009) have also found evidence of net positive effects of offshoring on domestic workers. These results are consistent with the theoretical contributions by Grossman and Rossi-Hansberg (2008) and others. Other studies find little to no effect of offshoring on domestic workers at an aggregate level (Slaughter (2000), Braconier and Ekholm (2000), and Konings and Murphy (2006)).

We also investigate the employment effect of offshoring and find that offshoring exposure leads to an increase in county-level employment. Because offshoring data are at the industry level, it is possible to capture the offsetting effects of offshoring beyond what would be observed by only considering individual plants where US workers were replaced by offshore workers. For example, if offshoring increases in the automobile industry, that will show up as an increase in offshoring exposure in both counties with large initial employment shares in basic auto assembly (which may be more subject to negative substitution effects) and in counties in which automobile firms are headquartered (where positive scale effects may be more likely to appear).

The existing literature and our own results also show that the labor market effects of offshoring vary by workers' characteristics. It is the occupations and tasks that are not offshorable that have been shown to expand due to the positive productivity and scale effects of offshoring. However, negative effects for certain groups of workers are also well-documented. Workers who are most likely to be harmed by offshoring are those whose jobs are more easily substituted with foreign labor. These include workers with less education (Hummels et al. (2014)), who perform routine tasks (Ebenstein et al. (2014); Hummels et al. (2014); Ottaviano et al. (2013); and Oldenski (2014)), and who work in industries that offshore more to low-income countries (Ebenstein et al. (2014); Harrison and McMillan (2011)). These losses are often offset by gains to workers with more education or who perform nonroutine tasks (Hummels et al. (2014)). We also find evidence that, in our period of

analysis, the labor market effects of offshoring are heterogeneous according to these same worker characteristics.

While ours is the first paper to consider the effects of offshoring on voting patterns, several others have studied the effects that different types of globalization have on elections. Some recent papers have looked at the impact of trade on election outcomes in the US. The basic idea of these works is that voters in areas characterized by higher shares of workers employed in import-competing (exporting) sectors lose (gain) with open policies and vote for (against) the party that is more likely to restrict trade. Choi et al. (2024) show that voters in counties that were harmed by the 1994 North American Free Trade Agreement (NAFTA) were less likely to vote for the Democratic party post-NAFTA, as this was the party of Bill Clinton who was president when NAFTA took effect. Autor et al. (2020) and Che et al. (2016) both focus on the vote share of the Democrats vs. Republicans as a function of local import exposure, and find results which are consistent with the changing positions of the two parties on the topic of trade. Traditionally, Republicans have been the pro-trade party, while Democrats have been more critical of free trade. Over time, these positions have become more nuanced, such as with the rise of the anti-trade “Tea Party” wing of the Republican party. By 2016, with the arrival of the Republican candidate Donald Trump, the positions of the two parties on trade had shifted, with the Republicans being perceived as much more protectionist than the Democrats.

In line with this political landscape, Che et al. (2016) find that counties that were more exposed to imports from China increased their support for the Democrats in the first decade of 2000, relative to the 1990s, though this effect fades after the rise of the Tea Party in 2010. Autor et al. (2020) show that, between 2010 and 2016, electoral districts more exposed to import competition from China were on average more likely to vote for the Republicans (and to become more polarized with greater support for both strong-left and strong-right views). Jensen et al. (2017) adopt a different approach and, like in our analysis, look at changes in the incumbent party vote share. Their main results are that, between 1992 and 2012, counties that were specialized in low-skilled (high-skilled) goods and services decreased (increased) support for the incumbent party. Overall, the evidence from papers on imports and voting is consistent with the literature on import competition, which generally finds negative impacts of imports on exposed workers (see, for example, Autor et al. (2013) or Pierce and Schott (2016)). In relation to this literature, note that offshoring is different from importing primarily because the headquarters of the firm remain in the US, potentially providing greater opportunities for positive productivity and scale effects.

Another strand of the literature has examined the relationship between migration and voting patterns. For the United States, the main paper in this literature is Mayda et al. (2022), who study

the effect of low-skilled and high-skilled immigrants on US voting patterns at the county level between 1990 and 2016. The main results of the analysis are that low-skilled immigration has a pro-Republican effect, while high-skilled immigration has a pro-Democrat impact: These effects are not driven by the votes of new (naturalized) immigrants themselves, rather they are due to the effect of immigration on how existing US citizens vote. Our empirical approach is similar to that of Mayda et al. (2022) except for the fact that, while Mayda et al. (2022) focus on the relationship between migration and the Republican vote share, we instead consider the share of votes cast for the incumbent party candidate. We do this because, unlike migration, offshoring is an issue that is not as clearly divided along party lines. Like in Jensen et al. (2017) and other work on voting in the political science literature, we assume that voters increase (decrease) support for the incumbent party when they perceive an improvement (worsening) in economic conditions.

The rest of the paper is organized as follows. Section 2 describes the offshoring and voting data and the empirical approach, including the tests we carry out to provide supporting evidence for the identification strategy. Section 3 presents our estimates of the impact of offshoring exposure on the incumbent party vote share, including differential effects based on workers' skill levels, the employment share of offshorable occupations, and the manufacturing employment share in the county. We conduct robustness checks in Section 4 and conclude in Section 5.

2 Data and Empirical Approach

We are interested in the causal relationship between offshoring and voting patterns at the local level. However, there are several potential threats to identification when estimating the relationship between offshoring exposure and voting. First, many variables that influence the offshoring decisions of firms in a given local labor market may also influence election outcomes directly. For example, it could be that offshoring is more likely to impact areas that are less urban or have lower average incomes, which would be a problem if less urban or lower income voters were systematically more or less likely to vote for incumbent party candidates. We address this by including a number of control variables at the commuting-zone level. We also include county-level fixed effects to control for any time-invariant geographic characteristics, and state-year fixed effects to control for any trends at the state level.

Second, reverse causality could be a problem if votes cast at the county-level impact offshoring decisions by firms in that county. This could happen if voters elect officials who then enact policies to restrict offshoring in key counties, or if firms observe the outcomes of elections and make decisions about offshoring based on the local political climate. We address this by constructing a shift-share

measure of offshoring exposure at the local labor market level. Our goal is to construct a measure that is uncorrelated with local political and economic changes that affect local voting patterns. The shift share approach combines *national* changes in offshoring patterns by industry, which are likely to be exogenous to local voting patterns, with the pre-existing distribution of industry employment across local labor markets, which is unlikely to be affected by future offshoring decisions.

To construct a measure of local labor market exposure to offshoring, we use a weighted average of industry-level foreign affiliate employment, where the industry weights reflect the distribution of employment across industries within each commuting zone (CZ) in 2000. We use CZ, rather than county, level employment because CZs better reflect actual local labor markets. Workers may live in a neighboring county to the one in which they work, and can change jobs across counties within a CZ more easily than across CZs, potentially mitigating county-level shocks. Our offshoring exposure measure, O_{zt} , is a weighted average of industry-level foreign affiliate employment, where the industry weights reflect the distribution of employment across industries within each CZ in 2000, the initial year of our sample. This measure captures each CZ z 's exposure to offshoring in year t , following a procedure similar to Topalova (2010), Autor et al. (2013), Kovak et al. (2021), and others.

$$O_{zt} \equiv \sum_j \sigma_{zj}^{2000} O_{jt} \quad (1)$$

where $\sigma_{zj}^{2000} \equiv L_{zj}^{2000} / \sum_{j'} L_{zj'}^{2000}$, L_{zj}^{2000} is employment in CZ z and industry j in 2000, and O_{jt} is the number of employees at foreign affiliates of US MNEs in industry j and year t . Because counties are a strict subset of CZs, we apply the CZ-level offshoring exposure measure to each county, i , within the CZ, z .

We use data from the Bureau of Economic Analysis's surveys of US direct investment abroad for the years 2000 to 2020 to capture industry-level offshoring. The BEA collects data on many aspects of the operations of the firms, including the number of workers that US multinational firms employ in the US and at each of their foreign affiliates, the country and industry of each affiliate, industry of the US parent firm, and sales by each affiliate and US parent. Affiliate sales are further broken down by whether they are destined for the host market, the US, or a third country, and by whether they are sold to affiliated or unaffiliated parties. For this paper we are interested in how offshoring affects local voting patterns, however, the BEA surveys do not collect any information on where within the US each parent firm is located, which is another reason that we use BEA data at the industry level, which is available publicly on the BEA website. These data include affiliate employment in both manufacturing and nonmanufacturing firms.⁶

⁶Industries are classified according to the BEA's ISI system, which closely follows 4-digit NAICS industries.

We also distinguish between vertical and horizontal offshoring, where vertical offshoring refers to production of goods and services to be sold back to the US and horizontal offshoring refers to sales to the host country.⁷ We focus on vertical offshoring because it is of greatest concern to most voters and candidates and may be more likely to substitute for US production and employment. However, the results are qualitatively similar when we include all foreign affiliate employment, regardless of the horizontal or vertical distinction. Because our measure of offshoring is at the industry level, we construct an industry-level measure of vertical offshoring intensity. This measure is the share of US multinational firms within the industry that have positive sales to the US. We use vertical offshoring in our analysis and construct the offshoring exposure measure in Equation (1) only considering offshoring in the top 50% of industries in terms of vertical offshoring intensity. The mean and median industries in our sample both have a vertical intensity of 46%. Thus our preferred measure of vertical offshoring includes all industries in which at least 46% of firms have some sales to the US. We also conduct robustness checks using the top 25% and top 75% most vertical industries, and get very similar results.⁸

