Winners and Losers in International Trade: The Effects on U.S. Presidential Voting[*]

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Abstract This paper demonstrates that international trade directly influences U.S. presidential elections. In contrast to prior studies, we explore the electoral implications of the increasing tradability of services and the large U.S. surplus in services trade. Our paper builds on prior work showing that job insecurity from import competition in manufacturing diminishes such support. We construct novel measures of the tradability of an industry using establishment-level data covering nearly all U.S. economic activity. We find increases in incumbent party vote shares in counties with concentrations of employment in high-skilled tradable services as well as goods, and decreases in counties with concentrations of employment in low-skilled manufacturing. Incumbent parties are particularly vulnerable to losing votes in swing states with high concentrations of low-skilled manufacturing workers. In national-level models, we show for the first time that increasing imports (exports) are associated with decreasing (increasing) presidential incumbent vote shares. These effects are large and politically consequential. We find an Electoral College incentive to protect the manufacturing sector and to oppose trade agreements.

Do the economic effects of international trade influence who wins the U.S. presidency? The expansion of international trade has produced favorable employment conditions for firms producing high-skilled tradable goods (e.g. petrochemical manufacturing) and services (e.g. software) because the United States has a comparative advantage in these activities. Likewise, trade has led to increased competition and unfavorable employment conditions for firms producing low-skilled goods (e.g. apparel). Building on research demonstrating that economic conditions explain support for incumbent presidents and their parties,[1] we expect citizens to cast their votes for president in part based upon their employment exposure – either favorable or unfavorable – to trade. Employees in high-wage tradable goods and services sectors are more likely to support incumbent presidents and their parties, whereas those in low-wage manufacturing jobs will be more likely to support the opposition. Examining county-level election results from 1992 to 2012 and national-level results beginning in 1936, we find strong support for our argument: voters' exposure to trade influences who wins the U.S. presidency.

Our primary contribution is to examine both the favorable and unfavorable effects of trade exposure on U.S. presidential elections. To do so, we develop comprehensive measures of trade exposure in goods *and services* using census data covering nearly all economic activity in the United States. Including trade-exposed service workers in the analysis is important for three reasons. First, the manufacturing sector's share of employment has been in secular decline for decades; the manufacturing sector now accounts for less than 10 percent of the labor force. Second, trade in services is increasing, and now accounts for 30 percent of U.S. exports. Casual observation and recent studies suggest that trade in services significantly increases the trade

[1] Fair 1978, Tufte 1978, Lewis-Beck and Tien 2008, Wright 2012, Margalit 2011.

exposure of the U.S. economy.[2] Third, tradable services have qualitatively different factor demands: they are significantly more skill intensive than either the manufacturing sector or non-tradable services.[3] The United States remains a relatively skill-abundant country, suggesting that it should have a comparative advantage in skill-intensive industries; the persistent and growing trade surplus in services demonstrates its comparative advantage in this sector.

Including tradable service workers enables us to identify those who are likely to gain from increased trade, and to determine the impact on trade-exposed manufacturing workers who are likely to lose from increased international competition.[4] We are thus able to determine the types of firms, industries and locations that benefit – or are displaced by – increased economic integration. We estimate how county-level variation in employment in firms in comparatively advantaged and disadvantaged sectors affects voting in U.S. presidential elections. County-level data also allow us to aggregate results by states. We compare the estimated results in swing states (in which the outcomes of U.S. presidential elections are generally determined) to those of non-swing states.

Our main results are as follows. We find that concentrations of workers in high-skilled exportable services and high-skilled exportable manufacturing are associated with increasing incumbent party vote shares. To our knowledge, we are the first to demonstrate that increasing

[2] See Jensen 2011 and Gervais and Jensen 2013.

[3] See Jensen 2011 and Gervais and Jensen 2013.

[4] See Bernard, Jensen and Schott 2006 and Autor, Dorn and Hanson 2013 for research documenting the impact of increased import competition on U.S. manufacturing industries. See Che et al. 2016 and Autor et al. 2016 for research on how Chinese imports affect U.S. voting in legislative elections.

employment in high-skilled industries affects voting. We confirm Margalit's[5] finding that manufacturing losses harm incumbent vote shares over an extended period (1996–2012).[6] Examining the crucial swing states, we find that the negative effect of comparatively disadvantaged manufacturing employment on incumbent vote shares is approximately three times as large as in non-swing states, which leads to a powerful Electoral College incentive to protect this sector. We also study, to our knowledge for the first time, the effects of trade in established U.S. national-level election models from the American politics literature. Our results indicate that voters punish (reward) the incumbent party against a backdrop of rising imports (exports).

This paper contributes most directly to a nascent literature on the effects of trade on voting. Building on recent research demonstrating that the employment dislocations and wage adjustments from trade are larger and more long-lasting than previously thought,[7] the work has focused on the effects of increasing import competition on citizen voting preferences.[8] This work, detailed below, finds that import shocks have a substantial effect on voting in congressional and presidential elections. With the exception of Margalit, the existing research focuses exclusively on the electoral effects of manufacturing import competition from China.

In contrast, our paper examines how the tradability of industry output creates the potential for voting to reflect the divergent distributional effects among losers *and winners* in international trade. By focusing on trade's varied distributional consequences, we contribute

[5] Margalit 2011.

[6] Margalit 2011 examines the 2000 and 2004 elections.

[7] Autor, Dorn, and Hanson 2013.

[8] Margalit 2011; Feigenbaum and Hall 2016; Autor, Dorn, Hanson and Majlesi 2016, Che, Lu, Pierce, Schott, and Tao 2016.

more broadly to a large literature examining how firms' and individuals' exposure to the global economy affects support for trade. Prior work demonstrates that firms' demands for trade protection (or liberalization) depend on their international integration through global supply chains and trade patterns,[9] or as a result of industry characteristics such as the degree of exchange rate pass-through to prices[10] or global sourcing.[11] Evidence from survey data finds that the globalization of production increases wage and employment volatility, leading workers to feel economically insecure.[12] Less is known about whether exposure to these factors affects voter support for incumbent presidents.

Our paper also relates to studies examining how the subnational distribution of economic activity in comparatively advantaged and disadvantaged sectors influences trade policymaking. Following Rogowski, who argues that political divisions over trade reflect factor-based distributional concerns,[13] a number of studies link the expected winners and losers of global trade and financial flows to U.S. international economic policymaking in Congress. Hiscox finds that legislator support for trade between 1824 and 1994 reflects the expected gains and losses experienced by class- and industrial-based constituencies.[14] Other studies examine how industry structure at the district level, which proxies for concentrations of voters with similar economic interests, influences legislator voting on trade and other international economic policymaking

[9] See, for example, Milner 1988; Jensen, Quinn, and Weymouth 2015; Blanchard and Matschke 2015.

[10] Broz and Werfel 2014.

[11] Chase 2003; Manger 2009.

[12] Scheve and Slaughter 2004; Walter 2010.

[13] Rogowski 1987, 1990.

[14] Hiscox 2002. See also Baldwin and Magee 2000 and Fordham and McKeown 2003.

issues.[15] Districts with concentrations of high-skilled voters are associated with greater legislator support for trade.[16] Representatives from districts affected by import competition from China[17] and those representing higher concentrations of offshorable employment[18] vote in a more protectionist manner. If trade has the distributional consequences implied by these studies and developed in the ensuing section, voters who are harmed by (benefit from) trade will be more likely to shift away from (toward) the incumbent or the incumbent's party.

U.S. Trade Integration and Presidential Voting

We draw on a long tradition in the American politics literature investigating how economic conditions affect voting. These established national-level (macro) studies show that voters are more likely to reward incumbent presidents and their parties during good economic times, and to reward the opposition when economic conditions deteriorate.[19] Starting with the Fair and Tufte

[15] An important assumption of this work is that the distributional consequences of policy reflect local-level economic characteristics.

[16] Milner and Tingley 2011. Conconi, Faccini, and Zanardi 2012 demonstrate that congressional support for trade promotion authority reflects how export oriented the constituency is compared to the country as a whole. Rickard 2015 demonstrates the linkage between export success in a Congressional House member's district and his or her likelihood to support TAA.

[17] Feigenbaum and Hall 2015

[18] Owen 2015.

[19] Initial works in the area include Fair 1978 and Tufte 1978. Other contributions include the papers in a 2008 special issue of the *Journal of International Forecasting* Campbell and Lewis-Beck 2008. See also Fair 2009, Erikson 2009, Lewis-Beck and Stegmaier 2000, and Lewis-Beck and Nadeu 2011. Lewis-Beck and Tien 2008

models, scholars have empirically demonstrated that positive economic performance strongly improves either incumbent or incumbent party re-election prospects.[20]

The macro voting models are necessarily parsimonious, however, because of the few degrees of freedom involved in the data, and have yet to include trade variables explicitly.[21] Invariably, macro models assume that certain aspects of economic performance are the key determinants of incumbent vote shares: economic growth,[22] disposable income, employment, job growth[23] and business sentiment[24] are contending variables. Quinn and Woolley show that economic volatility drives down vote shares for incumbent candidates and parties in a comparative, cross-national setting.[25] Given the few degrees of freedom and the many competing plausible correlates of incumbent vote shares, it is not surprising that trade variables have so far been omitted in general from the discussion.

While the macro studies have neglected the direct impact of trade on voting outcomes, as noted above, several recent studies examining subnational election results have found trade's

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provide a comprehensive review of the literature. See also the April 2014 special issue of *PS*, "US Presidential Election Forecasting."

[20] Fair 1978 and Tufte 1978. See the reviews in Campbell 2008, Kayser and Leininger 2015, and Lewis-Beck and Tien 2008.

[21] Most studies date from either 1948 or 1952, owing to changes in the U.S. economy after the Second World War. Fair 2009, discussed below, is an exception.

[22] Fair 2009.

[23] Lewis-Beck and Tien 2008.

[24] Erikson 2009.

[25] Quinn and Woolley 2001. For a contending view on the effects of economic volatility, see Hibbs 2000, who suggests that volatility is not relevant in the U.S. setting at the macro level.

distributional effects influence how people vote. Examining county-level election results, Margalit demonstrates that job loss from import competition – measured as applications for Trade Adjustment Assistance (TAA) – had a negative aggregate effect on the incumbent vote share in the 2004 election.[26] Studying the specific effects of economic shocks from Chinese import competition, Feigenbaum and Hall find that legislators from exposed districts vote in a more protectionist manner,[27] while Autor et al. find increased polarization in U.S. congressional districts.[28] Che et al. show that congressional districts that face more competition from China are more likely to elect Democrats, and that Democrats are more likely to oppose free trade legislation.[29] These studies are persuasive in demonstrating that foreign competition affects electoral and other outcomes, although trade exposure in low-skilled manufacturing is unlikely to be the only channel through which international integration influences voting behavior.

