Cell Phones and Soybeans: How U.S. Trade with China Affects Unions

Union Membership, Dues, and Locals

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Contents

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Abstract

I assess how local area exposure to Chinese import competition affects unions in the U.S. I estimate the effects of import competition at the commuting zone level using administrative data that detail union membership and dues for every union local in the U.S. from 2000-2020. I find there is no statistically significant relationship between import exposure and union membership, dues, or count of locals. Separating my analysis into two time periods, 2000-2010 and 2010-2020, I find that relationships between import exposure and union outcomes change over time. Increases in trade exposure predicted decreases in union membership over 2000-2010 but increases over the subsequent decade. Results among a subgroup of manufacturing unions and another subgroup of health and education unions were similar.

1 Introduction

Unions have received renewed attention in 2022 and 2023 as strikes and unionization petitions have increased.[1] From January 1, 2021 to March 2023, Cornell University's School of Industrial and Labor Relations tracked 746 labor actions across over 1,100 locations.[2] These include strikes and labor protests.[3] While myriad factors affect the U.S. labor market, one challenge facing U.S.

[1] See Zhang (2022) for a comparison of 2021 and 2022 labor activity.
[2] See the Labor Action Tracker.
[3] Cornell ILR define a strike as an instance in which workers cease performing their tasks; a protest is any collective action to enforce a worker demand without stopping work.

workers, particularly in U.S. manufacturing jobs, has been increased competition from Chinese imports.[4] This has led to several national unions calling for the creation and preservation of tariffs against Chinese goods.[5]

Given this background, I explore the role that trade with China has had on unions in the U.S. I consider union membership, union dues collected from members, and counts of union locals.

My paper draws on the empirical framework established in Autor, Dorn, and Hanson (2013), who first examine changes in Chinese import competition over 1990-2007 and identify the effects on U.S. employment, labor force participation, and wages. The authors find that increases in Chinese imports account for higher unemployment levels, lower labor force participation, and lower wages in a local labor market, defined as a commuting zone. Specifically, a \$1000 increase in a commuting zone's import exposure per worker causes a predicted decrease of 0.75 percentage points for manufacturing employment.[6] Subsequent analysis from Acemoglu et al. (2016) found that 2.0-2.4 million manufacturing jobs were lost due to increases in Chinese imports from 1999 to 2011.

An emerging category of studies has considered the effects of local area exposure to Chinese imports with a focus on unions. Ahlquist and Downey (2019) study how import competition affects union membership in the U.S. using Current Population Survey data with methods that draw on the work of Autor, Dorn, and Hanson (2013) and Pierce and Schott (2016). Ahlquist and Downey find that, from 1990-2014, industries that face greater Chinese competition see

[4] See Autor, Dorn, and Hanson (2013), which notes that competition with China increased unemployment, reduced labor force participation, and decreased wages from 1990-2007 for U.S. workers in affected industries.

[5] See the Alliance for American Manufacturing, the United Steel Workers, the Steel Manufacturing Association, and the AFL-CIO.

[6] The authors compare effects between one commuting zone that is in the 25^{th} percentile of exposure against another in the 75^{th} percentile, and they find that the commuting zone with greater import exposure sees a manufacturing employment decline of 4.5% compared to the commuting zone with lesser import exposure.

more significant declines in employment and unionization, but that jobs outside of manufacturing - particularly in healthcare and education - see statistically significant increases in unionization. Using similar methods, Charles, Johnson, and Tadjfar (2021) look at a different measure involving unions: the rate of union certification elections, which are overseen by the National Labor Relations Board (NLRB) and which demonstrate workers' desire to unionize. They find that from 1990-2007, Chinese import competition led to 4.5% fewer union certification elections in manufacturing industries that were directly exposed to more trade competition. I examine these papers and others in the broader labor-trade literature in greater detail in the Literature Review.