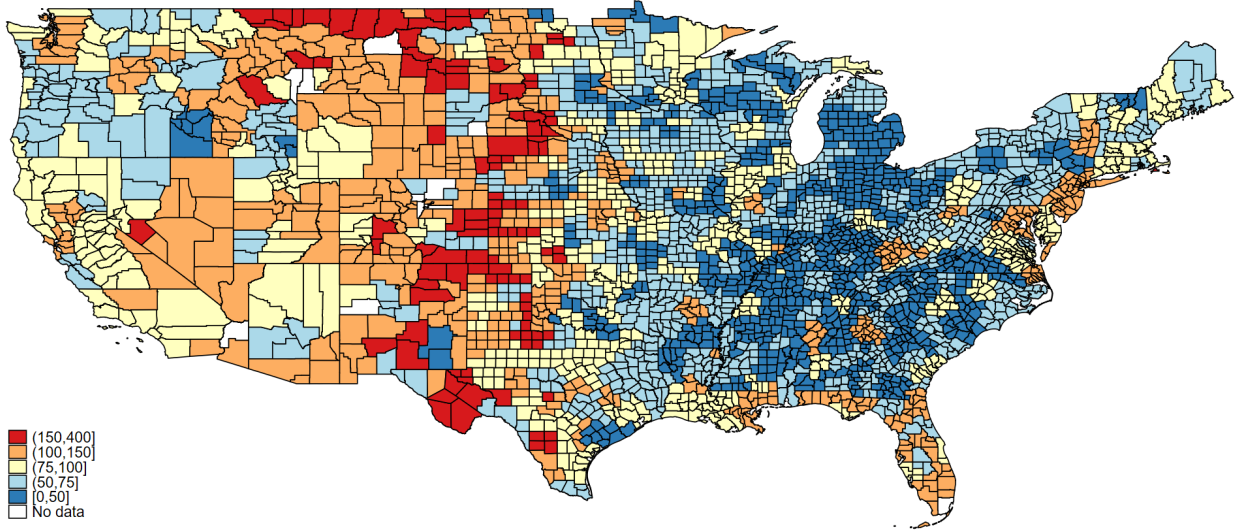
For our main specifications, we use the log of our offshoring exposure measure, $\ln(O_{zt})$. However, as we show in the robustness section, the results are robust to using the level, rather than log, of this measure. We also construct an offshoring exposure measure using offshore employment relative to domestic employment of US MNEs in each industry, rather than the total number of employees at foreign affiliates of US MNEs. The results are also robust to this measure. We focus on the log results throughout most of the paper, both to make the interpretation of our results more straightforward and to reduce the impact of any potential outlier observations.

Figure 1 shows the geographic distribution of changes in offshoring exposure over our sample period. The largest increases in offshoring exposure were concentrated in Western states, such as Arizona, Nevada, New Mexico, Colorado, Montana, and Wyoming, as well as parts of Northern Virginia and the San Francisco Bay Area. This pattern is driven by relatively high initial employment shares in industries with large increases in offshoring exposure in those regions. Examples include semiconductors, industries associated with agricultural manufacturing such as agricultural machinery manufacturing and chemical manufacturing, and defense-related industries such as communications equipment and navigational, measuring and other equipment. Note that the geographic distribution of increases in exposure to offshoring by MNEs differs from exposure to import competition

⁷Sales may also be shipped to third countries through export platform FDI. For the purpose of this paper, which focuses on vertical FDI, we combine export platform sales with horizontal sales.

⁸The classification of industries by vertical versus horizontal orientation was constructed using firm-level data and was conducted at the Bureau of Economic Analysis (BEA), US Department of Commerce, under arrangements that maintain legal confidentiality requirements. The views expressed are those of the authors and do not reflect official positions of the US Department of Commerce. The industry-level offshoring measure was constructed using publicly available BEA data.

Figure 1: Percentage change in offshoring, by County (2000-2020)



from China. As documented by Autor et al. (2013), exposure to the China shock was more highly concentrated in the Rust Belt. Costinot et al. (2011) show that the tasks MNEs offshore within the firm are less routine than the tasks traded at arms-length. In light of this work, it's not surprising that we find different industrial and geographic patterns than the literature on import competition, as we focus on offshoring that takes place within the boundaries of multinational firms, which is likely to impact a different mix of industries, and thus a different set of geographic areas, than overall trade exposure.

We combine the CZ-level offshoring exposure measure with county-level election data from CQ Press Library (2016) supplemented with data from David Leip's US Election Atlas (Leip (2025)) and ICPSR (2013) and include all federal elections, i.e., Presidential, House, and Senate elections, from 2000 to 2020. Because we only include years in which an election takes place in our sample, the frequency of the data is every two years. Our main outcome variable is the share of total votes within a county going to the candidate affiliated with the incumbent party:

$$s_{ite} \equiv \frac{IncumbentVotes_{ite}}{Votes_{ite}}, \quad (2)$$

where $IncumbentVotes_{ite}$ is the number of votes for the incumbent party candidate, and $Votes_{ite}$ represents the total number of votes in county i , year t , and election type e . We use the incumbent party vote share, rather than the share of votes cast for a specific political party, for several reasons. First, as mentioned in the introduction, both major political parties have proposed policies to restrict offshoring during our sample period, suggesting that views on offshoring are not clearly

divided along party lines. Second, a large body of work in the political science literature has shown that voters increase (decrease) support for the incumbent party when they perceive an improvement (worsening) in economic conditions (see for example Jensen et al. (2017)).

Determining the incumbent party vote share at the county-level is straightforward for presidential and senate elections, as presidents are elected at the national level and senators are elected at the state level, and each county falls entirely within one state. House elections are more complicated, however, because while most counties fall entirely within one congressional district, some counties are split across multiple districts. When this occurs, we take a weighted average of the incumbent vote shares for each county-district cell, using the share of total county voters residing in each district as weights. However, our results are also robust to dropping all counties that are split across districts, just dropping counties that are split across districts with different incumbent parties, or applying the incumbent party of the largest congressional district within each county to the entire county. About 13 percent of our total county-year observations are for counties that are split across congressional districts. However, for about half of those split county observations, each district in the county is represented by the same political party, such that less than 7 percent of the total observations are for counties that are split across congressional districts with different incumbent parties. Note that split counties are only a concern for us when they are represented by different parties.

We control for a variety of economic and demographic characteristics that might impact the incumbent party vote share using data on these variables from the US Census for the year 2000 and interacting them with linear trends over our sample period. In selecting the controls, we follow the existing literature on the determinants of voting behavior in the United States (see Della Vigna and Kaplan (2007)) and include the share of citizens in the labor force, the share of low-skilled natives and, out of the citizen population (i.e., those who have the right to vote: US-born and naturalized immigrants): the rural share, the African-American share, the share that is male, and the share that is married. As these detailed demographic data are not available at the county level on the Census website, we use the 5 percent census sample from the IPUMS website to compute these shares at the commuting zone level (Flood et al. (2020)), and we apply those to all counties in the commuting zone (counties are a strict subset of commuting zones).

As discussed in the introduction, the existing literature shows evidence that other dimensions of globalization, such as trade and immigration, have an impact on US election outcomes at the local level. Because trade and immigration are likely correlated with offshoring at the local level, we control for them, to avoid an omitted variable bias. More specifically, we include the import

Table 1: Summary Statistics

	N	Mean	SD	Min	Max
Election Data					
Incumbent party vote share (Total)	74657	0.575	0.165	0.000	1.000
Incumbent party vote share (House)	33626	0.647	0.134	0.000	1.000
Incumbent party vote share (Senate)	22571	0.564	0.146	0.077	1.000
Incumbent party vote share (President)	18460	0.457	0.169	0.031	0.962
FDI Data					
Log offshoring exposure	33626	10.068	0.631	5.995	12.938
Demographic Data					
Share of the citizen population	33626	0.915	0.071	0.362	1.000
Share of African American citizens in 2000	33626	0.118	0.095	0.000	0.598
Share of urban citizens in 2000	33626	0.467	0.357	0.000	1.000
Share of male citizens in 2000	33626	0.479	0.011	0.454	0.550
Share of married citizens in 2000	33626	0.570	0.038	0.447	0.694
Autor Dorn Hanson Instrument for trade	33626	1.222	1.630	0.000	39.276
Bartik instrument for employment in 2000	33626	13.135	1.642	5.112	16.296
Instrument for share of immigrants	33626	0.159	0.138	0.000	0.677
Instrument for share of low-skilled immigrants	33626	0.035	0.043	0.000	0.352
Instrument for share of high-skilled immigrants	33626	0.088	0.100	0.000	0.511
College educated share in 2000	33626	0.535	0.074	0.263	0.706
Offshorable occupation share in 2000	33626	0.261	0.260	0.001	1.000
Manufacturing employment share 2000	33626	0.161	0.071	0.001	0.552
NAFTA exposure 1990	33626	0.023	0.020	0.000	0.249
Export exposure instrument	33626	14.052	13.050	-0.609	705.034

Notes: Data are for election years between 2000 and 2020.

penetration per worker measure from Autor et al. (2013). We also control for immigration using the instruments for the share of low-skilled (less than a high school education) and high-skilled (high school diploma or greater) immigrants from Mayda et al. (2022). Finally, to control for the role of industry growth that may occur for reasons other than offshoring, we include a “Bartik” indicator that proxies for industry-specific labor demand shocks in a given commuting zone. We follow Bartik (1991) and take a weighted average of the industry-specific employment in year t , using as weights the employment shares across industries in the commuting zone in 2000. In robustness exercises, we also consider a measure of vulnerability to the North American Free Trade Agreement (NAFTA) from Choi et al. (2024) and a commuting-zone level measure of exposure to export industries that we construct using a shift share instrument similar to the one used to capture offshoring exposure. Table 1 summarizes our main variables and controls.

Our primary estimating equation is

$$s_{ite} = \delta_i + \delta_{rt} + \delta_{et} + \beta \ln O_{zt} + \gamma X_{zt} + \varepsilon_{ite} \quad (3)$$

where s_{ite} is the share of total votes that were cast for the incumbent party in county i , year t , election type e , with $e \in p, s, h$ indicating whether each election was for President, Senate, or House. δ_i , δ_{rt} , and δ_{et} are county, state-by-year, and election-type-by-year fixed effects. Our coefficient of interest is β , which captures the relationship between offshoring exposure, as defined in Equation (1), and the incumbent party vote share. X_{zt} is a vector of controls, described above, and ε_{ite} is an error term. Regressions are weighted by county-level voting population (age 18 and over) in the initial year (2000) and standard errors are clustered by commuting zone, which is the level of the offshoring shock.

The shift-share approach has been used in the trade and migration literature (Topalova (2010), Autor et al. (2013), Mayda et al. (2022)), and to a lesser extent in the offshoring literature (Kovak et al. (2021)). To verify its validity in our context, we examine the relationship between our shift-share measure and pre-period incumbent vote shares. If the offshoring measure in Equation 1 truly is exogenous to voting outcomes, then it should not be correlated with previous election results. In Panel (a) of Table 2, we show the results of regressing changes in the county-level incumbent vote share between 1990 and 1998 on the change in our county-level offshoring exposure measure between 2000 and 2020. We are only able to perform this exercise for President and Senate elections because the data that allow us to match House districts with counties are not available prior to 2000.⁹ Given this data limitation, to test for pre-trends in the House data, Panel (b) of Table 2 looks at the relationship between changes in the county-level incumbent vote share between 2000 and 2008 and the change in offshoring exposure between 2010 and 2020. We find no evidence of a statistically significant relationship for any of our specifications, which is reassuring evidence that the estimates we report in Section 3 are not picking up pre-existing trends in voting outcomes. To save space, the pre-trend analysis in Table 2 only reports results using overall offshoring exposure and does not include interactions of offshoring with county-level characteristics such as skill endowments, the offshorable occupation share, or the manufacturing employment share. However, in Appendix Table A.1, we show that the interaction terms are not correlated with pre-period incumbent vote shares. In the Appendix, we also include robustness checks following contributions to the recent literature on shift share identification strategies by Borusyak et al. (2022) and Goldsmith-Pinkham et al. (2020), as well as a two stage least squares approach instrumenting for US offshoring using offshoring by firms from other OECD countries. While the scope of the IV analysis is limited by the

⁹These data are from uselectionatlas.org

availability of cross-country offshoring data, all of these exercises taken together provide support for the main results presented in this paper.