We propose two modifications to the existing literature. We argue and demonstrate using newly available measures of trade exposure in services that the trade's likely winners – workers employed in tradable, high-skilled industries – are more likely to vote for incumbents and their parties. That is, we explore the electoral consequences of the gains, as well as the losses, from trade. We also extend the macro voting models to include trade indicators, including changes in imports and exports. Next, we develop a conceptual framework to guide our analysis.

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[26] Margalit (2011, 175). Antoniades and Calomiris (2014) study county-level presidential voting and find that constrained credit conditions hurt incumbent vote shares.

[27] Feigenbaum and Hall 2015.

[28] Autor et al. 2016. They demonstrate that districts that experienced a larger import shock were more likely to remove moderate incumbents (that is, to replace a moderate Republican with a more conservative Republican or a moderate Democrat with a more liberal Democrat).

[29] Che et al. 2016.

The Possible Effects of Trade Integration on U.S. Presidential Voting

We hypothesize that service sector trade exposure is also likely to influence voting behavior in U.S. elections. Our hypothesis is based on three main facts.

First, the service sector is large, accounting for at least half and, depending on how it is defined, upwards of 80 percent of the U.S. labor force.[30] (In contrast, the manufacturing sector is a relatively small share of the labor force – accounting for less than 10 percent in 2012.) Figure 1 shows the changing levels of employment in two broad categories of employment that are largely tradable – manufacturing (NAICS 31–33) and business and professional services (BPS, NAICS 54–56). The figure indicates that employment in BPS has nearly doubled since 1990, whereas manufacturing employment has contracted by nearly a third.[31] If even some relatively small portion of the service sector is trade exposed, increased international integration potentially affects a larger number of service jobs than manufacturing jobs.

Second, while services were traditionally considered to be largely non-tradable, the 'tradability' of the service sector has increased markedly with technological changes and

[30] U.S. Census Bureau, 2012 Economic Census, USDA Agricultural Census, and Census of Governments. If we define services as business services NAICS industries in the 1950s plus personal services NAICS industries in the 1960s, 1970s, and 1980s – but exclude retail and wholesale trade and government – the service sector accounts for about 50 percent of the labor force. If retail and wholesale trade; transportation, warehousing, and utilities; and government are included in the service sector, it would account for more than 80 percent of the labor force.

[31] We distinguish below between and among types of tradable and non-tradable services and manufacturing goods.

financial current account liberalizations. Services accounted for 33 percent of the value of U.S. exports in the first quarter of 2016.[32]

Third, tradable services are more skill-intensive than both non-tradable services and the manufacturing sector. Jensen and Kletzer, Jensen, and Gervais and Jensen report that tradable services are significantly more skill-intensive (as measured by educational attainment or average earnings) than service industries classified as non-tradable and the manufacturing sector.[33] Because tradable services differ in their intensity of use of high skilled labor relative to other sectors, they are likely to face different levels of competition and different levels of opportunity from increased international integration. Heckscher-Ohlin trade theory suggests that regions with an abundant factor will have a comparative advantage in industries that make intensive use of that factor. The United States is still skill-abundant vis-à-vis the rest of the world – suggesting that it should have comparative advantage in skill-intensive activities like tradable services. The United States' persistent and growing trade *surplus* in services is corroborating evidence that it indeed has a comparative advantage in services (in stark contrast to its large and persistent trade deficit in goods).

Because the United States is a relatively high-skill-abundant country, it has a comparative advantage in high-skilled activities and a comparative disadvantage in low-skilled activities. Jensen argues that tradable business service activities are consistent with U.S. comparative advantage, and that therefore, firms and workers in high-skilled tradable service activities will

[32] Bureau of Economic Analysis BEA. For example, through the 1950s, U.S. services exports were less than 1 percent of U.S. GDP, and roughly 15 percent of the total value of U.S. exports. In the 2010s, U.S. services exports are 4–5 percent of GDP. Authors' calculations from BEA data.

[33] Jensen and Kletzer 2005, Jensen 2011, and Gervais and Jensen 2013.

benefit from the increased tradability of services.[34] By contrast, firms in low-skill, labor-intensive tradable manufacturing industries tend to face greater import competition, particularly as trade agreements have brought previously trade-isolated countries, especially China, into the global economy.[35] The differential effects of trade exposure on workers in these two tradable sectors suggest that their voting behaviors will differ.

The differences in the effects of trade exposure are compounded by differences in wage premia across sectors. Previous empirical literature strongly suggests that workers with similar skills receive higher wages in the manufacturing sector than in the service sector.[36] Because that premium is significantly reduced if the worker leaves the sector, workers in the manufacturing sector suffer greater harm when being displaced from their job compared to workers in the service sector.

Tradable Services

If employment in tradable services is higher than in the manufacturing sector, and if the workers employed in tradable services are qualitatively different than those in the manufacturing sector,

[34] Jensen 2011.

[35] Bernard, Jensen and Schott 2006 document these patterns. One study finds that import competition resulting from China's integration into the world trade system explains a quarter of the decline in U.S. manufacturing employment since 1990 Autor, Dorn and Hanson 2013.

[36] See, for example, Krueger and Summers 1988. In 2009, the wage premium in tradable manufacturing for those industries in which fewer than 20% of employees had college degrees (compared to services industries with similar employee educational attainment levels) was $9,136. (The average wages, given the 20% educational attainment cutoff, in the sectors were $39,906 and $30,770, respectively.) Authors' calculations from Census Data.

then tradable service workers may influence elections differently than manufacturing workers do. To empirically investigate this possibility, we need to identify employment in tradable services.

While we would ideally use statistics on international trade in service flows to identify tradable and traded services (as can be done for trade in manufacturing), the U.S. trade-in-services data, which are collected by the U.S. Bureau of Economic Analysis (BEA), are inadequate for our purposes. An important shortcoming of the BEA trade-in-services data is that, in contrast with merchandise trade statistics that are produced for 10,000 manufacturing product categories – allowing detailed identification of the trade exposure of individual manufacturing industries – service trade data are only available for about 30 categories (beginning in 2006). Prior to that year, fewer than 20 categories are available for trade in services. The highly aggregated categories of services trade are therefore certainly combining tradable and non-tradable industries into the same category, making identification of exposed industries difficult.[37] Another shortcoming is that the BEA data are believed to understate the size of trade in services because official BEA trade statistics are potentially missing a significant share of service trade. Because services do not pass through ports (as merchandise does), the data collection system for international trade-in-services statistics relies on surveys instead of Customs forms. Relatively small budgets for service trade data collection and relatively high reporting thresholds (BEA requires firms to report service transactions greater than $6 million; in contrast, the reporting threshold in manufacturing is $2,500) suggest that the services trade is not well measured.[38]

[37] See Gervais and Jensen 2013 for evidence on the heterogeneity in tradability across industries within service sectors.

[38] See Jensen 2011 and Sturgeon et al. 2006 for more details.

Given these data limitations for trade in services, we instead identify variation in tradability among disaggregated industries within the manufacturing and services sectors by adapting the methodology developed in Jensen and Kletzer[39], who classify industry tradability according to the geographic concentration of the six-digit NAICS industry in the United States.[40] They make the assumption that when production exceeds local demand, the excess supply must be consumed elsewhere – that is, exported to another region.[41] For example, grocery stores are distributed throughout the United States in proportion to population. For grocery stores, trade costs are high, so local demand is served by local production: low concentration implies low tradability. In contrast, software production is highly concentrated in Silicon Valley and Seattle. In software, trade costs are low, so production is concentrated in a few regions and shipped around the country (and around the world). This intuition can be applied to goods as well as services, and allows us to construct consistent measures for the whole economy.

In particular, we use the Gini coefficient of the geographic concentration of production above what would be predicted by local demand to identify tradable industries.[42] Since we have a good understanding of the tradability of manufactured goods, we use the manufacturing sector as the basis for setting the cutoff for the geographic concentration Gini that signifies tradability. We define the tradability cutoff as the Gini coefficient that classifies 90 percent of manufacturing

[39] Jensen and Kletzer 2006.

[40] NAICS is the North American Industrial Classification System used by U.S., Canadian, and Mexican government agencies to classify products produced by establishments.

[41] Ibid.

[42] We classify the manufacturing and service industries as being tradable according to this definition using data from the 1992 Economic Census. For a more formal development of the intuition, see Gervais and Jensen 2013.

sector employment being tradable.[43] We use the same Gini coefficient as the tradability cutoff for the service sector. If the Gini coefficient for a service industry is above the threshold that results in 90 percent of manufacturing sector employment being classified as tradable, that industry is classified as tradable.

We note here that we adopt the definition of services trade defined by balance-of-payments accounting conventions and the World Trade Organization's General Agreement on Trade in Services (GATS).[44] These include cross-border exports ("Mode 1"), services consumption abroad ("Mode 2"), a commercial presence abroad ("Mode 3) and foreign services contractors abroad ("Mode 4"). Our measure of tradability, which is based on the geographic concentration of production in the United States, captures the employment impact of Modes 1, 2 and 4. [45]

Tradability under GATS differs from the concept of offshorability, which relates to the ability to perform work from abroad. Not all tradable services and not all tradable manufacturing jobs are offshorable.[46] For instance, tradable service industries include U.S.-based tourism-

[43] See Jensen 2011 for further discussion of choosing a tradability cutoff.

[44] See https://www.wto.org/english/tratop_e/serv_e/cbt_course_e/c1s3p1_e.htm#boxa.

[45] Mode 3 service exports are those that require "face to face" interactions to undertake commercial activity and which therefore require a commercial presence abroad. For example, Walmart, in order to do sell products in India, needs to establish a commercial presence in India. We deem it unlikely that Walmart (or other service firm) workers in the U.S. will be concerned about the impact of service firms' Mode 3 investments in other countries. Our methodology does not include Mode 3 type services in tradable services.