I expand on the current studies on unions by applying previous methods to a union dataset from the U.S. Office of Labor Management Standards (OLMS). The OLMS is responsible for collecting annual union tax returns, which detail a union's total membership, dues collected, and other financial details. I describe the dataset in greater detail in the Data section. Following previous authors in the literature, I collect data on local industry structure at the commuting zone level, using employment data from the U.S. Census Bureau's County Business Patterns (CBP). I pull trade data from the UN Comtrade database. My period of analysis spans 2000-2020, but I specifically examine the decadal change from 2000-2010 and 2010-2020 in union outcome variables and trade exposure. I also offer analysis that focuses on each decade individually in my Results section.

My primary analysis follows that of Autor, Dorn, and Hanson (2013). I consider the effects of local labor market exposure to Chinese trade by constructing an import measure that weighs the proportion of each industry in a given commuting zone. I use geographic data from the OLMS to identify the commuting zone for each labor union and conduct analysis at the commuting zone level.[7] Following the recent literature, I use trade data from eight countries that are similar to the U.S. to address possible simultaneity bias that can occur when using U.S. imports from China as the trade exposure measure. For each union outcome, I provide different models that include fixed effects and state-level demographic controls. I consider possible alternative samples and estimation techniques in the Subgroup Analysis and in the Appendix.

I find a negative relationship between U.S. import exposure (trade exposure to Chinese imports) and union membership across models, although the effects are not statistically significant.

I then focus my analysis on a subgroup of manufacturing unions in the Subgroup Analysis. In my overall model, I find that a one standard deviation increase in trade exposure causes an estimated decrease of 60.6 union members in a commuting zone over a decade (Table 2). Among manufacturing unions, I find an estimated decrease of 47.3 union members, a slightly lesser magnitude loss (Table 8). I also find a lower expected increase in union dues collected in the manufacturing sample. Finally, there is an expected decrease of 0.08 union locals within a commuting zone over a decade for manufacturing unions (Table 10) compared to a 0.19 decrease for union locals in the total sample (Table 4).

I find that there are smaller estimated decreases in the counts of union members, smaller estimated increases in union dues, and smaller predicted decreases in union counts among the sample of unions that consist overwhelmingly of manufacturing workers. Results in another subgroup consisting of health and education unions are comparable to those found in the manufacturing subgroup. In my overall sample, I find a slightly more positive relationship between import exposure and dues collected, and I find a slightly more negative relationship

[7] One challenge of the OLMS data is that it does not identify the sector for each union. However, the OLMS does identify a zip code for each union local, which I use to map to the commuting zone level.

between import exposure and the count of union locals.

Overall, most results of my paper qualitatively match the existing literature. A number of authors have linked exposure to Chinese trade with declines in manufacturing jobs, including Autor, Dorn, and Hanson (2013), who find that trade exposure explains one-quarter of the declines in U.S. manufacturing employment over 1990-2007. Acemoglu et al. (2016) estimates trade exposure to explain about 2.0-2.4 million manufacturing jobs lost, and Ahlquist and Downey (2019) extend this work to unionization. They find a statistically significant decrease in union membership for union members in manufacturing industries. Qualitatively, I also find a negative relationship between import exposure and union membership as well as union local counts among manufacturing unions. I supplement the existing research by including union dues, which may reflect union behaviors. I differ from Ahlquist and Downey (2019) in that I find similar results among two different subgroups, manufacturing unions and health and education unions, while Downey finds that trade exposure explains increases in membership health and education sectors. I discuss this further in my Subgroup Analysis.

I structure the rest of the paper as follows. The Institutional Background outlines relevant aspects behind union formation and operation and details the relevant findings in previous research. I provide information regarding data sources and offer some descriptive analysis in the Data section. I explain my Empirical Methods before providing findings in the Results section. I consider alternate specifications and samples in the Subgroup Analysis. I follow with a Conclusion of my main analysis.