Table 2: Pre-Trends Analysis

(a) Relationship between incumbent party vote shares in 1990-1998 and offshoring in 2000-2020						
Election type	All	All	President	President	Senate	Senate
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln(\text{Offshoring Exposure } 2000-2010)$	0.988 (1.304)		1.645 (2.130)		0.519 (1.378)	
$\Delta \ln(\text{Offshoring Exposure } 2000-2020)$		0.731 (1.366)		0.630 (2.241)		0.752 (1.441)
N	3,080	3,080	3,080	3,080	3,080	3,080
Adjusted R^2	0.410	0.408	0.335	0.334	0.599	0.595

(b) Relationship between incumbent party vote shares in 2000-2008 and offshoring in 2010-2020				
Election type	All	President	Senate	House
	(1)	(2)	(3)	(4)
$\Delta \ln(\text{Offshoring Exposure } 2010-2020)$	-1.399 (1.554)	-1.020 (3.403)	-2.854 (2.119)	-2.973 (3.022)
N	3,080	3,080	3,080	3,080
Adjusted R^2	0.392	0.443	0.537	0.268

Notes: .01 - ***; .05 - **; .1 - *; Standard errors clustered by commuting zone are in parentheses. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. Regressions include the full set of controls described in Section 2

As mentioned in the introduction, the literature on the labor market effects of offshoring has shown a small net positive relationship between offshoring by US MNEs and domestic employment, with underlying heterogeneous effects that vary based on worker and occupational characteristics (Oldenski (2021)). Before moving on to our estimation of the effects of offshoring exposure on voting patterns in the US, we first confirm that these relationships between offshoring and employment hold in our data, as this is the primary channel through which offshoring is likely to impact incumbent party vote shares. Indeed, Column (1) of Table 3 shows that a 1% increase in offshoring exposure, as defined by Equation 1, leads to a 0.08% increase in county-level employment. This is consistent with Kovak et al. (2021), who use an instrumental variables approach and find that a 1% increase in offshoring exposure leads to a 0.017% increase in employment at the MSA level. However, these results are not uniform across counties. Consistent with previous findings on the heterogeneous effects of offshoring on different types of workers, Column (2) of Table 3 shows that the positive effects of offshoring primarily benefit counties with a higher share of college educated

workers. Columns (3) and (4) show that counties with a larger share of their workforce in occupations that are more easily offshored or that are in the manufacturing sector experience negative employment effects of offshoring. When US-based firms take advantage of offshoring opportunities, they tend to move lower skilled and more routine tasks abroad, leading to productivity gains that allow them to expand more high-skilled headquarters services in the US (Grossman and Rossi-Hansberg (2008)). We next move on to the primary focus of this paper, which is whether these relationships between offshoring and employment are reflected in incumbent party candidate vote shares at the county level for Presidential, House, and Senate elections.

Table 3: Offshoring and Employment at the County-Level

Dependent Variable:	ln(Employment)			
	(1)	(2)	(3)	(4)
ln(Offshoring Exposure)	0.0801*** (0.0224)	-0.209*** (0.0295)	0.176*** (0.0229)	0.125*** (0.0215)
ln(Offshoring Exposure)*College Share		0.379*** (0.0300)		
ln(Offshoring Exposure)*Offshorable Occ Share			-0.251*** (0.0250)	
ln(Offshoring Exposure)*Mfg Emp Share				-1.300*** (0.095)
Controls	Yes	Yes	Yes	Yes
N	74,856	74,856	74,856	74,856
Adjusted R^2	0.997	0.997	0.997	0.997
Within R^2	0.0652	0.135	0.106	0.107

Notes: .01 - ***; .05 - **; .1 - *; Standard errors clustered by commuting zone are in parentheses. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. Regressions include the full set of controls described in Section 2

3 Results

Table 4 presents the results of estimating Equation 3. We find no statistically significant relationship between offshoring exposure and the incumbent party vote share for any of the election types we study – President, Senate, or House. For all election types combined, the point estimate is positive, but due to the large standard errors, we can’t rule out the possibility that a doubling of offshoring exposure leads to as large as about a 2.5 percentage point increase or a 0.87 percentage

point decrease in the incumbent vote share with 95 percent confidence.¹⁰ The results are similarly noisy across each of the individual election types, though point estimates are positive and insignificant for Presidential and Senate sections, but negative and insignificant for House elections.¹¹

Table 4: Offshoring Exposure and the Incumbent Party Vote Share

Dependent Variable:	Incumbent Vote Share			
Election type	All	President	Senate	House
	(1)	(2)	(3)	(4)
ln(Offshoring Exposure)	1.143 (1.223)	2.439 (2.459)	2.319 (1.733)	-0.215 (1.801)
N	74,657	18,490	22,571	33,626
Adjusted R^2	0.438	0.377	0.647	0.515

Notes: .01 - ***; .05 - **; .1 - *; Standard errors clustered by commuting zone are in parentheses. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. Regressions include the full set of controls described in Section 2

The results in Table 4 suggest that the net positive effects of offshoring exposure on county-level employment that we find in Table 3 may not directly translate to aggregate increases in the incumbent party vote share. These overall positive labor market effects could be mitigated in the voting booth for a variety of reasons, including the political rhetoric described in the introduction; concern for groups that are negatively impacted by offshoring, even on the part of groups that benefit or are unaffected; increased employment or wage risk, even for workers that do not actually lose their jobs (Senses (2010)); or non-economic factors such as social-issue positions and racial identity (Choi et al. (2024)).

Even though the net effects of offshoring on the incumbent party vote share are insignificant, we find very different effects for counties with different characteristics, which essentially cancel out in aggregate. The literature on the labor market effects of offshoring has shown that there is a great deal of heterogeneity underlying these net effects. Worker characteristics such as education and the types of tasks performed on the job have been shown to be especially relevant in determining who

¹⁰We frame our results in terms of a doubling of offshoring exposure not only because it is straightforward to interpret 100 percent increases using our coefficient values, but also because the 75th percentile county in our sample based on offshoring exposure is 94 percent more exposed to offshoring than the 25th percentile county, suggesting that a doubling of offshoring is a reasonable magnitude to consider. Throughout this section, we interpret a doubling of offshoring exposure by multiplying the relevant coefficient values by $\ln(2)$.

¹¹As mentioned in the introduction, it has been shown both theoretically and empirically that offshoring has both positive and negative effects on domestic workers depending on their characteristics, with the sign of the net effects being ambiguous (Kovak et al. (2021)). The insignificant effects in Table 4 are consistent with this, though small positive or negative relationships would be, as well.

is likely to be made better or worse off as a result of offshoring (Hummels et al. (2014); Ebenstein et al. (2014); Hummels et al. (2014); Ottaviano et al. (2013); Oldenski (2014)), and in the following analysis we confirm that these differences do indeed lead to different results in the voting booth.

Table 5 interacts the offshoring exposure measure with the share of workers with a college degree in each county in 2000. In this specification, the coefficient on “ln(Offshoring Exposure)” captures the effect of offshoring on the incumbent vote share in a county with no college-educated workers, and the interaction term captures the differential effect for counties with more college graduates. For all types of elections except Senate, the coefficient on offshoring exposure is negative and statistically significant. However the interaction between offshoring and skill is positive and significant for all election types, providing evidence of heterogeneous effects across counties based on their skill endowments. Considering Column (1) of Table 5, if a county had no college educated voters, a doubling of offshoring exposure would lead to a 8.12 percentage point decrease in the incumbent vote share for all election types combined. For a county in which all of the workers were college educated, a doubling of offshoring exposure would result in a 7.43 percentage point increase in the incumbent vote share. The counties in our sample are extremely heterogeneous in skill endowments, with college educated shares ranging from 36 percent at the 5th percentile of the distribution to 64 percent at the 95th percentile. These numbers imply that impact of a doubling of offshoring on the incumbent vote share ranges from about -2.52 percentage points at the 5th percentile of education to about 1.83 percentage points at the 95th percentile. The results are even more striking when looking just at presidential elections, for which the effect of offshoring on the incumbent party vote share ranges from -8.27 to 5.11 percentage points when moving from the 5th to the 95th percentile county in terms of the college educated share. The mean county in our sample has a college educated share of 0.535, implying that a doubling of offshoring would lead to a 0.20 percentage point increase in the incumbent vote share for all election types, a 0.12 percentage point increase for presidential elections, a 1.23 percentage point increase for Senate elections, and a 0.47 percentage point decrease for House elections. Thus on average the effects on high and low skilled counties essentially cancel each other out, consistent with the insignificant aggregate effects in Table 4, though there is a great deal of heterogeneity in effects depending on the skill composition of the county.

Table 6 interacts the offshoring exposure measure with the share of employment in offshorable occupations in each county in 2000, as defined by Autor and Dorn (2013).¹² In this specification, the

¹²This measure uses occupational task data from the Department of Labor’s Occupational Information Network (O*NET) to identify which occupations are more likely to be offshored based on the importance of proximity to a specific worksite in the US and face-to-face contact with US-based workers. Because offshoring firms keep some functions in the US and only move some jobs abroad, this measure is meant to provide insight into which occupations are more likely to be performed overseas and which are more likely to remain in the US.