[46] There are two notions of offshorability. The first is related to moving particular tasks in the production process (typically back-office service activities) overseas. (The second is described in the footnote below.) Measures of the first type of offshorability are typically constructed using occupation characteristics from the O*Net database, a

related industries. (For example, Disney World is an exporter of amusement park services under the Balance of Payments Manual classification when non-residents "consume" a U.S. service.) Moreover, most manufacturing jobs require workers to be physically present in an establishment to complete a job, implying tradability of the product, but not offshorability of the manufacturing job. [47]

Table 1 provides examples of industries that we classify as tradable and non-tradable, high skilled and low skilled, manufacturing and services. The results are intuitively appealing. The manufacturing industries classified as tradable are well-known examples of manufacturing industries that are geographically concentrated and traded. Those classified as non-tradable – corrugated boxes, cement and quick printing – all have high transport cost-to-value ratios. In these industries, production is distributed throughout the United States, and international trade shares are low.

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catalog of occupational titles and job descriptions. See, for example, Crino 2010, Jensen and Kletzer 2010, Oldenski 2014, and Owen and Johnson 2015. This conception of offshorability has important political implications. See Owen 2015 and Walter 2016. An important limitation of the implementation of offshorability measures for this study is that most manufacturing production jobs require the worker to be physically present to complete a task. Thus, in this methodology, manufacturing industries often end up being classified as non-tradable because they are non-offshorable, against all reasonable evidence. Most manufacturing is clearly contestable by imports. See Jensen and Kletzer 2006, 2010 for a discussion.

[47] The second conception of offshorability – different from the task-based conception – is, for example, embedded in the TAA legislation, in which a company relocates a plant abroad for comparative advantage reasons, and the workers are therefore eligible for TAA owing to their jobs being offshored. Our measure of trade contestability picks up the risks of such relocations.

The service industries are also intuitively appealing. Computer system design services, investment banking and software publishing are all highly tradable and geographically concentrated in the United States. The same is true for credit card issuing, amusement parks, and limousine services. The latter two are tourism-related industries that are geographically concentrated; they are examples of Mode 2 trade, serving customers from all over the world. The non-tradable service industries make sense as well. Restaurants, dentist offices and grocery stores all have high trade costs relative to value. Production in these industries is distributed throughout the country.

In addition to tradability, we also expect that skill intensity is an important dimension for trade exposure. High-skilled intensive activities are consistent with U.S. comparative advantage, and thus the United States should specialize in these activities (that is, these industries should grow relative to others) in the face of trade liberalization. In contrast, low-skilled intensive industries are not consistent with U.S. comparative advantage and should shrink in response to trade liberalization.[48] We use average wages at the establishment (described in more detail in the empirical methodology section) to identify workers in high- and low-skill firms.

Thus, we distinguish between and among: goods and services that are tradable vs. non-tradable (that is, internationally contestable or not), high- vs. low-skilled work (consistent with U.S. comparative advantage) and manufacturing vs. services industries (owing to inter-industry wage differentials). Given these distinctions, we propose that:

[48] For example, Bernard, Jensen and Schott 2006 find significant variation in manufacturing firm survival probabilities and employment growth across and within industries that is consistent with import competition affecting low-wage manufacturing industries and firms more than capital-intensive firms and industries. Autor, Dorn and Hanson 2013 exploit this variation across manufacturing industries to identify the impact of China's rise.

- Low-skilled tradable manufacturing workers are experiencing deep economic losses due to international trade competition, because their products are tradable and intensively use factors in which the United States lacks a comparative advantage. Moreover, low-skilled manufacturing workers receive a relatively large inter-industry wage differential compared to their peers in service sector work. Employees in low-skilled tradable manufacturing firms are likely to vote against incumbents.
- High-skilled tradable service workers are gaining from increased globalization because of the United States' comparative advantage in high-skilled activities, which is consistent with U.S. factor abundance in educational attainment. These employees are likely to vote for incumbents.
- High-skilled workers in manufacturing have a wage premium (owing to inter-industry wage differentials) that contributes to the sector's potential import vulnerability, as employee wages are "higher" than skills require. However, the United States has factor abundance in skilled workers, which some U.S. manufacturing firms use intensively. We expect, on average, support for incumbents from employees in high-skilled manufacturing.

We have ambiguous expectations regarding how trade exposure affects voting among workers in low-skilled tradable services. The risks that these workers will be displaced are lower than for their manufacturing low-skilled counterparts, because their alternative employers pay similarly (that is, services have lower inter-industry wage differentials).

We use employment concentrations of *non-tradable* manufacturing and services workers in a county as base cases for comparing the effects of trade integration to those of technological innovation. We know that the non-tradable manufacturing and service sectors have both experienced productivity improvements from technological changes, but because these sectors

are shielded from global competition, productivity gains (and job losses) have been limited.[49] We do not expect employment in non-tradable industries to influence presidential voting.

Our argument does not require employees of companies to understand the broad distributional effects of trade. Indeed, the overwhelming evidence is that most citizens have only a modest understanding of the effects of trade.[50] Rather, we expect that employees will understand their employers' economic circumstances. Employees in firms producing in comparatively disadvantaged tradable sectors likely recognize that their jobs are contestable and are thus vulnerable to increased trade competition. Trade is likely to affect workers before the effects of either imports or exports are reflected in the unemployment rate. Even before import-competing firms cut jobs, workers can anticipate the effects of reduced production orders (for example, shorter hours, reduced wages and eventual layoffs). Employees of firms in the import-competing sector might retain their jobs or find new ones, but the terms of employment are likely to worsen in quality. In contrast, employees of firms in industries in which the United States has a comparative advantage are more likely to experience the benefits of U.S. trade integration. These heterogeneous distributional consequences imply that subnational voting for incumbent parties will reflect concentrations of employment activity in winning and losing firms.

Empirical Implications

[49] Mano and Castillo 2015. Distinguishing between the effects of technological innovation and globalization on changes in wages and employment is difficult because, as Adam Smith observed centuries ago, increasing the size of the market spurs innovation, and vice versa.

[50] Gussinger 2009, Rho and Tomz forthcoming.

Here we summarize the empirical implications of our conceptual framework that we will examine using county- or national-level data.

At the county level, we expect:

H1. The concentration of employment in high-skilled tradable services and manufacturing will be associated with increasing support for the incumbent.

H2. A concentration of employment in low-skilled tradable manufacturing will be associated with decreasing support for the incumbent.

H3. There will be no statistically meaningful association between the concentration of employment in non-tradable industries and support for the incumbent.

At the national level, we expect:

H4. Imports (exports) will be associated with decreased (increased) support for the incumbent. The correlations will be larger in the manufacturing sector.

Voters' Trade Exposure and Presidential Voting at the County Level

We first examine the determinants of incumbent party vote share at the county level. The baseline ordinary least squares (OLS), year- and county-fixed effects model is:

$$\Delta \text{Incumbent 2-Party Vote Share}_{i,t} = ß_0 + ß_1 (\text{Unemployment Rate}_{i,t}) + ß_2 (\Delta \text{ Unemployment (1-year}_{i,t})) + ß_3 (\text{Unemployment Volatility}_{i,t}) + ß_4(\text{LnAveragePay}_{i,t}) + ß_5 (\Delta \text{ Average Pay (1-year)}_{i,t} + ß_6(\text{High-Wage Tradable Manufacturing Employment}_{i,t}) + ß_7(\text{Low-Wage Tradable Manufacturing Employment}_{i,t}) + ß_8(\text{High-Wage Tradable Services Employment}_{i,t}) + ß_9(\text{Low-Wage Tradable Services Employment}_{i,t}) + \varphi_i + \tau_t + \varepsilon_{i,t}$$

$$t=1992, 1996, 2000, 2004, 2008, 2012 \quad (1)$$

The dependent variable, $\Delta Incumbent\ 2\text{-}Party\ Vote\ Share_{i,t}$, is the change in incumbent party vote as a share of the total Democratic and Republican votes in county *i* in year *t*. The models begin in 1992 because the key census coverage of all services industries begins in that year. We include county φ_i and election year τ_t dummies.[51]

Trade Exposure in Services and Manufacturing

We generate a number of different measures of voters' exposure to trade. Our goal is to examine the international exposure of the entire local economy – not merely to assume, for example, that all manufacturing industries are trade exposed. For this task, we need to classify workers according to their skill and the tradability of the goods or services produced by their employer.

Our measures of economic contestability capture employment in high- and low-wage tradable services and manufacturing. To capture county-level variation in trade exposure within sectors, we rely on confidential, establishment-level data from the Census Bureau's Longitudinal Business Database (LBD), which contains information on plants and other establishments in the Census Bureau's County Business Patterns (CBP) program.[52] The CBP program covers most of

[51] A Hausman test of random vs. fixed effects rejects the random-effects model: an χ^2 test produces a typical value of over 500. An alternative to year fixed effects is to enter an indicator for the number of continuous successive terms of a presidential party *Duration*. The post-estimation properties of county models with *Duration* are very poor at the county level, however. An alternative to county fixed effects is to include prior incumbent vote share as a regressor $Incumbent\ 2\text{-}Party\ Vote\ Share_{it\text{-}1}$, as in Fair 2009 and Powell and Whitten 1993. Diagnostic statistics for the county-level regressions suggest that the fixed-effects model is preferred. In contrast, at the macro level the lagged vote share is entered, which improves the diagnostic statistics.

[52] See Jarmin and Miranda 2002.

the country's private sector economic activity.[53] The data allow us to measure the number of employees who are: (1) engaged in tradable activities and producing goods and services for which the United States has a comparative advantage (for example, high skilled, capital intensive) and (2) in positions vulnerable to import competition, such as low-skilled manufacturing.[54] We categorize establishments based on the sector and the tradability of the industry to construct measures of the number of jobs in a county that is potentially exposed to international trade.

We classify employment in establishments as high or low skilled using the median national household income in the relevant year as the threshold for "high wage."[55] Workers are classified as high wage and high skill if their place of employment has average wages above the national median household income. Using these data, we are further able to distinguish between employment in high-wage, highly traded industries and employment in non-traded industries. We sum across establishments to capture the number of workers in each county that is in each of

[53] The major exclusions are self-employed individuals, employees of private households, railroad employees, agricultural production employees and most government employees.

[54] We use "tradability" as defined in Jensen and Kletzer 2006 and conceptualize tradable activities as those that are internationally "contestable" as described in Leamer 2007. See below for a more detailed discussion.