2 Institutional Background and Literature

2.1 Unions as an Institution

Unions negotiate with their employer for improved benefits, higher wages, or other employment conditions.[8] Unions can have different structures; some are purely local while others belong to a national organization, the most prominent of which include the American Federation of Labor and Congress of Industrial Organizations (AFL-CIO), the International Brotherhood of Teamsters, and the National Education Association.[9] Unions rely on several methods to raise revenues and finance activities. Most unions revenues are collected at the local level through annual dues and fees that members pay upon joining a union.[10] Unions decide how to spend their revenue, but some unions, especially those with a significant membership, hire part-time and full-time staff.[11]

While many consider the primary role of a union to be to negotiate within a workplace environment for the needs of their workers, unions also take on a political role (Ahlquist, 2017) . The activism of unions in national politics dates to the twentieth century (Lipset, 1983). Not all unions represent the same preferences, however; while some scholars note the prominent role some unions played in advocating for higher tariffs at different points in the previous century, not all unions believed tariffs would improve their labor position (Leiter, 1961). Trade involving Chinese goods, and associated tariffs against these goods, are important political topics to unions, although some unions believe tariffs may hurt their workers (Kim and Margalit, 2017).

[8]See the AFL-CIO description of union causes and motivations.

[9]See the (U.S. Department of Labor) for technical details regarding union activities and formation.

[10]There appears to be relatively little research into union dues. There is limited recent analysis, such as this piece from the Midwestern Economic Policy Institute. There is more dated research such as that of Raisian (1983) and Petshek and Paschell (1952).

[11]Union Plus, 2023.

To advance their positions, unions have a variety of options, including strikes and protests, political training and voting, and contributing to political campaigns (Ahlquist, 2017). While the OLMS data is limited, some data points on strike benefits and political contributions reflect how unions elevate the preferences of members beyond the workplace.[12] Union dues broadly enable unions to act, which motivates my inclusion of union dues as a relevant outcome in this analysis. Specific union financial actions, particularly for political activism, offer opportunities for further research.[13]

I consider papers that define the instrumental variables and empirical methodology needed to study how trade competition with China affects U.S. labor and wages. I then consider a subset of these that have applied this methodology to questions involving unions.

2.2 "China Shock" Methodology

My paper draws from the work of several prominent papers that exist in the trade and labor economics literature. Autor, Dorn, and Hanson (2013) study how changes in imports from China have affected several labor market outcomes in the U.S., including unemployment, wages, and labor force participation. I construct my own import exposure measures based off of their main empirical specification (below). A commuting zone is a geographical area that loosely encompasses a local economy; it often crosses multiple county borders.[14] The authors create a local labor market exposure measure to capture how employment in a given commuting zone is affected by that commuting zone's industry

[12] From 2010 to 2017, labor unions in the U.S. spent \$1.3 billion on political campaigns. See Projections IRI.

[13] The main political utility of unions may not rest in their financial strength but rather their endorsement of particular candidates; see Fouirnaies (2021), Rosenfield (2014), and Anzia (2011).

[14] The U.S. Department of Agriculture provides a list of commuting zones and the counties they enclose.

structure[15] and the national change in imports for a given industry (ΔM_{ucjt}):

$$\Delta IPW_{uit} = \sum_{j} \frac{L_{ijt}}{L_{ujt}} \frac{\Delta M_{ucjt}}{L_{it}} \tag{1}$$

To isolate Chinese industry growth and efficiency improvements from U.S. demand, I follow the literature and construct an instrumental variable with trade data from eight similar OECD countries. I maintain this sample in my own analysis and discuss this further in my Empirical Methods. Acemoglu et al. (2016) adopt the same import exposure measure. They motivate the use of a commuting zone as a unit of observation. The total effect of Chinese imports on U.S. national employment can be expressed as the sum of direct effects on exposed industries (that must compete with Chinese imported goods), indirect impacts on linked industries, aggregate reallocation effects, and aggregate demand effects.[16] A commuting-zone level analysis captures local labor market effects, which would include the aggregate reallocation and aggregate demand components.