Table 5: Offshoring Exposure, Skill Endowments, and the Incumbent Party Vote Share

Dependent Variable:	Incumbent Vote Share			
Election type	All	President	Senate	House
	(1)	(2)	(3)	(4)
ln(Offshoring Exposure)	-11.714*** (2.793)	-36.637*** (6.878)	-5.284 (4.541)	-7.133* (3.705)
College Share x ln(Offshoring Exposure)	22.431*** (4.649)	68.761*** (11.470)	13.195* (7.302)	12.059** (6.064)
N	74,657	18,460	22,571	33,626
Adjusted R^2	0.439	0.382	0.647	0.515

Notes: .01 - ***; .05 - **; .1 - *; Standard errors clustered by commuting zone are in parentheses. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. Regressions include the full set of controls described in Section 2

coefficient on “offshoring exposure” captures the effect of offshoring exposure on the incumbent vote share in counties that had the lowest share of workers in offshorable occupations. If a county had no offshorable occupations, a doubling of offshoring would lead to a 2.39 percentage point increase in the incumbent vote share. To the extent that the offshorable employment share measure accurately captures the true ability of occupations to be offshored, this 2.39 percentage point increase in the incumbent vote share would capture the impact on votes of positive productivity effects of offshoring on domestic employment, as such a county would be isolated from any negative substitution effects of offshoring. In contrast, for a county in which all of the workers were employed in offshorable occupations, a doubling of offshoring exposure would result in a 1.80 percentage point *decrease* in the incumbent vote share. The mean county in our sample has an offshorable occupation share of 0.261, implying that a doubling of offshoring would lead to a 1.30 percentage point increase in the incumbent vote share for all election types, a 3.92 percentage point increase for presidential elections, a 1.63 percentage point increase for Senate elections, and a 0.16 percentage point increase for House elections, though the results for Senate elections are not statistically significant. Once again, we see extremely heterogeneous effects based on county characteristics, which are masked in the aggregate effects shown in Table 4.

Table 7 includes an interaction of the offshoring exposure measure with the share of county-level employment in manufacturing industries. Manufacturing jobs tend to be more easily offshored than nonmanufacturing occupations, thus we may expect to see results that are similar to the ones using the offshorability index. The results in Column (1) of Table 7 suggest that if a county had no manufacturing employment, a doubling of offshoring would lead to a 1.48 percentage point increase in the incumbent vote share. In contrast, for a county in which all of the workers were employed

Table 6: Offshoring Exposure, Offshorable Occupations, and the Incumbent Party Vote Share

Dependent Variable:	Incumbent Vote Share			
Election type	All	President	Senate	House
	(1)	(2)	(3)	(4)
ln(Offshoring Exposure)	3.455** (1.399)	11.463*** (2.758)	2.496 (1.922)	1.220 (1.968)
Offshorable Emp Share x ln(Offshoring Exposure)	-6.049*** (1.253)	-23.230*** (3.007)	-0.459 (1.714)	-3.808** (1.530)
N	74,657	18,460	22,571	33,626
Adjusted R^2	0.439	0.386	0.647	0.515

Notes: .01 - ***; .05 - **; .1 - *; Standard errors clustered by commuting zone are in parentheses. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. Regressions include the full set of controls described in Section 2

in the manufacturing sector, a doubling of offshoring exposure would result in a 18.60 percentage point *decrease* in the incumbent vote share. The mean county in our sample has a manufacturing share of 0.161, implying that a doubling of offshoring would lead to a 1.75 percentage point decrease in the incumbent vote share for all election types, a 8.90 percentage point decrease for presidential elections, a 0.83 percentage point decrease for Senate elections, and a 0.09 percentage point decrease for House elections, though the results for House elections are not statistically significant. Once again, the effects vary greatly based on county characteristics.

Table 7: Offshoring Exposure, Manufacturing Share, and the Incumbent Party Vote Share

Dependent Variable:	Incumbent Vote Share			
Election type	All	President	Senate	House
	(1)	(2)	(3)	(4)
ln(Offshoring Exposure)	2.136* (1.282)	8.251*** (2.857)	3.252* (1.763)	-0.235 (1.840)
Manufacturing Emp Share x ln(Offshoring Exposure)	-28.967*** (5.755)	-131.012*** (18.686)	-27.678*** (7.602)	0.670 (6.555)
N	74,657	18,460	22,571	33,626
Adjusted R^2	0.439	0.386	0.648	0.515

Notes: .01 - ***; .05 - **; .1 - *; Standard errors clustered by commuting zone are in parentheses. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. Regressions include the full set of controls described in Section 2

The results presented in Tables 4 through 7 are robust to different definitions of vertical offshoring, (see Appendix Table A.2), different approaches to handling counties split across multiple congress-

sional districts (Appendix Table A.4), and different definitions of skill, offshorability, and manufacturing intensity (Appendix Table A.5). They are also robust to controlling for various other globalization shocks, as shown in Section 4. Appendix Table A.6 shows that the relationship between offshoring exposure and the incumbent vote share can’t be explained by migration in and out of exposed counties. The results hold when both horizontal and vertical offshoring are included in the measure of offshoring exposure (Appendix Table A.3)

We use a shift-share approach, which allocates current offshoring shocks across counties using their initial (2000) employment distributions, to help address concerns about the possible endogeneity of these shocks. The pre-trend analysis shown in Table 2 and Appendix Table A.1 shows no evidence of a statistically significant relationship for any of our specifications, suggesting that the estimates we report in Section 3 are not picking up pre-existing trends in voting outcomes. However, as an additional check, we also include a specification that instruments for offshoring by US firms using offshoring by firms from other OECD countries. Those results are described in detail in Appendix C. Appendix D shows the results of robustness checks following contributions to the recent literature on shift share identification strategies by Borusyak et al. (2022) and Goldsmith-Pinkham et al. (2020). These exercises provide support for the main results presented in this paper.

4 Robustness

In this section, we present the results of robustness exercises that control for different types of globalization shocks and consider alternate approaches to defining our offshoring exposure measure. Additional robustness checks are included in Appendix A.

Robustness to Other Globalization Shocks

As mentioned in Section 2, all of the specifications shown so far control for the China shock using a measure of import exposure from Autor et al. (2013) and for both high and low skilled migration using measures from Mayda et al. (2022). In this section we consider the robustness of our results to including other types of globalization shocks, specifically changes in exports and the implementation of NAFTA.

In Table 8, we present results controlling for county-level exposure to export opportunities. We do this for two reasons. First, one of the ways in which offshoring could exert a positive effect on local labor markets, and therefore incumbent party vote shares, is if cost savings from offshoring allow US MNE’s to expand their global market share, possibly by exporting larger quantities from the

US. However, it's also possible that counties in which exposure to offshoring by MNEs increased the most also happen to be counties where exports by non-MNEs have grown, leading to a spurious correlation between offshoring exposure and employment growth.

To address this, we construct a shift share measure of export exposure at the local labor market level, similar to our measure of offshoring exposure:

$$E_{zt} \equiv \sum_j \sigma_{zj}^{2000} E_{jt} \quad (4)$$

where $\sigma_{zj}^{2000} \equiv L_{zj}^{2000} / \sum_{j'} L_{zj'}^{2000}$, j denotes industries, L_{zj}^{2000} is employment in CZ z and industry j in 2000, and E_{jt} is US exports by industry j in year t . We further instrument for E_{jt} using industry-level exports by other OECD countries to address the possibility that unobserved shocks could impact both exports and employment, leading to increased incumbent vote shares that are correlated with, but not caused by, export growth.¹³ We apply the CZ-level measure to each county within the CZ.

Table 8: Offshoring Exposure and the Incumbent Party Vote Share, Controlling for Exports

Dependent Variable:	Incumbent Vote Share			
Election Type:	All	All	All	All
	(1)	(2)	(3)	(4)
ln(Offshoring Exposure)	1.077 (1.219)	-11.628*** (2.811)	3.447** (1.404)	2.075 (1.279)
College Share x ln(Offshoring Exposure)		22.221*** (4.687)		
Offshorable Occ Share x ln(Offshoring Exposure)			-6.038*** (1.271)	
Mfg Emp Share x ln(Offshoring Exposure)				-28.835*** (5.758)
Export Exposure	-0.016 (0.010)	-0.009 (0.009)	-0.001 (0.009)	-0.014 (0.010)
N	74,657	74,657	74,657	74,657
Adjusted R^2	0.438	0.439	0.439	0.439

Notes: .01 - ***; .05 - **; .1 - *; Standard errors clustered by commuting zone are in parentheses. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. Regressions include the full set of controls described in Section 2

Table 8 shows the results of our main specifications also controlling for county-level export exposure.

¹³Specifically, we use exports by Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

The coefficients on export exposure are not significant in any of the specifications, suggesting that high initial employment in export industries is not a significant driver of the county-level incumbent vote share. Reassuringly, the results for offshoring exposure, including its interactions with skill, offshorability, and the manufacturing employment share, are all robust to controlling for export exposure.

Choi et al. (2024) show that the 1994 North American Free Trade Agreement (NAFTA), had a significant impact on voting behavior. They find that voters in counties that were more vulnerable to NAFTA were less likely to vote for the Democratic party post-NAFTA, as this was the party of Bill Clinton who was president when NAFTA took effect. In Table 9, we control for the county-level measure of NAFTA vulnerability from Choi et al. (2024). Perhaps surprisingly, the coefficient on NAFTA exposure is positive, though generally not significant. This is likely because NAFTA was implemented in the 1990s, and our sample begins in 2000. Choi et al. (2024) consider the effect on support for the Democratic party, but we look at the incumbent vote share. To the extent that voters exposed to NAFTA switched their political affiliation from Democrat to Republican, and to the extent that the new affiliation persisted, we would not pick this up as a change in the incumbent vote share during our 2000-2020 sample period. Reassuringly, our results on the effects of offshoring exposure on the incumbent party vote share are not affected by controlling for this measure of NAFTA exposure.

Table 9: Offshoring Exposure and the Incumbent Party Vote Share, Controlling for NAFTA

Dependent Variable:	Incumbent Vote Share			
Election Type:	All	All	All	All
	(1)	(2)	(3)	(4)
ln(Offshoring Exposure)	1.264 (1.234)	-11.946*** (2.827)	3.542** (1.396)	2.347* (1.297)
College Share x ln(Offshoring Exposure)		23.060*** (4.654)		
Offshorable Occ Share x ln(Offshoring Exposure)			-6.122*** (1.259)	
Mfg Emp Share x ln(Offshoring Exposure)				-29.494*** (5.784)
NAFTA Vulnerability	1.039 (1.158)	1.905* (1.136)	1.312 (1.120)	1.547 (1.152)
N	72,038	72,038	72,038	72,038
Adjusted R^2	0.438	0.439	0.439	0.439

Notes: .01 - ***; .05 - **; .1 - *; Standard errors clustered by commuting zone are in parentheses. Initial NAFTA vulnerability is interacted with a linear time trend. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. Regressions include the full set of controls described in Section 2

Robustness: Offshoring Exposure Measure

Our main specifications use the log of our commuting zone level offshoring exposure measure, $\ln(O_{zt})$. One potential concern with this approach is that defining the CZ-level measure in logs implies that locations with initially lower levels of offshoring exposure may be subject to larger relative increases. To make sure that the decision to use the log of offshoring exposure is not driving our results, we conduct robustness checks using the level, rather than log, of O_{zt} to capture offshoring exposure. Panel A of Table 10 shows that the results using O_{zt} are very similar to the results using $\ln(O_{zt})$. All of the interaction terms have the same sign and level of significance regardless of whether we use logs or levels. The main difference is that overall offshoring exposure has a positive and significant impact on the incumbent party vote share when measured in levels rather than logs.