[55] Appendix Figure A1 demonstrates the relatively strong correlation between wages and education in both the manufacturing and tradable services sectors. Nontradable service sector jobs exhibit a much lower correlation between wages and education than either of the other sectors.

the following bins: high-wage tradable services, high-wage tradable manufacturing, low-wage tradable services, low-wage tradable manufacturing.[56]

We also construct measures of the number of workers in the manufacturing sector, the number of workers at manufacturing establishments that export (derived from establishment-level responses to the Census of Manufacturers question about whether the establishment has direct exports), and the number of workers at establishments that export with high and low wages. We aggregate establishment-level employment for each category to the county level.

We also construct measures of the number of workers in non-tradable services and manufacturing goods, distinguishing between high- and low-skilled employment. We do so to distinguish the potential effects of job losses or gains from technological innovation vs. from trade. The indicators are entered as control variables.

Our estimates control for economic conditions using county-level data on unemployment and wages. The variable *Unemployment Volatility* is the standard deviation of the unemployment rate in county *i* over the three years prior to the election year and the election year.[57] The income data are from the Quarterly Census of Employment and Wages, conducted by the Bureau of Labor Statistics (BLS). We also enter change in unemployment from the year prior to the election and change in average income.

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[56] An alternative to counties is commuting zone CZ or labor market LM data from either the Department of Agriculture or the Census Bureau, respectively. We rely on county-level analysis because voting data per se are not collected for either CZs or LMs.

[57] For example, in 1996, *Employment Volatility* is the standard deviation of the unemployment rate in county *i* for the years 1993, 1994, 1995 and 1996. The unemployment data are from the BLS.

Following Margalit, some of our models control for aggregate job losses due to globalization – the lagged sum of the estimated number of workers filing for TAA as a share of the labor force.[58] Following Wright, some of our models include a Democratic incumbent indicator interacted with either unemployment levels or changes in unemployment (for example, *Democratic Incumbent x ΔUnemployment (1-year)*$_{i,t}$).[59]

The analysis with census microdata includes 3,105 U.S. counties for which complete economic and voting data are available for our period of study (1992–2012). Consistent with Margalit (2011) and Wright (2012), we exclude Alaska because the voting data are reported in districts that cannot be mapped to specific counties.

County-level Election Results

The results using the census microdata measures are presented in Table 2. Column 1 examines the relationship between the levels of employment at manufacturing establishments that export and incumbent party presidential vote shares. We find a negative relationship between employment in low-skilled manufacturing firms that export and incumbent vote shares. This result is consistent with prior findings in Feigenbaum and Hall, and Margalit, in which exposure to competition from low-wage imports influences either Congressional roll-call votes or incumbent president vote shares, respectively.[60] However, since this measure is unavailable for a

[58] Margalit 2011. The TAA data come from Public Citizen. Available at http://www.citizen.org/Page.aspx?pid=4536 accessed March 2, 2015.

[59] Wright 2012.

[60] Feigenbaum and Hall 2015, Margalit 2011.

wide range of export industries, especially in services (as noted above), the rest of our estimates rely on our measures of trade-exposed employment.

We find that exposure to trade strongly influences presidential voting. The results in Column 2 use our preferred indicators of tradability in services and manufacturing. They indicate that employment in low-skill tradable manufacturing industries is associated with lower incumbent vote shares. In contrast, employment in high-wage tradable services and high-wage tradable manufacturing is associated with higher incumbent vote shares. Both estimated coefficients are statistically significant.

The results are politically meaningful. Substantively, a one-standard-deviation increase in (the log of) high-wage tradable manufacturing employment is associated with a 0.5 percent increase in incumbent vote share. The estimates indicate substantively larger effects for low-wage manufacturing, where a one-standard-deviation change is associated with a decrease of 1.3 percent. For high- and low-wage tradable services, a one-standard-deviation change increases incumbent vote share by 1.3 percent and 1.5 percent, respectively.

In results not reported to save space, we add four indicators of non-tradable high- and low-skilled goods and services to Model 1.2.[61] The coefficient estimates for the non-tradable sectors are not statistically significant in this (or other) models, and the estimated effects of the indicators for the tradeable sectors retain the general size, sign and level of statistical significance.

[61] Formally, these indicators are $ß_{10}$*High-Skill Non-Tradable Manufacturing Employment* $_{i,t}$ + $ß_{11}$*Low-Skill Non-Tradable Manufacturing Employment*$_{i,t}$ + $ß_{12}$*High-Skill Non-Tradable Services Employment*$_{i,t}$ + $ß_{13}$*Low-Skill Non-Tradable Services Employment*$_{i,t}$. Details are available upon request.

Column 3 reports the regression results without population weights. Compared to the baseline (weighted) results, the unweighted results are qualitatively similar for our main variables of interest, with the exception of high-skill tradable manufacturing employment, which is no longer statistically significant. However, the number of workers in tradable low-wage manufacturing is negatively associated with incumbent vote shares, and the number of workers in tradable services (both high and low wage) is associated with increasing incumbent vote shares.

Column 4 reports the results for swing states, which display a few notable differences from the baseline results. The coefficient estimate for low-wage tradable manufacturing employment is larger than the baseline (approximately double) and statistically significant. High-wage tradable manufacturing and service employment are not statistically significant in the swing states subsample.

Column 5 reports the results for non-swing states. The coefficient estimate for tradable, low-wage manufacturing employment is about a third of the size in non-swing states compared to swing states. In addition, the tradable, high-wage manufacturing and service employment measures are positively and statistically significantly associated with incumbent vote share.

Column 6 reports the baseline specification plus county-level demographic controls for the full sample of counties. The baseline coefficient estimates are quantitatively very similar to the baseline specifications.

We provide the results of a number of robustness tests designed to subject our analysis to prior findings. To save space, these model estimates appear in Appendix B. Table B1 demonstrates that TAA is negatively associated with incumbent votes shares, a result that

confirms Margalit's finding from the 2004 presidential election.[62] Our measures of exposure to trade retain statistical significance to the inclusion of TAA, with the exception of low-wage tradable manufacturing. This is not surprising, given that TAA is largely designed to address dislocations in that sector.

To examine partisan effects established in the literature, in Table B2, following Wright, we account for the established argument that unemployment is a partisan issue by including a *Democratic Incumbent* indicator variable interacted with unemployment (both in levels and changes).[63] The results strongly support Wright's argument that higher unemployment is associated with increasing vote shares for Democrats. Including this interaction term (and its constitutive terms) does not affect our main results.

Our results from the county-level analysis can be summarized as follows. Employment volatility and unemployment vary substantially across the United States, and we find strong evidence that both outcomes significantly reduce support for the incumbent. Counties with more workers in trade-exposed industries that are inconsistent with U.S. comparative advantage (that is, tradable low-wage manufacturing) are less likely to vote for the incumbent. Counties with more workers in tradable, high-wage manufacturing and tradable services are more likely to vote for the incumbent. The larger coefficient estimate for tradable, low-wage manufacturing employment and the lack of statistical significance of high-wage manufacturing and high-wage services employment in swing states might explain the persistence of policy attention to the manufacturing sector in spite of its declining share of the labor force.

[62] Margalit 2011.

[63] Wright 2012.

Imports, Exports and National-level U.S. Presidential Voting

We now turn to examine the implications of our framework for national-level economic voting models from the American politics literature. Our theory predicts that trade should have an independent, direct effect – above and beyond trade's potential indirect effects on national economic performance per se – on voting in U.S. presidential elections. In this section, we examine this conjecture using national election data covering an extended period.

The standard approach in the national-level economic voting literature has been to estimate OLS time-series models of incumbent party presidential two-party vote shares with a necessarily parsimonious set of explanatory variables. While investigators differ in specifications, the most commonly used approach contains measure(s) of economic performance, voter sentiment, and either prior incumbent terms or vote share. We adapt these core models and methods from the literature to examine our argument at the macro (national) level.[64] We add changes to the U.S. trade balance as a variable of interest to national-level voting models. Our analysis indicates that trade contains information that is different from measures of growth and employment. Figure A2 displays the time series of the key dependent and independent trade variables.

Because the list of plausible measures of the explanatory variables of *Incumbent Vote Share*$_t$ exceeds the plausible degrees of freedom given at most 20 observations, there is a risk of omitted variable bias in the estimations. As noted above, prior incumbent vote share (*IncVoteShare* $_{t-1}$) is a plausible correlate of current vote share, and is entered to attenuate this

[64] We do not seek to identify a single "right" model of economic voting. Rather, we assume that each of the main scholarly models of economic voting has merit, but that much can be gained from examining the role of international trade and considering subnational variation in exposure to trade.

possible bias.[65] The timing of the variables is such that monthly data (when available) after the presidential elections in November are excluded. In most of our models, the investigation starts with the 1952 data.

Additional independent variables used in prior studies include retrospective indicators of economic performance: per capita real economic growth, changes in personal disposable income, job growth during a presidential term,[66] inflation during the 12 months prior to the election and changes in unemployment. Common variables for representing voter sentiment are perceived business confidence in quarter 15,[67] net candidate advantage[68] and presidential approval in the election-year July Gallup poll.[69] We also examine the valence vs. partisan effects of economic conditions, as suggested by Wright.[70] Abramowitz also incorporates how long a party has governed (*Duration*), which captures the "costs of governing."[71] As we do not take a stand on the "right" macro model, we present many variants of the models with these regressors.

The dependent variable is the post-war incumbent party's share of the two main party presidential votes (*Incumbent 2-Party Vote Share*$_t$) from 1952 to 2012. The sample is determined

[65] The absence of a cross-sectional dimension to the data precludes the use of unit fixed effects.

[66] Lewis-Beck and Tien 2004.

[67] Erikson 2009.

[68] Erikson 1989. Net candidate advantage is given by subtracting 'unfavorable' from 'favorable' in Gallup surveys.

[69] Abramowitz 2008, Lewis-Beck and Tien 2004.

[70] Wright 2012.