It is important to note that Pierce and Schott (2016) formulate a separate approach also used in the literature to address similar questions. Analyses that more closely follow methods from Autor, Dorn, and Hanson (2013) use this approach as a robustness check. To address whether declines in manufacturing employment stemmed from trade with China, Pierce and Schott (2016) use the Census Bureau's Longitudinal Business Database and the Census of Manufacturers to gauge employment and the number of firms in an industry, and they exploit variation in tariff rates across goods and industries. Performing such

[15] $\frac{L_{ijt}}{L_{ujt}}$ is the share of industry (j) employment (L) in a given commuting zone (i) for a time period (t) divided by national (u) employment for that industry.

[16] For example, indirect effects on linked industries include industries that may supply inputs to an affected industry (downstream effects), or a different industry that uses an affected industry's output (upstream effects).

an analysis with the OLMS data remains a path for future study. One issue with implementing this methodology, which requires industry level data, is that identification of industries in the OLMS dataset is difficult.[17]

2.3 Framework and Expectations

U.S. unions today are far different than those from several decades ago, and these changes can be important when considering the effects of trade shocks. Fewer union members work in manufacturing jobs, and more work in health and education, which are only indirectly affected by trade shocks. I consider some explanations for how trade changes can affect unionization and union behaviors.

Ahlquist and Downey (2019) present a story that explains why unions are increasingly supporting tariffs. Foreign goods, specifically those produced in China, have a competitive advantage over goods produced in the U.S. due to lower costs for labor. Firms that employ unionized workers will have to compete with these goods and find ways to cut costs. Thus, these firms may fire workers or demand concessions from unions, threatening the status of unions in affected industries. Given this narrative, I expect to see decreases in union membership in commuting zones more exposed to trade competition with China.

Charles, Johnson, and Tadjfar (2021) supplement this theory with their own ideas that trade competition with China reduces the profitability of firms in exposed industries. This competition decreases the surplus rents over which unions could bargain with firm owners. As a result, workers have fewer incentives to join a union and are therefore less likely to create new unions. Analysis of NLRB union certification elections finds an inverse relationship between trade

[17] The OLMS does not identify the industry for each union local, and it does not identify the employer(s) that employ union members. I attempted to match union locals to their employers through a series of merges and fuzzy matches using data from collective bargaining agreements organized through the Federal Mediation and Conciliation Service, but such efforts led to matches for approximately 10% of union locals. I therefore focus my analysis at the commuting zone level.

exposure and new union certifications, which I explain further in the following section. Fewer union certification elections combined with decreases in union membership lead me to hypothesize that areas with greater trade exposure will see decreases in the number of union locals.

Changes in the dues that unions charge may be the most theoretically ambiguous outcome to predict. If unions face greater pressure from employers, they could charge higher dues in order to enable greater union activity and win concessions. An alternative story follows from Charles, Johnson, and Tadjfar (2021) - it may be that unions struggle to amass support and therefore have to collect fewer dues or risk losing even more support.

2.4 Applications to Unions

Two papers apply the same Bartik instrument analysis and build on the "China Shock" data with applications to different union datasets.

Ahlquist and Downey (2019) examine how increases in Chinese imports have affected union membership using union membership data from the Current Population Survey (CPS), ultimately finding that Chinese manufacturing has contributed to declines in union membership, particularly in manufacturing sectors and in Right-to-Work states. They closely follow the empirical techniques of Autor, Dorn, and Hanson (2013) and Pierce and Schott (2016) and find that their results are robust to both identification methods after aggregating industry-level data to fit the CPS industry codes and aggregating commuting zone data to the state level. Ahlquist and Downey find that while Chinese import competition reduces unionization within manufacturing from 1990-2014, it partially offsets these decreases by increasing unionization in surrounding sectors. The authors argue that family members of former unionized workers are more likely to enter health and education fields, which are highly unionized.