Another potential concern is that because industry-level offshoring is defined as the number of employees at foreign affiliates of US-owned multinationals, this measure could be correlated with industry scale. If an industry's employment is growing for reasons unrelated to offshoring, this could lead to an increase in both offshoring and the incumbent party vote share in areas with high initial employment shares in that industry. We address this potential source of omitted variable bias directly in our main specifications by controlling for a measure of industry-specific labor demand shocks at the commuting zone level following Bartik (1991). In this section, we address potential concerns about industry scale by defining offshoring exposure relative to domestic US MNE employment, rather than as the number of offshore employees.

$$Oshare_{zt} \equiv \sum_j \sigma_{zj}^{2000} Oshare_{jt} \quad (5)$$

where $Oshare_{jt} \equiv O_{jt}/(L_{USMNE,jt})$ is foreign employment by US-owned MNEs in industry j year t , relative to employment by US-owned MNEs in the US ($L_{USMNE,jt}$) and σ_{zj}^{2000} is the same as in equation (1).

As shown in Panel B of Table 10, the results are robust to using this measure of offshoring exposure. As with Panel A of 10, the main difference relative to our primary specification is that overall offshoring exposure has a positive and significant impact on the incumbent party vote share when using this alternate definition of offshoring exposure.

Table 10: Offshoring Exposure and the Incumbent Party Vote Share: Alternative Measures of Offshore Employment

Panel A. Offshoring Exposure (Employment Levels)				
Dependent Variable:	Incumbent Vote Share			
Election type	All	All	All	All
	(1)	(2)	(3)	(4)
Offshore Employment Level	6.203** (2.545)	-22.656*** (5.505)	7.783*** (2.288)	15.836*** (2.480)
College Share x Offshore Empl. Level		47.464*** (9.636)		
Offshorable Occ. Share x Offshore Empl. Level			-16.773*** (3.477)	
Mfg. Emp. Share x Offshore Empl. Level				-48.680*** (8.034)
N	74,682	74,682	74,682	74,682
Adjusted R^2	0.438	0.439	0.439	0.439

Panel B. Offshoring Exposure (Employment Share)				
Dependent Variable:	Incumbent Vote Share			
Election type	All	All	All	All
	(1)	(2)	(3)	(4)
Offshore Employment Share	13.224*** (1.753)	-30.240*** (7.969)	15.645*** (1.985)	24.825*** (3.015)
College Share x Offshore Empl. Share		76.923*** (14.481)		
Offshorable Occ. Share x Offshore Empl. Share			-25.208*** (4.907)	
Mfg. Emp. Share x Offshore Empl. Share				-67.444*** (12.684)
Observations	74,682	74,682	74,682	74,682
Adjusted R^2	0.439	0.440	0.440	0.440

Notes: Standard errors clustered by commuting zone are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Panel A measures offshoring exposure using the level, rather than log, of offshore employment. Panel B measures exposure using offshore employment relative to domestic employment by US MNEs. All regressions include the full set of controls described in Section 2.

5 Conclusion

Politicians often criticize offshoring while on the campaign trail. However economic research on the relationship between offshoring by US multinational firms and domestic employment shows that the story is much more nuanced, as some US workers benefit from the opportunities provided by offshoring, while others are harmed. In this paper we show that these heterogeneous effects of offshoring on different types of US workers are reflected in the impact that offshoring has on

voting patterns in the US. Offshoring has a positive effect on the incumbent vote share in counties with higher shares of college graduates, as more highly skilled workers are more likely to gain from offshoring and therefore reward the politicians that were in office when the offshoring occurred. In contrast, offshoring has a negative effect on the incumbent vote share in counties with higher shares of offshorable occupations and higher employment in the manufacturing sector. These results are consistent with our own employment results and evidence from the literature that has shown that offshoring by US multinationals has either a small positive or zero effect on US employment overall, but that outcomes for individual workers vary based on their skill level and the tasks that are being offshored (Oldenski (2021)). At the same time, a robust political science literature has shown that voters reward incumbents when local employment levels are higher. This paper links those two literatures, by presenting new evidence that county-level voting patterns respond to offshoring in a way that is consistent with the evidence on the labor market effects of offshoring.

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Appendix

A Additional Results

Pre-trend analysis with interaction terms

Table A.1: Pre-trends: Relationship between pre-period incumbent party vote shares and offshoring exposure

Election type	All	All	All	All
	(1)	(2)	(3)	(4)
Panel A. Relationship between incumbent party vote shares in 2000-2008 and offshoring in 2010-2020				
$\Delta \ln(\text{Offshoring Exposure } 2010-2020)$	-1.399 (1.554)	2.010 (6.139)	-1.138 (1.663)	-2.662 (1.951)
College share x $\Delta \ln(\text{Offshoring Exposure } 2010-2020)$		-0.0594 (0.104)		
Offshorable Occ share x $\Delta \ln(\text{Offshoring Exposure } 2010-2020)$			-1.312 (1.743)	
Mfg Emp Share x $\Delta \ln(\text{Offshoring Exposure } 2010-2020)$				0.0904 (0.0747)
N	3,080	3,080	3,080	3,080
Adjusted R^2	0.392	0.392	0.392	0.392
Panel B. Relationship between incumbent party vote shares in 1990-1998 and offshoring in 2000-2010				
$\Delta \ln(\text{Offshoring Exposure } 2000-2010)$	0.988 (1.304)	-2.330 (5.513)	0.657 (1.754)	0.999 (1.443)
College share x $\Delta \ln(\text{Offshoring Exposure } 2000-2010)$		0.0589 (0.114)		
Offshorable Occ share x $\Delta \ln(\text{Offshoring Exposure } 2000-2010)$			0.860 (1.578)	
Mfg Emp Share x $\Delta \ln(\text{Offshoring Exposure } 2000-2010)$				-0.00185 (0.0497)
N	3,080	3,080	3,080	3,080
Adjusted R^2	0.410	0.412	0.411	0.410
Panel C. Relationship between incumbent party vote shares in 1990-1998 and offshoring in 2000-2020				
$\Delta \ln(\text{Offshoring Exposure } 2000-2020)$	0.731 (1.366)	-2.411 (4.460)	0.544 (1.529)	0.821 (1.450)
College share x $\Delta \ln(\text{Offshoring Exposure } 2000-2020)$		0.0513 (0.0878)		
Offshorable Occ share x $\Delta \ln(\text{Offshoring Exposure } 2000-2020)$			0.743 (1.102)	
Mfg Emp Share x $\Delta \ln(\text{Offshoring Exposure } 2000-2020)$				-0.0267 (0.0500)
N	3,080	3,080	3,080	3,080
Adjusted R^2	0.408	0.409	0.408	0.408

Notes: .01 - ***; .05 - **; .1 - *; Standard errors clustered by commuting zone are in parentheses. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. Regressions include the full set of controls described in Section 2

In the interest of saving space, the pre-trend analysis in Table 2 only shows results using overall offshoring exposure and does not include interactions of offshoring with skill, offshorability, or the manufacturing employment share. In Table A.1 presented here, we confirm that the interaction terms are not correlated with pre-period incumbent vote shares.

Alternate vertical offshoring cutoffs

Our main results presented in Section 3 define vertical offshoring using the 50 percent of industries with the largest shares of affiliates that ship goods and services back to the US. Table A.2 shows the results of estimating Equation 3 using different thresholds for vertical offshoring. Table A.2 Panel A uses a more narrow definition of vertical offshoring, only including the 25 percent of industries with the highest shares of affiliates that export back to the US. Panel B expands the definition, including the top 75 percent of industries in terms of vertical affiliate share. Both alternate definitions of vertically oriented industries produce results that are qualitatively similar to our main results in Table 4. Coefficients on the interaction terms have the same signs and are statistically significant regardless of which offshoring cutoff we use. However, results only using the most vertical industries (top 25 percent in terms of vertical offshoring share) are the strongest, while coefficient values become smaller and less precisely estimated as we include foreign affiliate employment in more horizontally-focused industries.

Table A.3 shows that the main results hold when we define offshoring using all industries, not just industries with vertical offshoring. When horizontal industries are included, the signs of the interactions of offshoring exposure with skill endowments, offshorability, and manufacturing remain the same and they are all still significant, though the coefficients on the interaction terms are smaller and less precisely estimated. The non-interacted offshoring variables all have the same signs as the results using only vertical offshoring, however they are not statistically significant. These results suggest that the relationship between offshoring and the incumbent party vote share isn't as strong for horizontal offshoring as it is for vertical offshoring.