[71] Abramowitz 1988, 2008. Abramowitz's argument is that "the longer a party has been in power, the more likely the public is to feel that "it's time for a change."" (1988, 844). (Quotes in the original.)

by the availability of quarterly data on economic growth.[72] We also estimate a model, 1936–2012, using data from Fair.[73] The passage of the Reciprocal Trade Agreements Act (RTAA) of 1934 repealed the Smoot-Hawley Tariff, and is widely seen as marking the modern era of U.S. trade integration.[74]

In light of prior theory and statistical testing, our base time-series OLS macro model is:

$$\textit{Incumbent 2-Party Vote Share}_t = ß_0 + ß_1(\textit{Incumbent Vote Share}_{t-1}) + ß_2(\textit{Economic Growth}_{t-1}) + \varepsilon_t \; t=1952\text{-}2012 \qquad \textbf{(2)}$$

To this model will be added change in the trade indicators:

either $ß_3(\Delta \textit{TradeBal/GDP}_{t-1})$ or $ß_3'(\Delta \textit{Import/GDP}_{t-1})$ *and* $ß_4'(\Delta \textit{Exports/GDP}_{t-1})$, plus an indicator of either *Business Sentiment* or *July Approval*: $ß_5(\text{Sentiment/Approval}_{t-1})$. A model that replaces prior incumbent vote share with prior incumbent terms (*Duration*) will also be estimated. [75]

Omitted variable bias is possible in the macro models, given the few degrees of freedom. We therefore also estimate and report instrumental variable models using two-stage least squares

[72] Quarterly data for the four quarters prior to the election Q12 through Q15 are used rather than annual growth data Q13 through Q16. The latter indicator includes information for the 53 to 59 days of economic activity after the election depending on the date of the election in a particular year.

[73] Fair 2009.

[74] See Bailey, Goldstein and Weingast 1997 and Hiscox 1999 for discussions of the RTAA. As Goldstein 1994 notes, U.S. trade policy post-RTAA contained important legacies of prior protectionist policies and programs, which attenuated slowly over time. Therefore, we expect and find weaker estimated effects in earlier periods. Results are available from the authors.

[75] We also estimate a "least absolute deviations" or quartile regression as a robustness check alternative to the main time-series OLS models. OLS can magnify the influence of outliers, in contrast to quartile regressions.

(2SLS) estimators. The instruments for changes in U.S. trade flows are the global averages of the subcomponents of a liberalization index of restrictions on payments and receipts of international trade and finance transactions for all countries except the United States lagged by two periods, and used previously as instruments for trade flows by Owen and Quinn.[76]

To assess the statistical adequacy of the OLS time-series models, a number of diagnostic tests are reported. This is especially important in the context of a small number of observations with potentially correlated errors.[77] Our county-level indicators show modest levels of inter-correlation. The macro-level variables, however, contain overlapping information, and cannot all be entered in any event owing to limited degrees of freedom.

To explore both the identifying and common-pool variances contained in the explanatory variables, we undertake factor analysis. Given the need to avoid omitted variable bias while

[76] Owen and Quinn 2016. The intuition is that the ability of foreigners to export to the United States and U.S. firms to export abroad is limited by the ability of foreign nationals to make payments for U.S. goods or to receive payments for their exports to the United States. The instruments are plausibly theoretically exogenous, as global averages of financial restrictions several years in advance of an election are theoretically unlikely to respond to expectations about incumbent party vote shares. In any event, the instruments satisfy the exogeneity tests; the first stages are highly significantly significant.

[77] See Grant and Lebo 2016. Because the models include some form of lagged endogenous variable, the classical Durbin-Watson statistic is replaced with a Lagrange-multiplier test for first- and second-order residual autocorrelation—the AR 1-2 test. To account for possible error correlation and heteroskedasticity, which can bias standard errors, Newey-West heteroskedasticity and autocorrelation consistent standard errors are reported. A normality test for residuals, based on Jarque-Bera with the Doornik-Hansen small-sample correction, is also reported. Finally, an ARCH test for conditional first-order heteroscedasticity is reported. Statistically significant p-values signify assumption violations. Unit root tests indicate that the null of a unit root can be rejected for the key regressors with a high level of confidence.

maintaining a parsimonious model, factor analysis can help determine which measures of the baseline model provide unique identifying variances. The details of the factor analysis are described in Appendix A. At the national level, most of the various economic growth indicators and business sentiment/presidential approval ratings show extensive inter-correlations. In contrast, the evidence suggests that *ΔImports/GDP* is not subsumed in the other factors, and, as indicated by its "uniqueness score," contains useful identifying variance. The *ΔExports/GDP* indicator, by contrast, is likely to overlap in information with the economic performance and voter sentiment variables. (The *ΔTrade Balance/GDP* does not load on any factor.) Hence, the trade variables partly contain independent information.[78]

National-level Election Results

Table 3 reports the main results. In column, prior incumbent vote share and economic growth are entered. The estimation properties of the model are good, and the results are consistent with prior findings. In all models reported, economic growth has an estimated coefficient that is positive, significant and substantively large. The lagged endogenous variable has a negative and significant coefficient, which is consistent with the theories regarding the "costs of governing" and the standard findings of a decline in incumbent vote margins in subsequent elections. Taking the mean of two-party *Incumbent Vote Share*$_{t-1}$ (53.7 percent for the 1948–2008 elections), multiplying it by the parameter estimate, and adding the estimate of the constant to its product produces an estimate of *Incumbent Vote Share*$_t$ of 46.8 percent, or a -6.9 percent change from the prior election, assuming a zero increase in economic growth. Multiplying the estimated

[78] As expected, the county-level factor analysis shows far less information overlap. Details available upon request.

coefficient of growth by the sample mean (a growth rate of 2.2 percent) and adding it to the above calculation produces an estimate for *Incumbent Vote Share*$_t$ of 52 percent. A growth rate of 1.25 percent or lower brings the estimate for *Incumbent Vote Share*$_t$ below 50 percent. The adjusted R-squared is 0.61.

In column 2, change in the trade balance has a statistically significant positive coefficient that is substantively large and consistent with the theory developed above. A one-unit increase (decrease) in the U.S. trade balance as a percentage of GDP is associated with a 4 percent estimated increase (decrease) in incumbent vote shares.[79] Column 3 substitutes prior incumbent terms from the time for change model[80] for incumbent vote shares: a one-unit increase (decrease) in the U.S. trade balance as a percentage of GDP is associated with a 3 percent estimated increase (decrease) in incumbent vote shares. Change in imports (column 4) has a statistically significant negative coefficient, which is substantively large and also consistent with our theory. A one-unit increase (decrease) in imports as a percentage of GDP is associated with a 4 percent decrease (increase) in incumbent vote shares. Change in exports as a percentage of GDP has a positive and statistically significant coefficient that is substantively large; a one-unit increase is associated with a 6 percent increase in presidential vote shares. The explanatory power of the

[79] Using a quantile estimator for Model 3.2 produces identical signs on the coefficient estimates and similar levels of statistical significance. The coefficient estimates are modestly smaller than the estimates using OLS time-series methods.

[80] Abramowitz 1988. The OLS version of this model shows strong evidence of serial correlation. We therefore estimate and report the results of a Prais-Winsten AR1 regression with a correction for serial correlation.

models, judged via adjusted R-squared indicators, rises 19 points with the inclusion of the trade variables.[81]

Models 3.5 and 3.6 are 2SLS models (described earlier). The estimated coefficients for the trade variables are similar in size, sign and level of statistical significance to their OLS counterparts. The levels of statistical significance of the models (given as the generalized adjusted R^2 for instrumental variable (IV) models from Pesaran and Smith)[82] are similar to their OLS counterparts.

In columns 7 and 8, using $\Delta Import/GDP_{t-1}$ and $\Delta Exports/GDP_{t-1}$, we add *Business Sentiment Q15* and *July Gallup*, respectively. The models have good estimation properties and explanatory power. Both *Business Sentiment Q15* and *July Gallup* have positive, statistically significant, and substantively large estimated coefficients that are consistent with prior theory and findings.[83] The estimated coefficient of $\Delta Import/GDP_{t-1}$ remains negative and highly statistically significant, and the estimated coefficient of $\Delta Export/GDP_{t-1}$ remains positive and statistically significant.

As a further test, we extend the sample back to the 1936 election, which is post-RTAA, using data and models from Fair.[84] Column 9 enters changes in the trade balance, and column 10

[81] Change in exports loads on Factor 1 Table A3a along with the growth indicators. The variable therefore contains overlapping information with the indicators of economic growth.

[82] Pesaran and Smith 1994.

[83] The *Business Sentiment Q15* data are available only from 1954 onward, making the 1956 election the first election in the sample. The *July Gallup* variable is available from the 1940s onward. In order to compare the estimated effects of changes in imports across the different specifications, the 1956–2012 sample is used. The results for the models with *July Gallup* in the 1952–2012 sample are nearly identical to the models reported.

[84] Fair 2009.

enters changes in imports and exports. The coefficient estimates retain similar signs and levels of statistical significance.

Other variables are not the main focus, but the estimated coefficient of economic growth, while always positive and statistically significant beyond the 0.01 confidence level, is diminished in size with the inclusion of either *Business Sentiment Q15* or *July Gallup*. The coefficient estimates for both are always positive, statistically significant and substantively important.[85]

In Appendix Table A4, we use Model 3.4 as the base model and add additional indicators proposed by other investigators, including changes in Multifactor Productivity to measure technological innovation, changes in the unemployment rate, changes in inflation and a time trend. (The time trend is included in light of observation in Abramowitz that U.S. presidential elections have become increasingly competitive over time.[86]) The magnitudes, directions and statistical significances of the trade results are strongly robust to including these other regressors. In all cases, the export and import coefficient estimates retain the expected sign, and the estimated coefficients are statistically significant at the 0.05 level or better.

We note here several significant results from the robustness checks. First, the change in manufacturing jobs has a highly statistically significant estimated coefficient, consistent with Lewis-Beck and Tien.[87] Second, when we distinguish between trade in goods and trade in services, the estimated coefficients for trade in goods are highly statistically significant and in

[85] Models that include both *Business Sentiment Q15* and *July Gallup* leave neither with statistically significant estimated coefficients, though the trade variable estimates are substantively similar. Details are available upon request.

[86] Abramowitz 2014.

[87] Lewis-Beck and Tien 2004.

the expected direction. The evidence is that trade in goods is largely responsible for the national results found here. Finally, in unreported models, we serially interact the independent regressors from the main table and the Appendix table with a *Democratic Party Incumbent* dummy variable to explore possible partisanship effects, but find no interaction effects remotely close to statistical significance.[88]

Conclusion

Prior academic research indicates that globalization – characterized by increases in financial integration, rising exports and import competition, and the offshoring of production – shapes politics through its effects on employment, wages and economic insecurity. Our paper demonstrates that changes in trade flows and changes in the concentration of employment in firms in winning and losing service and manufacturing industries are unique contributors to explaining presidential voting.