Empirically, Ahlquist and Downey demonstrate that the effects of Chinese import competition hold at broader industry categorizations than previously used in the literature; furthermore, the most important geographic distinctions occur at the state level, where U.S. states may have differences in the Right-to-Work legislation. I therefore include models with state fixed effects in my analysis.

Charles, Johnson, and Tadjfar (2021) explore a similar analysis regarding the effects of trade competition but consider outcomes in union organizing using data from the National Labor Relations Board (NLRB). They again follow Autor, Dorn, and Hanson (2013) with a robustness check that uses the techniques from Pierce and Schott (2016) to confirm results. They conclude that from 1990-2007, increases in trade contributed to 4.5% and 8.8% fewer union certification elections in manufacturing industries and industries adjacent to manufacturing, respectively.

Several papers have previously leveraged OLMS data. Applebaum (1996) studies union local officer turnover and salaries, using data from the OLMS to build a sample of about 1,000 union officers across 93 different locals from 1960-1963. Wilmers (2017) studies 16,500 unions in the OLMS data from 2000-2014 and finds that there is significant variation across union locals in their reliance upon investment and asset income to support their union activities. Other authors have previously published descriptive analyses of unions using similar data, such as Holmes and Walrath (2007), who examine changes in union membership across locals.

3 Data

I use several data sources to gather data on unions, trade, local employment, and county demographics. I describe these below. The outcome variables on unions come from the OLMS. I use trade data from the UN Comtrade Database. Local business data comes from the U.S. County Business Patterns. I gather controls from the American Community Survey.

3.1 OLMS Union Tax Return Data

The OLMS provides tax data on all U.S. union locals from 2000-2022 on their public data dashboard. The OLMS is an agency within the U.S. Department of Labor that collects tax data on union locals and ensures that unions file annual tax reports as required by the Labor Management Reporting and Disclosure Act of 1959.[18] Every labor union must file a Labor Management (LM) Information Report, its constitution and bylaws, as well as one of the following financial reports, depending on the size of the union: LM-2, LM-3, or LM-4 (hereafter "financial reports").[19]

The financial reports offer different levels of detail on a union's finances, but all reports present the following information: total value of union assets at end of fiscal period, total value of union liabilities at end of fiscal period, total receipts of union collected (through membership dues, interest received on investments, and other possible fees collected), and total payments to union officers. The OLMS asks each union if they changed their membership dues during the fiscal year of reporting. The OLMS also collects data at the union official level, providing details such as name, leadership position, and annual compensation for each officer in a union local.

There are several challenges to using OLMS data, however, due to key

[18] The OLMS conducts its own criminal investigations and presents the number of investigations into union finances conducted each year along with a brief description of each case in this database.

[19] Unions that collect $250,000 or more in annual receipts must file an LM-2 while unions that collect $10,000 or more but less than $250,000 must file the LM-3. The smallest unions, those collecting less than $10,000 annually, file the LM-4. See the following OLMS Labor Organization Information Report Guide.

information omitted from the LM reports. LM reports do not provide the employer that a union works for, and they do not ask unions to identify their industry. Another challenge is that there is no identifier for national unions, leading most union members to be double-counted in the dataset - once at their local level and once as a member of their respective national union. While there is no indicator for which variables are national unions, I exclude the largest 1% of unions in the dataset in all of my analysis. This elimination likely removes the majority of national unions and addresses the double-counting concern.[20]