Counties spanning multiple congressional districts

As described in Section 2, determining the incumbent party vote share at the county-level is not as straightforward for House elections as it is for Presidential and Senate elections. While most counties fall entirely within one congressional district, some counties are spilt across multiple districts. When this occurs, our main specifications in Section 3 use a weighted average of the incumbent vote

Table A.2: Offshoring Exposure and the Incumbent Party Vote Share: Alternate Vertical Offshoring Cutoffs

Panel A. Top 25% Vertical Offshoring Industries				
Dependent Variable:	Incumbent Vote Share			
Election type	All	All	All	All
	(1)	(2)	(3)	(4)
ln(Offshoring Exposure)	1.712** (0.813)	-10.503*** (2.366)	6.342*** (1.141)	3.251*** (0.909)
College Share x ln(Offshoring Exposure)		24.678*** (4.598)		
Offshorable Occ Share x ln(Offshoring Exposure)			-8.006*** (1.140)	
Mfg Emp Share x ln(Offshoring Exposure)				-24.461*** (4.389)
Observations	74,682	74,682	74,682	74,682
Adjusted R^2	0.438	0.440	0.439	0.441
Panel B. Top 75% Vertical Offshoring Industries				
Dependent Variable:	Incumbent Vote Share			
Election type	All	All	All	All
	(1)	(2)	(3)	(4)
ln(Offshoring Exposure)	0.504 (1.483)	-5.636** (2.764)	0.969 (1.552)	1.135 (1.564)
College Share x ln(Offshoring Exposure)		10.283** (4.232)		
Offshorable Occ Share x ln(Offshoring Exposure)			-2.390** (1.065)	
Mfg Emp Share x ln(Offshoring Exposure)				-13.049*** (4.800)
Observations	74,682	74,682	74,682	74,682
Adjusted R^2	0.438	0.438	0.438	0.438

Notes: Standard errors clustered by commuting zone are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Panel A defines offshoring exposure using foreign employment in the top 25% of industries ranked by vertical offshoring intensity. Panel B uses the top 75% of industries. All regressions include the full set of controls described in Section 2.

shares for each county-district cell, using the share of total county voters residing in each district as weights. In this section, we show that those results are robust to alternate approaches for dealing with split counties. Column (1) of Table A.4 presents results that use the incumbent party from the largest congressional district within each county as the incumbent party for the entire county. Column (2) shows results dropping counties that are split across districts with different incumbent parties. Column (3) drops all county-year observations that are split across districts. Our results are robust to these various approaches. This is not surprising, as a relatively small number of

Table A.3: Offshoring Exposure and the Incumbent Party Vote Share: Horizontal and Vertical FDI

Dependent Variable:	Incumbent Vote Share			
Election type	All	All	All	All
	(1)	(2)	(3)	(4)
ln(Offshoring Exposure)	1.311 (1.658)	-4.626 (2.858)	1.743 (1.723)	1.794 (1.725)
College Share x ln(Offshoring Exposure)		9.828** (4.251)		
Offshorable Occ. Share x ln(Offshoring Exposure)			-2.329** (1.074)	
Mfg. Emp. Share x ln(Offshoring Exposure)				-12.299*** (4.737)
Observations	74,657	74,657	74,657	74,657
Adjusted R^2	0.438	0.438	0.438	0.438

Notes: Standard errors clustered by commuting zone are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Offshoring exposure is defined using outward FDI in all industries, both horizontal and vertical. All regressions include the full set of controls described in Section 2.

observations in our sample are affected. About 13 percent of our total county-year observations are for counties that are split across congressional districts. However, for about half of those split county observations, each district in the county is represented by the same political party, such that less than 7 percent of the total observations are for counties that are split across congressional districts with different incumbent parties.

Alternate definitions of skill, offshorability, and manufacturing shares

Section 3 demonstrated that the relationship between offshoring exposure and the incumbent vote share in a county varies considerably depending on the skill level, offshorable occupation share, and manufacturing employment share of that county. We next consider the robustness of these results to alternate definitions of skill endowments, offshorability, and the importance of manufacturing. In Table A.5 we define skill using the share of high school, rather than college graduates. We define the offshorable occupation share following Acemoglu and Autor (2011). And we use manufacturing hours worked as a share of total hours worked in a county, rather than the share of workers in each sector, as our measure of manufacturing importance. The results using all three of these alternate measures are very similar to our main results.

Table A.4: Offshoring Exposure and the Incumbent Party Vote Share: Alternate approaches to counties spanning multiple congressional district

Dependent Variable:	Incumbent Vote Share		
Approach:	Largest District	Drop Dif Party Split Counties	Drop Split Counties
Election type:	All	All	All
	(1)	(2)	(3)
ln(Offshoring Exposure)	1.365 (1.209)	1.490 (1.286)	1.212 (1.292)
N	74,621	72,324	70,137
Adjusted R^2	0.411	0.444	0.419
ln(Offshoring Exposure)	-11.296*** (2.854)	-9.877*** (2.979)	-11.532*** (3.172)
College Share x ln(Offshoring Exposure)	22.088*** (4.553)	20.230*** (5.008)	22.972*** (5.296)
N	74,621	72,324	70,137
Adjusted R^2	0.412	0.445	0.419
ln(Offshoring Exposure)	3.662*** (1.370)	4.007*** (1.512)	4.120*** (1.528)
Offshorable Occ. Share x ln(Offshoring Exposure)	-6.003*** (1.217)	-6.073*** (1.402)	-6.752*** (1.403)
N	74,621	72,324	70,137
Adjusted R^2	0.412	0.445	0.420
ln(Offshoring Exposure)	2.413* (1.280)	2.739** (1.375)	2.602* (1.407)
Mfg. Emp. Share x ln(Offshoring Exposure)	-30.496*** (5.787)	-31.943*** (6.422)	-35.183*** (6.837)
N	74,621	72,324	70,137
Adjusted R^2	0.412	0.445	0.420

Notes: .01 - ***; .05 - **; .1 - *. Standard errors clustered by commuting zone are in parentheses. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. Regressions include the full set of controls described in Section 2.

Table A.5: Offshoring Exposure and the Incumbent Party Vote Share, Alternative Definitions

Dependent Variable:	Incumbent Vote Share			
Election type:	All	All	All	All
	(1)	(2)	(3)	(4)
ln(Offshoring Exposure)	1.077 (1.219)	-3.340** (1.421)	2.944** (1.440)	2.619* (1.410)
HS Share x ln(Offshoring Exposure)		5.968*** (1.528)		
Offshorable Occ Share (ADH) x ln(Offshoring Exposure)			-4.772*** (1.337)	
Mfg hrs x ln(Offshoring Exposure)				-25.126*** (8.144)
N	74,657	74,657	74,657	74,657
Adjusted R^2	0.438	0.439	0.439	0.438

Notes: .01 - ***; .05 - **; .1 - *; Standard errors clustered by commuting zone are in parentheses. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. Regressions include the full set of controls described in Section 2

Population changes

Table A.6 shows the effect of offshoring exposure on county population, defined as the total population. The results are not significant, suggesting that migration in and out of counties in response to offshoring exposure cannot explain our results.

Table A.6: Offshoring Exposure and Population Changes

Dependent Variable:	Change Total Population	
ln(Offshoring Exposure)	(1)	(2)
	0.003 (0.004)	0.002 (0.004)
Controls	no	yes
N	27,693	27,693
Adjusted R^2	0.351	0.352

Notes: .01 - ***; .05 - **; .1 - *; Standard errors clustered by commuting zone are in parentheses. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. Regression in column (2) includes the full set of controls described in Section 2

Excluding uncontested elections

A small number of elections in our sample are uncontested, such that the incumbent party vote share is either 0 or 1. Table A.7 shows that our main results are virtually unchanged if we exclude these uncontested elections.

Table A.7: Offshoring Exposure and the Incumbent Party Vote Share, Excluding Uncontested Elections

Dependent Variable	Incumbent Vote Share			
Election type	All	All	All	All
	(1)	(2)	(3)	(4)
ln(Offshore Exposure)	0.929 (1.220)	-12.181*** (2.782)	3.212** (1.393)	1.921 (1.277)
College Share x ln(Offshoring Exposure)		22.871*** (4.663)		
Offshorable Occ. Share x ln(Offshoring Exposure)			-5.969*** (1.260)	
Mfg. Emp. Share x ln(Offshoring Exposure)				-28.889*** (5.749)
Observations	74,592	74,592	74,592	74,592
Adjusted R^2	0.443	0.444	0.444	0.443

Notes: Standard errors clustered by commuting zone are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. All regressions include the full set of controls described in Section 2.

Differentiating between new incumbents and sitting incumbents running again

Throughout the paper, we define incumbency based on the party of the candidate, not whether the individual running currently holds office. This assumes that voters respond to the party of the candidate more strongly than to individual characteristics. In this section, we examine that assumption more closely. Table A.8 includes a dummy variable that equals 1 if the incumbent party candidate is new, rather than the current office holder. The results show that, on average, new candidates in the incumbent party receive a lower vote share than incumbent candidates that are already in office. Controlling for this new candidate dummy has almost no effect on our main results.

Table A.8: Offshoring Exposure and the Incumbent Party Vote Share, Controlling for whether the Incumbent is a New Candidate from the Incumbent Party

Dependent Variable	Incumbent Vote Share			
Election type	All	All	All	All
	(1)	(2)	(3)	(4)
ln(Offshore Exposure)	0.962 (1.240)	-12.139*** (3.173)	3.740** (1.506)	2.346* (1.353)
College Share x ln(Offshore Exposure)		23.597*** (5.294)		
Offshorable Occ. Share x ln(Offshore Exposure)			-6.377*** (1.421)	
Mfg. Emp. Share x ln(Offshore Exposure)				-35.123*** (6.832)
New Candidate for Incumbent Party	-2.719*** (0.994)	-2.743*** (0.993)	-2.732*** (0.993)	-2.726*** (0.994)
Controls	Yes	Yes	Yes	Yes
Observations	69,938	69,938	69,938	69,938
Adjusted R^2	0.424	0.425	0.425	0.425

Notes: Standard errors clustered by commuting zone are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All regressions include the full set of controls described in Section 2.

Table A.9 splits the sample based on whether the incumbent party candidate is a current office holder or a new candidate within the incumbent party. The results are broadly consistent across these two samples, and the coefficients on the interaction terms are larger for the sample of new candidates in the incumbent party. We view this as support for our approach of defining incumbency based on the political party rather than the individual.

Table A.9: Offshoring Exposure and the Incumbent Party Vote Share, Sample Split between New Incumbents and Previous Incumbents Running Again

Panel A. Sample with New Candidates from Incumbent Party only				
Dependent Variable	Incumbent Vote Share			
Election type	All	All	All	All
	(1)	(2)	(3)	(4)
ln(Offshore Exposure)	-2.193 (2.412)	-34.521*** (5.345)	3.868 (2.465)	0.080 (2.458)
College Share x ln(Offshore Exposure)		56.932*** (8.803)		
Offshorable Occ. Share x ln(Offshore Exposure)			-14.229*** (1.902)	
Mfg. Emp. Share x ln(Offshore Exposure)				-54.609*** (13.328)
Observations	16,071	16,071	16,071	16,071
Adjusted R^2	0.323	0.328	0.327	0.325
Panel B. Sample with Sitting Incumbents only				
Dependent Variable	Incumbent Vote Share			
Election type	All	All	All	All
ln(Offshore Exposure)	2.470 (1.563)	-9.284*** (2.876)	4.602** (1.813)	3.421** (1.611)
College Share x ln(Offshore Exposure)		20.510*** (5.185)		
Offshorable Occ. Share x ln(Offshore Exposure)			-5.692*** (1.470)	
Mfg. Emp. Share x ln(Offshore Exposure)				-28.798*** (5.880)
Observations	58,805	58,805	58,805	58,805
Adjusted R^2	0.472	0.473	0.473	0.473

Notes: Standard errors clustered by commuting zone are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All regressions include the full set of controls described in Section 2.