One novel contribution is that we have shown that rising employment in high-skilled service exports – concentrated winners from trade – is associated with increasing incumbent vote shares. Rising employment in high-skilled tradable manufacturing is also associated with increasing incumbent vote shares, although the magnitude of the estimated effects is much smaller than for high-skilled tradable services. In line with other studies, we find strong evidence that the concentration of economic activity in low-skilled tradable manufacturing diminishes incumbent vote shares. At the national level, using standard models plus IV models, we report

[88] Details available from the authors. One possibility is that the Democratic Party has only recently emerged as the less "liberalizing" party, and we therefore experiment with a *Democratic Party Incumbency* dummy variable from 1992 onward, but find no statistically significant effects. We thank Prof. X for the suggestion.

the novel finding that rising exports (imports) are associated with rising (declining) incumbent vote shares.

We find some evidence that Electoral College considerations provide an incentive against the further liberalization of trade. The estimated negative effects of low-skilled manufacturing are largely found in the swing states. In contrast, the estimated effects of the concentrations of both high-skilled services and high-skilled manufacturing are found only in non-swing states. The extent to which the contestability of employment and economic insecurity from trade, rather than purely domestic economic concerns, shapes presidential election outcomes suggests a necessary coupling of previously isolated research streams in American politics and international political economy.

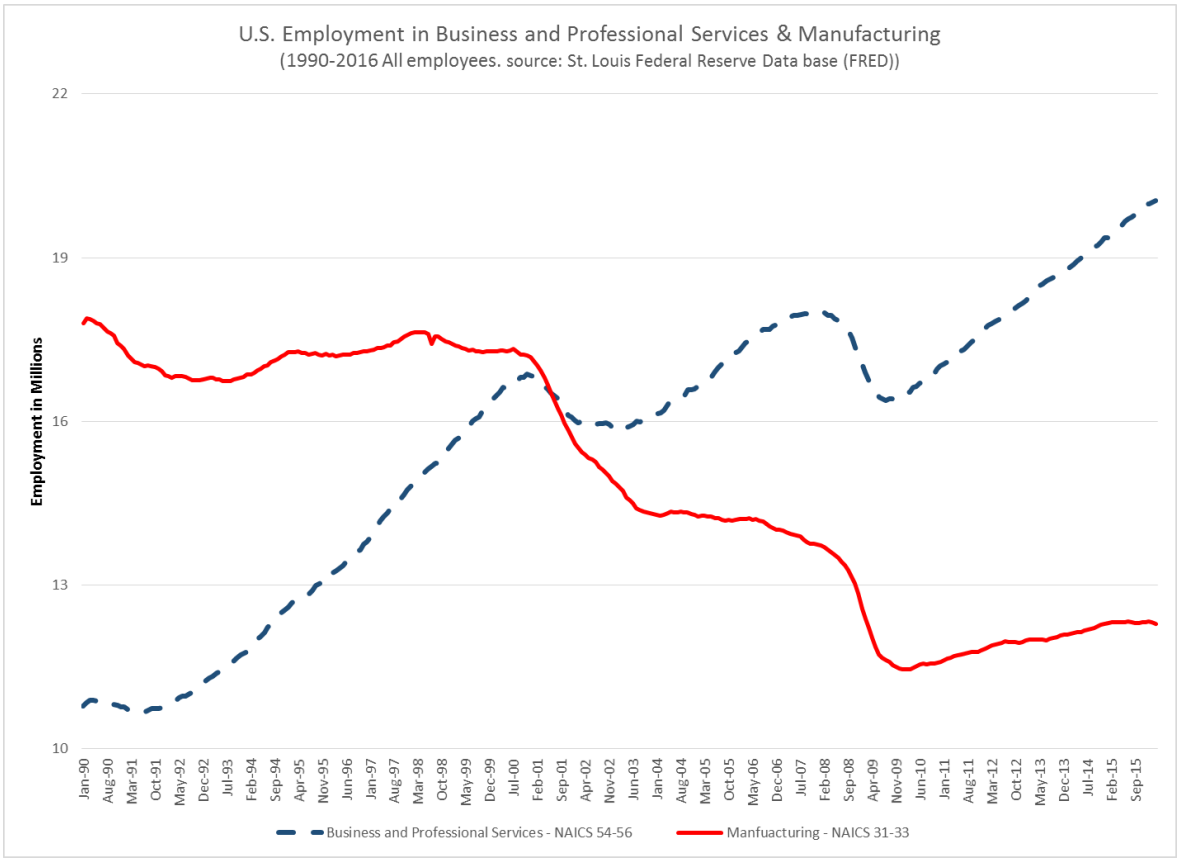

FIGURE 1. *Changing Composition of U.S. Employment, 1990-2016*

TABLE 1. *Industry Classifications by Tradability, Product, and Skill*

Tradable High-skill Manufacturing Automobile Manufacturing (336111) Breakfast Cereal Manufacturing (311230) Petrochemical Manufacturing (325110)	**Tradable High-skill Services** Computer System Design Services (541512) Investment Banking and Securities Dealing (523110) Software Publishing (511210)
Tradable Low-skill Manufacturing Carpet and Rug Mills (314110) Yarn Spinning Mills (313111) any industry in 313, 314 and most in 315, 316	**Tradable Low-skill Services** Amusement and Theme Parks (713110) Credit Card Issuing (522210) Limousine Services (485320)
Non-Tradable Manufacturing Corrugated and Solid Fiber Boxes (322211) Ready-Mix Concrete Manufacturing (327320) Quick Printing (323114)	**Non-Tradable Services** Dentist Offices (621210) Full Service Restaurants (722110) Grocery Stores (445110)

Notes: Authors' Calculations using Economic Census data.

TABLE 2. *County-level Determinants of Incumbent Two-Party Vote Shares, 1992–2012 Presidential Elections*

	(1)	(2)	(3)	(4)	(5)	(6)
			Unweighted	Swing States	Non-Swing States	Additional Controls
Unemployment	-0.002**	-0.0014**	-0.0022***	-0.0046***	-0.0007	-0.0015**
	(0.001)	(0.0068)	(0.0037)	(0.001)	(0.0008)	(0.0007)
Change in Unemployment (1 year)	-0.002	-0.0017	0.0004	-0.0002	-0.0021	-0.0015
	(0.001)	(0.0012)	(0.0004)	(0.0011)	(0.0014)	(0.0011)
Unemployment Volatility	-0.017***	-0.0172***	-0.0072***	-0.0121***	-0.0182***	-0.0174***
	(0.002)	(0.0023)	(0.0008)	(0.002)	(0.0027)	(0.0021)
Average Pay	0.020	0.0137	-0.0155**	-0.0317	0.0284*	0.0190
	(0.014)	(0.014)	(0.0062)	(0.021)	(0.0157)	(0.0144)
Change in Avg. Pay (1 year)	0.103***	0.0992***	0.0065	0.0399	0.1088***	0.0915***
	(0.021)	(0.021)	(0.011)	(0.0352)	(0.0248)	(0.0206)
Empl. High-wage Manuf. Exporters	0.000					
	(0.0004)					
Empl. Low-Wage Manuf. Exporters	-0.001*					
	(0.001)					
High-wage Tradable Manufacturing Empl.		0.001***	-0.000	-0.000	0.002***	0.001**
		(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
High-wage Tradable Service Empl.		0.005***	0.0019***	0.002	0.006***	0.005***
		(0.001)	(0.0005)	(0.001)	(0.001)	(0.001)
Low-wage Tradable Manufacturing Empl.		-0.006***	-0.005***	-0.012***	-0.004**	-0.006***
		(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
Low-wage Tradable Service Empl.		0.007***	0.003***	0.007***	0.007***	0.006***
		(0.0012)	(0.001)	(0.003)	(0.002)	(0.002)
Retired						-0.1513**
						(0.064)
Female						0.5222***
						(0.1413)
African American						0.0360

						(0.0395)
Hispanic Latino						-0.0182
						(0.0332)
Bachelor's Degree						-0.1156**
						(0.0559)
Population						0.0040
						(0.0081)
Constant		-0.2482*	0.1170*	0.3090	-0.4282***	-0.5707***
		(0.1387)	(0.0599)	(0.2003)	(0.1578)	(0.1635)
Observations	18,623	18,623	18,623	4,282	14,341	18,623
Adj. R-squared	0.546	0.550	0.436	0.554	0.556	0.552
Counties	3,105	3,105	3,105	714	2,391	3,105

Notes: The dependent variable is the change in the incumbent two-party vote share. All models include county and year fixed effects. The 10 swing states are Colorado, Florida, Iowa, North Carolina, New Hampshire, Ohio, Pennsylvania, Virginia, Nevada and Wisconsin. The trade exposure measures are log (relevant employment measure + 1) from the Census LBD. All estimates (except Column 2) are weighted by population size in 1990. The robust standard errors (reported in parentheses) are adjusted for clustering at the county level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Source: confidential plant-level employment data from the U.S. Census Bureau.