3.2 UN Comtrade Trade Data

I download my trade data from the UN Comtrade database, which includes trade flows by industry, importer, exporter, and year from 2000-2020. The data is provided at the commodity level, using Harmonized System (HS) codes. I then aggregate the data to industry-level Standard Industrial Classification (SIC) codes using a crosswalk provided by David Dorn, used in Autor, Dorn, and Hanson (2013). [21] The UN Comtrade data is national data, by nature; this means that every industry has the same trade flow data. Commuting zones have different import exposures solely because of the composition of their local employment, obtained through the County Business Patterns data. My estimation technique requires instrumenting for U.S. trade flows in order to avoid capturing demand-side shocks in the U.S. I follow Autor, Dorn, and Hanson (2013) and create an instrument using trade data from eight countries comparable to the U.S., which include Germany, Switzerland, Spain, Denmark, Finland, Japan, Australia, and New Zealand. I detail the construction of the

[20]Such a method is effective because instead of a union having several hundred or thousand members, a national union will typically register millions of members. In excluding the top 1%, I remove all unions that report over 22,987 union members.

[21]Dorn provides detailed descriptions regarding industry codes. He uses 1987 SIC 4-digit industry codes and includes crosswalks to other industry coding systems, such as the NAICS 1997 6-digit code system and Census data.

instrument and U.S. import exposure variables in the Empirical Methods. In the Appendix, I show first-stage results that substantiate the validity of this instrument.

3.3 County Business Patterns Local Labor Market Data

Another element in constructing import exposure is the composition of industries in a given commuting zone. I download all available data from the U.S. Census Bureau's County Business Patterns (CBP) from 2000-2020. This database documents all employment levels by industry in a given county. I then use a crosswalk provided by David Dorn to convert the geography to the commuting zone level.[22] The crosswalk uses weighting factors to properly split a county across multiple commuting zones when applicable.

Commuting zones define local labor markets, and understanding the industries in each ensures that we accurately assess which areas are more likely to be exposed to trade shocks. For example, a commuting zone with the majority of its employees in service jobs will be less directly affected than a commuting zone where the majority of workers are in manufacturing jobs. Just as Dorn constructs a measure of trade exposure using trade and local industry data to measure effects on employment in Equations (3) and (4) of Autor, Dorn, and Hanson (2013), I follow their technique to estimate new outcomes for unions. Local business composition is important in the construction of the import exposure treatment variables.

3.4 American Community Survey

I use data from the American Community Survey to create two main control variables: the percentage of a commuting zone's population that is male,

[22]For further details, read Dorn (2009) or visit Dorn's website to learn about the construction of the crosswalk.

and the percentage of a commuting zone's population that has a college degree for each year in the model. I use 5-year survey results. I report some summary statistics in the Results.

4 Empirical Methodology

Much as Autor, Dorn, and Hanson (2013) study the effects of Chinese import competition on U.S. labor, I extend this analysis to union membership and union behavior. I follow their primary estimation techniques by which they measure the extent of a local labor market's competition with Chinese goods. Chinese goods imported to the U.S. will affect commuting zones in which a higher percentage of workers labor in a manufacturing industry. There are several channels by which Chinese imports may affect U.S. labor market outcomes. The most direct of these is that Chinese goods may compete with U.S.-produced goods. To measure the extent of the shock that Chinese goods impose on a given commuting zone, I use Equation 2:

$$\Delta IPW_{uit} = \sum_{j} \frac{E_{ijt}}{E_{ujt}} \frac{\Delta M_{ucjt}}{E_{it}} \tag{2}$$