B The role of political parties

As discussed in Section 2, our main outcome of interest is the incumbent party vote share, rather than the share of votes cast for a specific political party. We take this approach because views on offshoring are not clearly divided along party lines and because a very robust political science literature has shown that voters increase (decrease) support for the incumbent party when they perceive an improvement (worsening) in economic conditions, suggesting that gains and losses from offshoring could impact incumbent party vote shares. In this section, we instead look at whether offshoring exposure impacts the vote shares for Republican versus Democratic candidates.

Column 1 of Table B.1 shows that overall offshoring exposure does not have a significant impact on political party vote shares. However, when we include the interaction terms, offshoring impacts the two major parties in very different ways. For counties with higher shares of college educated workers, an increase in offshoring exposure has a negative impact on the Republican vote share, but the impact is positive in counties with lower shares of college educated workers. For counties with higher employment shares in offshorable occupations and manufacturing, an increase in offshoring helps Republicans and hurts Democrats, but the opposite is true in counties with lower employment shares in offshorable occupations and manufacturing. Because more highly educated workers are more likely to gain from offshoring, while workers in offshorable occupations and the manufacturing sector are more likely to be harmed, the results in Table B.1 suggest that voters may view Democrats as being more supportive of offshoring than Republicans during our sample period.

There may also be systematic differences between counties that initially leaned more towards Democrat versus Republican candidates. For example, the share of the county-level population with a college degree and the Republican vote share in our base year (2000) are negatively correlated, with a correlation coefficient of -0.281, statistically significant at the 1 percent level. If more highly educated counties are more likely to vote for Democrats, then our finding that incumbents benefit most from offshoring in more educated counties may suggest that on average Democrats have gained and Republicans have lost due to offshoring. In Table B.2 we interact the Republican vote share in 2000 with our measure of offshoring exposure and find that in counties with higher initial Republican vote shares, the incumbent party was harmed by increased offshoring, while in counties with higher initial Democrat vote shares, the incumbent party gained from offshoring.

It is also possible that the relationship between offshoring and the incumbent party vote share could be impacted by political party in more nuanced ways. For example, if party loyalty is rising differentially across parties, this could impact the incumbent party vote shares, and if offshoring

Table B.1: Offshoring Exposure and the Party Vote Share: Republican versus Democratic Party Votes

Panel A. Republican Vote Share				
Dependent Variable	Vote Share for Republican Party			
Election type	All	All	All	All
	(1)	(2)	(3)	(4)
ln(Offshore Exposure)	-0.708 (1.783)	11.327*** (4.295)	-3.784** (1.844)	-1.346 (1.805)
College Share x ln(Offshore Exposure)		-20.999*** (8.106)		
Offshorable Occ. Share x ln(Offshore Exposure)			8.046*** (1.323)	
Mfg. Emp. Share x ln(Offshore Exposure)				18.600*** (4.875)
N	74,657	74,657	74,657	74,657
Adjusted R^2	0.780	0.781	0.782	0.781

Panel B. Democrat Vote Share				
Dependent Variable	Vote Share for Democratic Party			
Election type	All	All	All	All
	(1)	(2)	(3)	(4)
ln(Offshore Exposure)	1.057 (1.820)	-12.475*** (3.879)	4.117** (1.861)	1.709 (1.829)
College Share x ln(Offshore Exposure)		23.609*** (6.947)		
Offshorable Occ. Share x ln(Offshore Exposure)			-8.008*** (1.274)	
Mfg. Emp. Share x ln(Offshore Exposure)				-19.023*** (4.742)
N	74,657	74,657	74,657	74,657
Adjusted R^2	0.761	0.762	0.763	0.762

Notes: Standard errors clustered by commuting zone are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. All regressions include the full set of controls described in Section 2.

exposure is disproportionately concentrated in locations that lean towards one party or the other, this would show up as a correlation between offshoring and incumbent party vote shares. Table B.3 controls for the party of the incumbent candidate using a dummy variable indicating whether or not the incumbent was a Republican. This variable is not statistically significant and has no meaningful impact on our main results.

Table B.2: Offshoring Exposure and the Incumbent Party Vote Share, Political Party Interactions

Dependent Variable	Incumbent Vote Share			
Election type	All	President	Senate	House
	(1)	(2)	(3)	(4)
ln(Offshore Exposure)	12.162*** (1.821)	41.314*** (3.889)	12.144*** (4.007)	1.183 (2.542)
Rep. Vote Share 2000 x ln(Offshore Exposure)	-20.895*** (2.300)	-73.500*** (4.926)	-18.549*** (6.491)	-2.655 (3.615)
Observations	74,657	18,460	22,571	33,626
Adjusted R^2	0.442	0.414	0.652	0.515

Notes: Standard errors clustered by commuting zone are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. All regressions include the full set of controls described in Section 2.

Table B.3: Offshoring Exposure and the Incumbent Party Vote Share: Controlling for the Party of the Incumbent

Dependent Variable	Incumbent Vote Share			
Election type	All	All	All	All
	(1)	(2)	(3)	(4)
ln(Offshore Exposure)	1.143 (1.224)	-11.712*** (2.799)	3.455** (1.393)	2.136* (1.280)
College Share x ln(Offshore Exposure)		22.427*** (4.648)		
Offshorable Occ. Share x ln(Offshore Exposure)			-6.051*** (1.240)	
Mfg. Emp. Share x ln(Offshore Exposure)				-28.963*** (5.694)
Dummy for Republican Incumbent	-0.040 (0.806)	-0.013 (0.806)	0.016 (0.805)	-0.010 (0.804)
N	74,657	74,657	74,657	74,657
Adjusted R^2	0.438	0.439	0.439	0.439

Notes: Standard errors clustered by commuting zone are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. All regressions include the full set of controls described in Section 2.

C IV Approach

Our main results, presented in Tables 4 through 7, use a shift-share approach, which allocates current offshoring shocks across counties using their pre-period employment distributions. This approach has been widely used in the literature and should help alleviate any concerns about the possible endogeneity of offshoring to county-level voting patterns. The pre-trend analysis shown in Tables 2 and A.1 presents further evidence in support of our approach, showing that offshoring patterns are not correlated with previous election results. However, as an additional check, in this section we present a specification that instruments for offshoring by US firms using offshoring by other OECD countries. This is similar to the approach commonly used in the trade literature, in which imports by the US are instrumented for using imports by other high income countries (see for example Autor et al. (2013)).

The OECD collects data on annual outward FDI flows at the country-industry level for a selection of countries. These data are not as detailed as the BEA data on offshoring by US firms. The reported industries are much more aggregate than in the BEA data, most countries don't report any data until 2013 or later, any many countries have missing observations. The OECD data also don't break outward investment into vertical versus horizontal FDI. Yet despite these limitations, we believe that it is still useful to use these data to construct an instrument for US offshoring.

We choose to use outward FDI by French, German, and Italian firms as our instrument for offshoring by US MNEs. These three countries have the best coverage in the OECD data, reporting outward FDI for 50 industries from 2014 onward. Table C.1 shows that total outward FDI by French, German, and Italian firms is significantly correlated with our industry-level measure of offshoring by US firms. Our preferred specification, reported in column (3), includes year fixed effects and clusters standard errors at the industry-level. We also control for an industry-level measure of offshorability and the average years of schooling for workers in each industry in 2000. These control variables are constructed using occupational-level measures from Acemoglu and Autor (2011), which we aggregate to the industry level using shares of each occupation in each industry in 2000 from the US Bureau of Labor Statistics Occupational Employment Statistics (OES) database. Because the offshorability and education variables are industry-specific and time invariant, they take the place of industry fixed effects.

Results using offshoring by this set of OECD firms to instrument for offshoring by US firms are presented in Table C.2. Because the OCED sample includes a smaller set of industries and years than we use in our main analysis, we first repeat our primary OLS specifications using this smaller

Table C.1: Relationship Between Offshoring by OECD and US Firms at the Industry Level

Dependent Variable:	ln(US Offshoring)		
	(1)	(2)	(3)
ln(OECD Outward FDI)	0.373*** (0.106)	0.385*** (0.111)	0.392*** (0.106)
Offshorability		1.278 (0.911)	2.302** (1.079)
Years of Schooling			-0.671* (0.347)
N	353	353	353
Adjusted R^2	0.167	0.198	0.237
F-Stat	12.398	12.019	13.618

Notes: .01 - ***; .05 - **; .1 - *; Standard errors clustered by industry are in parentheses. All specifications include year fixed effects. OECD countries included are France, Germany, and Italy.

sample to understand the extent to which any differences between our main results and the IV results presented in this section may be driven by differences in the samples. These results are presented in Panel A of Table C.2 and they are qualitatively similar to our main results.

Panel B of Table C.2 reports the two stage least squares results using offshoring by French, German, and Italian firms to instrument for offshoring by US firms. We construct the instrument at the CZ level, following Autor et al. (2013) and other papers in the literature. The coefficients on the interactions of offshoring exposure with skill and the manufacturing employment share both have the expected signs and are statistically significant at the 1-percent level. The interaction of offshoring exposure with the offshorable occupation share is not significant. Unlike in the main results presented in the paper, overall offshoring exposure has a small and statistically significant negative effect on the incumbent party vote share (Column 1) when using this IV. We report Kleibergen-Paap Wald F-statistics, which are very high for the specifications using overall offshoring and the interactions with skill and the manufacturing employment share, but only 5.8 for the specification using interactions with the offshorable occupation share. Overall, we are reassured that even with the differences between the BEA and OECD data and the smaller sample of industries and years available for the IV analysis, these results are broadly consistent with our main results presented in Tables 4 through 7, as well as with the literature on offshoring and domestic employment, which predicts positive effects for more educated workers and negative effects for manufacturing workers, with the sign of the offsetting net effects being ambiguous.