TABLE 3. *Base Models – Dependent Variable is National Incumbent Party (Two-Party) Vote Shares (1952–2012, 1936–2012)*

	Model 1	Model 2	Model 3	Model 4	Model 5 IV	Model 6 IV	Model 7	Model 8	Model 9 (1936-)	Model 10 (1936-)
Prior Incumbent Vote $_{t-1}$	-0.74***	-0.773***		-0.764***	-0.775***	-0.743***	-0.746***	-.542***	-0.443	-0.441
	(0.216)	(0.155)		(0.152)	(0.144)	(0.176)	(0.122)	(0.157)	(0.255)	(0.265)
Duration (prior incumbent terms)			-0.01*							
			(0.006)							
Growth Q12_15	0.022***	0.031***	0.018***	0.032***	0.031***	0.034***	0.018**	0.023***	0.018***	0.018***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.006)	(0.005)	(0.004)	((0.004)
ΔTradeBal Q12_15		0.045***	0.033***		0.048***				0.026**	
		(0.012)	(0.011)		(0.016)				(0.01)	
ΔImportsQ12_15				-0.04**		-0.043**	-0.036***	-0.028**		-0.025*
				(0.013)		(0.017)	(0.011)	(0.012)		(0.015)
ΔExportsQ12_15				0.06***		0.073***	0.038*	0.044**		0.028*
				(0.018)		(0.02)	(0.019)	(0.017)		(0.014)
BusSentimentQ15							0.001**			
							(0.0002)			
July Gallup								0.0014**		
								(0.0005)		
War									0.007	0.009
									(0.034)	(0.02)
Constant	0.865***	0.869***	0.502***	0.853***	0.869***	0.846***	0.817***	0.69***	0.722***	0.719***
	(0.113)	(0.081)	(0.018)	(0.081)	(0.076)	(0.094)	(0.069)	(0.095)	(0.139)	(0.144)
Obs.	16	16	16	16	16	16	15	16	20	20
Adj. R^2	0.61	0.798		0.802	0.81	0.81	0.915	0.91	0.41	0.44
AR 1-2 test [p-value]	[0.87]	[0.37]		[0.94]			[0.42]	[0.92]	[0.25]	[0.28]
ARCH 1-1 test [p-value]	[0.51]	[0.85]		[0.96]			[0.98]	[0.16]	[0.93]	[0.99]
Normality test [p-value]	[0.85]	[0.53]		[0.85]			[0.85]	[0.88]	[0.40]	[0.38]
AR1 ρ or [1st Stage F-test]			-0.42		[15.33***]	[75.14***]				

Notes: Model 3 omits the lagged dependent variable, and reports a Prais-Winsten AR1 regression with a correction for serial correlation. Data for the 1936, 1940, 1944 and 1948 elections are from Fair (2009) and the BEA. The standard errors for the IV models (5 and 6) are robust standard errors corrected for small sample bias. The IV Adj. R^2 is the Generalized Adj. R^2 from Pesaran and Smith 1994 for IV models. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

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Appendix A

Correlations and Descriptive Statistics

The pairwise correlations among the dependent and independent macro variables are presented in Appendix Table A1. The descriptive statistics are reported in Tables A2a and A2b (macro and county levels, respectively).

Factor Analysis

Factor analysis examines the inter-correlations among the variables and assesses whether an underlying or latent variable nests the explanatory variables. At the macro level, the principal factor analysis shows that three latent variables undergird the macro data, accounting for 85 percent of the variance in the data. *Business Sentiment Q15, July Gallup Presidential Approval*, change in unemployment, economic growth and change in exports all load strongly on the first factor.[90] Two variables (*Change in Consumer Prices* and *Job Growth*: *ΔJobs*) load on multiple dimensions. *Incumbent Party Terms* and *Incumbent Prior Votes* load on separate factors. Only *ΔImports/GDP* fails to load on a factor: it consequently has a high uniqueness score.[91]

[90] As noted above, Campbell (2008) used the Gallup polls in early September of the election year instead of the July Gallup; Abramowitz (2008) used "net candidate advantage" derived from the June Gallup poll. Both variables load on the same first factor as *July Gallup* and other variables listed above.

[91] "Uniqueness" refers to the information overlap between and among variables. In principal component analysis, the assumption is that variables have a high "communality" of information. Principal factor analysis, used here, tests that assumption. A higher 0–1 "unique" score indicates that the variable is measuring a phenomenon that is different from that measured by other variables. Scores above 0.6 are considered to be "high" and a sign that the variable is a reliably different measure from other variables.

By contrast, the inter-correlations among the county-level variables are modest. Only underlying factor is present (which is correlated with income). All other variables have high uniqueness scores, suggesting that the information overlap among them is very low.

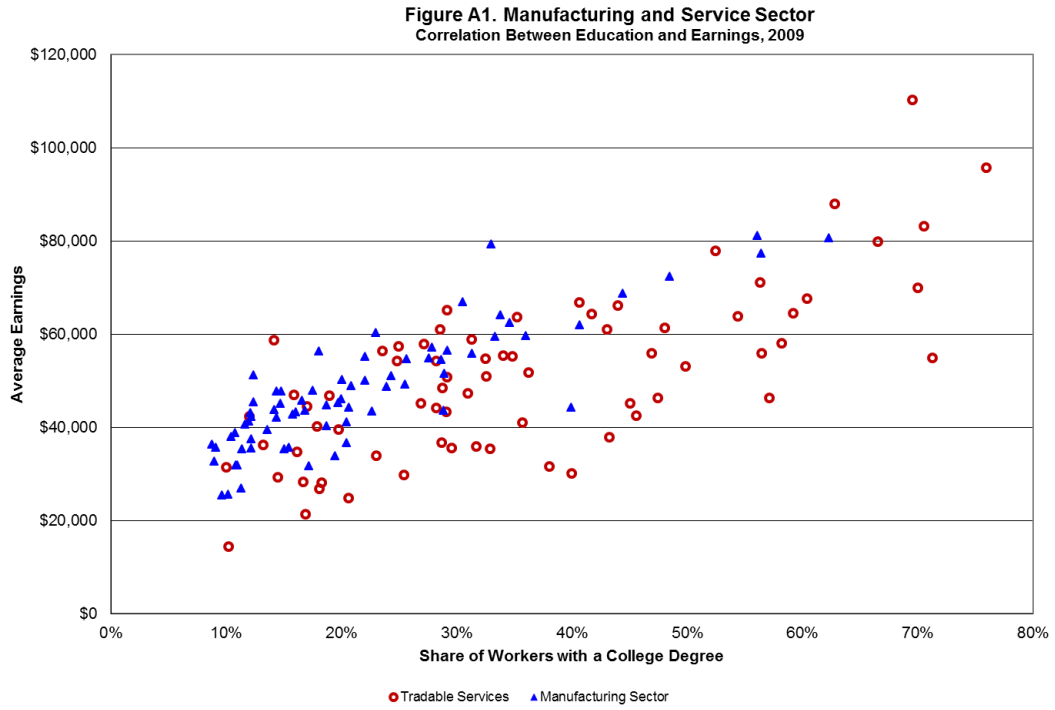

FIGURE A1. *Correlation between Education and Salary. Authors' Calculations from Census Data*

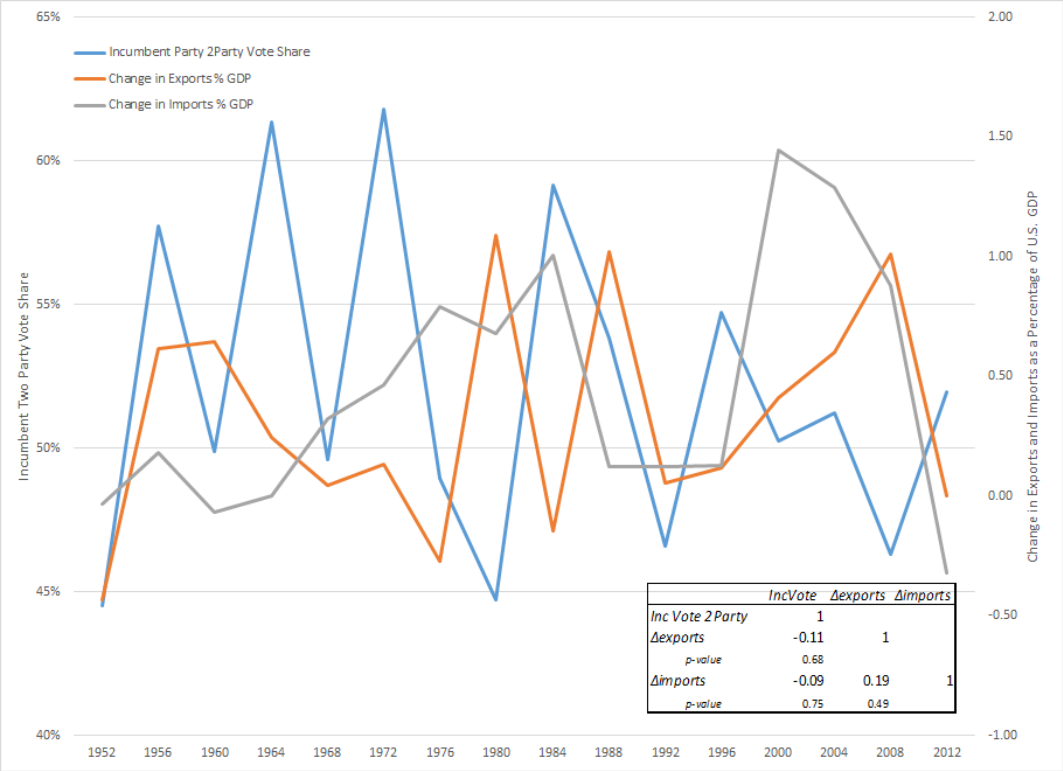

FIGURE A2. *Time Series of the Dependent and Key Independent Trade Variables*

TABLE A1. *Pairwise Correlations among the Dependent and Publicly Available Independent Variables (Macro Data)*

	Incumb. Vote Share	Growth Q12_Q15	Bus Sent Q15	ΔTradeBal Q12_Q15	ΔImports Q12_Q15	ΔExports Q12_Q15	#Incumbent Party Terms	ΔJobs (Q15-Q1)/Q1	Gallup (Q15)
Vote Share	1								
Growth	**0.58****	1							
Business Sent.	**0.068*****	**0.84*****	1						
ΔTradebal	-0.02	**-0.56****	-0.43	1					
ΔImports	-0.09	0.16	0.05	**-0.53****	1				
ΔExports	-0.08	**-0.55****	**-0.59****	**0.8*****	0.09	1			
Inc. Terms	**-0.48***	-0.02	-0.27	**-0.42***	-0.16	**-0.61*****	1		
ΔJobs	0.16	0.18	0.3	0.12	-0.1	0.05	-0.1	1	
July_gallup	**0.83*****	**0.42***	**0.73*****	0.1	-0.09	0.05	**-0.46***	0.06	1
ΔUnemploy	**-0.57*****	**-0.8*****	**-0.84*****	0.4	-0.01	**0.53****	0.14	-0.03	**-0.54****

TABLE A2a. *Descriptive Statistics – Macro Level*

	Mean	Std. Deviation	N
Vote Share	0.52	0.06	16
Growth Q12_Q15	2.08	2.44	16
Business Sent. Q15	103.3	37.9	15
ΔTradebal Q12_Q15	-0.12	0.63	16
ΔImports Q12_Q15	0.48	0.52	16
ΔExports Q12_Q15	0.32	0.47	16
Inc. Terms	1.81	1.28	16
ΔJobs (Q15–Q1)/Q15	8.59	2.99	16
July_Gallup Q15	47.6	14.17	16
ΔUnemployment	-0.28	0.81	16

TABLE A2b. *Descriptive Statistics – County Level*

Variable	Obs	Mean	Std. Dev.	Min	Max
Δ Incumbent Two-Party Vote Share	18,678	-0.031	0.056	-0.345	0.199
Unemployment	18,675	6.137	2.797	0.800	35.600
Change in Unemployment (1 year)	18,675	-0.068	1.211	-13.900	12.700
Unemployment Volatility	18,674	0.805	0.607	0.000	8.791
Average Pay	18,674	9.838	0.207	8.966	11.025
Change in Avg. Pay (-year)	18,673	0.006	0.036	-1.762	0.688
Tradable Services Concentration	18,260	0.619	0.347	0.000	6.893
Manufacturing Concentration	16,177	1.374	0.938	0.000	7.440

TABLE A3a. *Factor Analysis, Macro, National Data*

	Component			
VARIABLE	1	2	3	Uniqueness
Bus Sentiment Q15	0.95			0.06
ΔUnemployment	-0.89			0.20
Growth Q12–Q15	0.87			0.16
July Gallup Approval	0.74			0.18
ΔExports	-0.67			0.46
CPI	-0.54	0.52	0.56	0.13
Incumbent Prior Votes		0.84		0.15
ΔJobs		0.57	0.56	0.32
Incumbent Party Terms			-0.66	0.31
ΔImports				0.95
TS Squared Loadings	3.89	1.88	1.32	
% of Total Variance	47	23	16	
Cumulative % of Variance	47	69	85	

Note: Number of observations = 15. Unrotated matrix with Eigenvalues > 1.00. Principal factor analysis is used. The factor loading scores represent the correlation between the variable and the factor. Factor loading scores below 0.5 are considered substantively insignificant, and are thus omitted. The square of the factor loading score is the size of the variable's total variance represented by the factor. For example, *Business Sentiment Q15* loads roughly 90 percent on Factor 1.

TABLE A4. *Alternative Measures of Trade, Incumbency, Growth, Sentiment and Trade (Macro Models, 1952–2012)*

	Model 1	Model 2	Model 3 Man. Jobs	Model 4	Model 5	Model 6	Model 7 Goods	Model 8 Services
Prior Incumbent Vote $_{t-1}$	-0.529***	-0.831**	-0.619**	-0.745***	-0.746***	-0.752***	-0.774***	-0.876***
	(0.111)	(0.163)	(0.15)	(0.159)	(0.169)	(0.015)	(0.15)	(0.204)
Growth Q12_15	0.027***	0.031***	0.019***	0.029***	0.032***	0.032***	0.033***	0.024***
	(0.006)	(0.004)	(0.007)	(0.006)	(0.004)	(0.004)	(0.004)	(0.005)
ΔImportsQ12_15	-0.036***	-0.037**	-0.037***	-0.038***	-0.038**	-0.034**	-0.045**	-0.176**
	(0.012)	(0.014)	(0.012)	(0.014)	(0.015)	(0.014)	(0.015)	(0.078)
ΔExportsQ12_15	0.067**	0.053**	0.062***	0.061***	0.061***	0.064***	0.078***	0.098
	(0.014)	(0.019)	(0.015)	(0.019)	(0.019)	(0.018)	(0.021)	(0.103)
ΔMultifactor Productivity	0.19							
	(1.007)							
ΔJobs (Q15-Q1)/Q1		0.003	0.008***					
		(0.002)	(0.002)					
ΔUnemployment				-0.011				
				(0.014)				
Inflation (CPI)					-0.001			
					(0.003)			
Time Trend						-0.002		
						(0.002)		
Constant	0.724***	0.868***	0.804***	0.848***	0.847***	0.486***	0.858***	0.936***
	(0.065)	(0.081)	(0.074)	(0.083)	(0.087)	(0.024)	(0.079)	(0.103)
Obs.	16	16	16	16	16	16	16	16
Adj. R^2	0.69	0.81	0.85	0.79	0.78	0.81	0.81	0.68
AR 1-2 test [p-value]	[0.22]	[0.67]	[0.54]	[0.96]	[0.72]	[0.6]	[0.81]	[0.78]
ARCH 1-1 test [p-value]	[0.33]	[0.55]	[0.88]	[0.42]	[0.65]	[0.76]	[0.65]	[0.96]
Normality test [p-value]	[0.47]	[0.56]	[0.27]	[0.66]	[0.64]	[0.18]	[0.34]	[0.03]**

Appendix B: Examining Alternative Hypotheses

Trade Adjustment Assistance (TAA)

In Table B1, we estimate models that include the number of workers filing for TAA, which Margalit showed was negatively associated with changes in the incumbent's (George W. Bush) vote share between 2000 and 2004. TAA filings are measured as the number of workers filing for TAA in the four years leading up to and including the election year (as a share of the total workforce). Owing to TAA data limitations, we are unable to estimate our full period models, but the TAA models include all presidential elections between 1996 and 2012. The results confirm Margalit's finding over the longer period of our study: TAA is associated with decreases in incumbent vote shares. In Column B1, following Margalit, we model the change in incumbent vote shares, and include state (rather than county) fixed effects. Model 2 includes county fixed effects and county-level clustering, and the negative coefficient corresponding to TAA workers remains negative and statistically significant at the 90 percent level. We find that aggregate job losses associated with globalization, as captured by the TAA variable, reduce incumbent vote share, consistent with Margalit.[92]

The remaining columns incorporate our measures of trade exposure from the census data. Our results are broadly consistent with those reported in the paper. Low-wage tradable manufacturing is strongly associated with lower vote shares in swing states, while high-wage tradable services and manufacturing are strongly associated with increased vote shares in non-swing states.

[92] Margalit 2011.

TABLE B1. *County-level Determinants of Incumbent Two-Party Vote Shares (1996–2012 Presidential Elections)*

	State FE	County FE	County FE	Swing States	Non-Swing States
TAA Covered	-0.092**	-0.074*	-0.053	0.062	-0.088*
	(0.043)	(0.041)	(0.041)	(0.076)	(0.045)
Unemployment	0.001*	-0.001*	0.000	-0.002**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Average Pay	0.018***	0.057***	0.015	-0.063***	0.037**
	(0.004)	(0.014)	(0.015)	(0.023)	(0.017)
Change in Unemployment (1 year)			-0.001	0.003**	-0.003*
			(0.001)	(0.001)	(0.001)
Unemployment Volatility			-0.014***	-0.009***	-0.015***
			(0.002)	(0.002)	(0.002)
Change in Avg. Pay (1 year)			0.155***	0.152***	0.154***
			(0.029)	(0.044)	(0.034)
High-wage Tradable Manufacturing Empl.			0.003***	0.001	0.004***
			(0.001)	(0.001)	(0.001)
High-wage Tradable Service Empl.			0.007***	0.0004	0.009***
			(0.001)	(0.0004)	(0.001)
Low-wage Tradable Manufacturing Empl.			0.001	-0.008***	0.004*
			(0.002)	(0.003)	(0.002)
Low-wage Tradable Service Empl.			0.009***	0.000	0.012***
			(0.002)	(0.003)	(0.002)
Constant			-0.291	0.711***	-0.590***
			(0.151)	(0.218)	(0.175)
Observations	15,554	15,554	15,519	3,569	11,950
R-squared	0.485	0.456	0.483	0.500	0.491
Clusters	50	3,111	3,105	714	2,391

Note: The dependent variable is the change in the incumbent two-party vote share. The 1992 election is not included because TAA data are not available prior to 1994. TAA covered workers represents the total number of workers covered by TAA over the four-year period including the three years prior to the election and the election year, as the share of total employed workers in the county in the election year. Estimates are weighted by population size in 1990. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Source: Margalit 2011.

Partisan Employment Effects

In Table B2, following Wright, we allow unemployment to exert differential effects on incumbent vote shares depending on the incumbent's party.[93] Our main results are little changed with this alternative specification; the estimated interaction effects are consistent with Wright's.

TABLE B2. *County-level Determinants of Incumbent Two-Party Vote Shares (1992–2012 Presidential Elections)*

	(1)	(2)	(3)	(4)
	Interact Unemployment	Interact Delta Unemployment	Swing States	Non-Swing States
Unemployment	-0.002**	-0.002**	-0.005***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment Volatility	-0.015***	-0.017***	-0.009***	-0.016***
	(0.002)	(0.002)	(0.002)	(0.003)
Average Pay	0.012	0.016	-0.036*	0.027*
	(0.014)	(0.014)	(0.021)	(0.016)
Change in Avg. Pay (1 year)	0.098***	0.101***	0.038	0.108***
	(0.021)	(0.021)	(0.035)	(0.025)
Change in Unemployment (1 year)	-0.004***	-0.001	-0.004***	-0.004**
	(0.001)	(0.001)	(0.001)	(0.002)
Democratic Incumbent x Unemployment		0.001*		
		(.001)		
Democratic Incumbent x Change in Unemployment (1 year)	0.005***		0.007***	0.004**
	(0.002)		(0.002)	(0.002)

[93] Wright 2012.

High-wage Tradable Manufacturing Empl.	0.001***	0.001***	-0.004	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
High-wage Tradable Service Empl.	0.005***	0.005***	0.002	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Low-wage Tradable Manufacturing Empl.	-0.006***	-0.006***	-0.013***	-0.004**
	(0.001)	(0.001)	(0.003)	(0.002)
Low-wage Tradable Service Empl.	0.007***	0.007***	0.008***	0.008***
	(0.002)	(0.002)	(0.003)	(0.002)
Constant	-0.229***	-0.266*	0.344*	-0.413***
	(0.139)	(0.138)	(0.201)	(0.158)
Observations	18,623	18,623	4,282	14,341
R-squared	0.551	0.5505	0.5556	0.5568
Counties	3,105	3,105	714	2,391

Notes: We control for partisan employment effects. The dependent variable is the change in the incumbent two-party vote share. All models include county and year fixed effects. The *Democratic Incumbent* dummy is collinear with the year fixed effects and omitted from the model. The 10 swing states are Colorado, Florida, Iowa, North Carolina, New Hampshire, Ohio, Pennsylvania, Virginia, Nevada and Wisconsin. The trade exposure measures are log (relevant employment measure + 1) from the Census LBD. All estimates (except Column 2) are weighted by population size in 1990. The robust standard errors (reported in parentheses) are adjusted for clustering at the county level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Source: Wright 2012.