Another potential concern with using offshoring by firms in other OECD countries to instrument for offshoring by US firms is that shocks that drive industry growth in these countries could be

Table C.2: IV Analysis: Offshoring Exposure and the Incumbent Party Vote Share: OLS and 2SLS

Dependent Variable:	Incumbent Vote Share			
	(1)	(2)	(3)	(4)
Panel A: OLS with Same Sample as IV Analysis				
Election type	All	All	All	All
ln(Offshore Exposure)	-0.190*** (0.058)	-1.656*** (0.211)	0.222** (0.095)	0.138** (0.064)
ln(Offshore Exposure)*College Share		3.114*** (0.406)		
ln(Offshore Exposure)*Offshorable Occ. Share			-0.539*** (0.090)	
ln(Offshore Exposure)*Mfg. Emp. Share				-2.615*** (0.305)
N	26,871	26,871	26,871	26,871
Adjusted R^2	0.522	0.525	0.523	0.524
Panel B: 2SLS Analysis				
Election type	All	All	All	All
ln(Offshore Exposure)	-1.041*** (0.261)	-2.295*** (0.355)	-1.858** (0.872)	-0.512** (0.240)
ln(Offshore Exposure)*College Share		3.141*** (0.940)		
ln(Offshore Exposure)*Offshorable Occ. Share			0.731 (0.558)	
ln(Offshore Exposure)*Mfg. Emp. Share				-3.539*** (0.504)
N	26,871	26,871	26,871	26,871
Kleibergen–Paap Wald F	52.067	17.828	5.771	26.414

Notes: Standard errors clustered by commuting zone are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All regressions include the full set of controls described in Section 2.

correlated with shocks that drive growth in the US. We address this concern by defining offshoring relative to a broader measure of industry-level employment, rather than using the log of the offshoring level, to help remove overall scale effects that could be driving increases in both offshoring and incumbent vote shares. More specifically, we instrument for foreign employment by US MNEs relative to total domestic US employment by US MNEs at the industry level using outward FDI by French, German, and Italian firms in each industry relative to total industry employment in those countries.¹⁴

Table C.3 shows two-stage least squares results equivalent to the ones presented in Table C.2. As with the 2SLS results using offshoring level, these results are broadly consistent with our main

¹⁴The offshoring share measures for the US and other OECD countries are constructed slightly differently due to data limitations and different industry classifications, NACE for Europe and NAICS for the US.

specifications presented in Tables 4 through 7. The interactions of offshoring exposure with skill and the offshorable occupation share both have the expected signs and are statistically significant at the 1-percent level. The interaction of offshoring exposure with the manufacturing employment share is negative but not significant. Using this instrument, overall offshoring exposure has a small positive relationship with the incumbent party vote share, significant at the 10-percent level (Column 1). The Kleibergen-Paap Wald F-statistics suggest that this shares instrument is not as strong as the instrument used in Table C.2. We are hesitant to put too much emphasis on the results in Table C.3 given the relative weakness of the shares instrument, however we are reassured that the results are broadly consistent with our other approaches.

Table C.3: IV Analysis: Offshoring Exposure and the Incumbent Party Vote Share: OLS, and 2SLS Using Offshoring as Share of Employment

Dependent Variable:	Incumbent Vote Share			
	(1)	(2)	(3)	(4)
Panel A: OLS with Same Sample as IV Analysis				
Election type	All	All	All	All
Offshore Emp. Share	-0.188 (0.208)	-6.106*** (0.798)	0.985*** (0.369)	0.739*** (0.252)
Offshore Emp. Share*College Share		12.018*** (1.532)		
Offshore Emp. Share*Offshorable Occ. Share			-2.085*** (0.333)	
Offshore Emp. Share*Mfg. Emp. Share				-10.908*** (1.350)
N	26,871	26,871	26,871	26,871
Adjusted R^2	0.521	0.525	0.523	0.524
Panel B: 2SLS Analysis				
Election type	All	All	All	All
Offshore Emp. Share	4.637* (2.441)	-7.645*** (1.743)	2.690* (1.379)	6.280*** (2.038)
Offshore Emp. Share*College Share		18.007*** (2.763)		
Offshore Emp. Share*Offshorable Occ. Share			-3.039*** (0.725)	
Offshore Emp. Share*Mfg. Emp. Share				-5.583 (3.528)
N	26,871	26,871	26,871	26,871
Adjusted R^2	0.361	0.382	0.381	0.353
Kleibergen–Paap Wald F	7.991	4.761	11.238	6.031

Notes: Standard errors clustered by commuting zone are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All regressions include the full set of controls described in Section 2.

D Shift share analysis

Borusyak et al. (2022), henceforth BHJ, have shown how identification can be achieved using shift-share analysis by assuming the exogeneity of the shifters, and they propose tests to confirm that exogeneity. In our case, the shifters are offshoring shocks at the industry level, so the shift-share approach is essentially an industry-level regression where the data are aggregated using the CZ-level shares as weights. We perform a robustness check following the BHJ approach and present the results in Table D.1. Our main results still hold.

Table D.1: BHJ Approach

Dependent Variable:	Incumbent Vote Share			
Election type:	All	All	All	All
	(1)	(2)	(3)	(4)
ln(Offshoring Exposure)	6.104*** (2.073)	-6.786*** (2.567)	8.001*** (1.071)	5.496*** (1.243)
College Share x ln(Offshoring Exposure)		23.155*** (5.337)		
Offshorable Occ Share x ln(Offshoring Exposure)			-39.339*** (4.411)	
Mfg Emp Share x ln(Offshoring Exposure)				-19.463*** (3.636)
N	1661	1661	1661	1661
Adjusted R^2	0.877	0.996	0.997	0.996

Notes: .01 - ***; .05 - **; .1 - *; shift-share instrumental variable (SSIV) standard errors are in parentheses. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. Regressions include the full set of controls described in Section 2

We also follow Borusyak et al. (2025) and explore potential correlates of offshoring at the industry and county level using balance tests. These covariates include both initial characteristics of industries and counties, as well as pre-period trends.¹⁵ Panel A of Table D.2 reports the results from regressing pre-sample period industry-level variables on changes in offshoring exposure at the industry-level. We find no significant relationship between any of these variables and our measure offshoring exposure at the industry level. Panels B and C of Table D.2 show results from regressing county-level characteristics on changes in offshoring exposure. Of the 14 county-level characteristics we consider, 12 are not significantly correlated with offshoring exposure and two (the college-educated share in 1990 and the foreign-born share in 1990) are only significant at the 10 percent level. Taken together, we see this as evidence that our results are not being driven by initial industry or country characteristics or by other coincident shocks.

¹⁵Data sources are Acemoglu et al. (2016), Autor et al. (2013), Autor et al. (2021) and Choi et al. (2024).

Table D.2: Balance Tests: Correlation between Changes in Offshoring Exposure and Regional and Industry Characteristics

Panel A. Industry-level balance							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Prod. worker share 1990	Capital val-added 1990	Log real wage 1990	Computer share 1990	High-tech share 1990	Log Exports 1990	Export growth 1990-2000
$\Delta \ln(\text{Offshoring Exposure})$	-0.002 (0.001)	0.000 (0.000)	0.005 (0.003)	0.090 (0.070)	-0.040 (0.058)	0.025 (0.013)	-0.001 (0.003)
R^2	0.392	0.107	0.081	0.397	0.140	0.121	0.231
# of industry-periods	1,661	1,661	1,661	1,661	1,661	1,661	1,661
Panel B. Regional balance, part I							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Population 1990	Inc. growth 1980-2000	Inc. growth 1990-2000	College share 1990	Foreign-born share 1990	Routine job share 1990	Offshorable job share 1990
$\Delta \ln(\text{Offshoring Exposure})$	9.531 (10.877)	0.001 (0.001)	-0.001 (0.001)	0.232* (0.102)	0.156* (0.077)	0.026 (0.019)	-0.009 (0.005)
R^2	0.001	0.000	0.009	0.004	0.002	0.001	0.002
# of region-periods	33,825	33,825	33,825	33,825	33,825	33,825	33,825
Panel C. Regional balance, part II							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Black share 1990	Hispanic share 1990	Female emp. share 1990	Mfg. emp. growth 1970s	Mfg. emp. growth 1980s	China import pen. 1990-2000	China import pen. 1980-1990
$\Delta \ln(\text{Offshoring Exposure})$	0.007 (0.034)	0.089 (0.071)	0.067 (0.048)	-0.001 (0.011)	-0.013 (0.014)	-0.006 (0.004)	-0.007 (0.004)
R^2	0.003	0.000	0.001	0.003	0.004	0.001	0.002
# of region-periods	33,825	33,825	33,825	33,825	33,825	33,825	33,825

Notes: .01 - ***; .05 - **; .1 - *; Standard errors clustered by NAICS are reported in parentheses. All specifications include period fixed effects. Independent variables in both panels are normalized to have a variance of one in the sample. Regressions include the full set of controls described in Section 2

In contrast to the BHJ approach, Goldsmith-Pinkham et al. (2020), henceforth GSS, show how identification can be achieved assuming the exogeneity of the shares. They show that the standard shift share coefficient is actually a weighted sum of instrumental variables estimators that each use baseline employment shares in a given industry as the instrument. The weights, which they term Rotemberg weights, indicate which industries are contributing the most to the overall estimate. A potential concern is that a small number of industries may be driving the identification of the overall coefficient of interest.

To address this concern, Table D.3 presents the results of a pre-trend analysis for the top 15 industries with the largest weights in our sample. Reassuringly, there is no significant relationship between pre-sample period incumbent vote shares and baseline employment shares for the most important industries in our sample.

Table D.3: GSS Approach

Dependent Variable:	Share of industry emp in total county emp, 2000				
NAICS Industries:	4231	4821	448	711	483
	(1)	(2)	(3)	(4)	(5)
Δ Incumbent vote share (1990-2000)	-0.056 (0.572)	-0.089 (0.267)	0.444 (0.715)	-0.118 (0.234)	0.285 (0.400)
N	3,075	2,582	2,067	3,070	2,766
Adjusted R^2	0.101	0.550	0.434	0.177	0.066
NAICS Industries:	562	621	61	4238	4237
	(6)	(7)	(8)	(9)	(10)
Δ Incumbent vote share (1990-2000)	-0.043 (0.189)	-0.014 (0.081)	0.122 (1.021)	0.043 (0.088)	0.754 (0.505)
N	2,540	2,444	2,972	2,276	2,914
Adjusted R^2	0.356	0.123	0.236	0.522	0.315
NAICS Industries:	113	3122	4242	3366	4241
	(11)	(12)	(13)	(14)	(15)
Δ Incumbent vote share (1990-2000)	-0.003 (0.092)	-0.019 (0.174)	0.242 (0.256)	0.182 (0.562)	-0.156 (0.389)
N	1,726	2,736	1,948	2,079	3,034
Adjusted R^2	0.133	0.091	0.134	0.110	0.174

Notes: .01 - ***; .05 - **; .1 - *; Standard errors are in parentheses. Offshoring exposure only includes foreign employment in the top 50% of industries in terms of vertical offshoring intensity. Regressions include the full set of controls described in Section 2