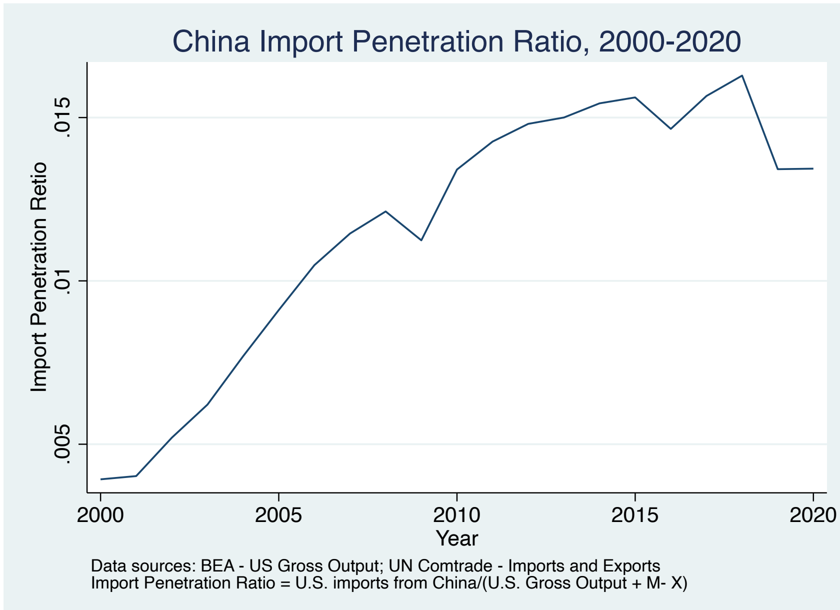
The unit of analysis is at the commuting zone(i) - year(t) level. Following the authors' technique, I estimate changes in import exposure over a ten year interval, leading me to two observation periods: 2000-2010 and 2010-2020. For each commuting zone, I generate an import exposure that is the summation of exposures for each industry (j). On the right side, each industry in a commuting zone is given a weighting according to its start-of-period share of the national employment for that industry; this is captured by the first term, in which employment for a given industry in a commuting zone (E_{ijt}) is divided by the national (u) employment at the start of the time period (E_{ujt}). The import exposure then uses the decadal change in imports from China (c) to the U.S. for each industry (ΔM_{ucjt}) and divides by total U.S. employment (E_{it}). I plot changes in the import penetration ratio in Figure 4.

However, there are two reasons why this equation may be biased and requires the use of an instrument. First, there is a potential for downstream effects that would create endogeneity with the trade data; trade with China could affect local labor market employment and unionization in a given industry, which in turn affects employers' demand for manufactured goods that are traded and used as inputs. A secondary concern in simultaneity bias in which employers consider future trade with China and base employment decisions off of these expectations, or workers unionize out of their expectations for how future trade with China may affect them. As a result, I construct the following instrument:

$$\Delta IPW_{oit} = \sum_j \frac{E_{ijt-1}}{E_{ujt-1}} \frac{\Delta M_{ocjt}}{E_{it-1}} \tag{3}$$

There are two important differences with Equation 3. First, instead of using the trade between the U.S. and China, I follow the literature and use an instrument that uses trade between China and eight countries comparable to the U.S., previously described in the Data Section. This is reflected in the M_{ocjt}, which uses Other *(o)* countries trade with China (c) instead of U.S. (u) trade with China. To address the simultaneity concerns, I use lagged employment in the U.S., taking employment data for each industry in a commuting zone from ten years prior. In Figure 4, I plot the change in the China import penetration ratio from 2000 to 2020. China joined the World Trade Organization (WTO) in December 2001 and has seen a nearly steady increase in U.S. demand over the last two decades.

For an example as to how one observation ΔIPW_{oit} is constructed for



the year 2000, I use employment in each industry (j) from 1990 divided by total U.S. employment (u) in that industry from 1990 and multiply by the change in imports from China (to the eight instrumental variables countries) that occurred from 2000-2010 before dividing by total U.S. employment in 1990. I sum across all industries (j) present in a commuting zone in 2000.

After constructing the import exposure variable ΔIPW_{uit} and its instrument ΔIPW_{oit}, I apply the following two-stage least squares model:

$$\Delta Y_{it} = B_1 \Delta IPW_{uit} + B_2 X_{st} + \gamma_t + \lambda_s + e_{it} \tag{4}$$

I construct a stacked-differences model that uses two time periods for U.S. commuting zone observations - 2000-2010 and 2010-2020. Decadal changes use data from the start and end of each respective time period. The left-hand side variables include decadal changes in three union outcomes: membership, dues, and union counts. Membership and dues are reported for each union in the OLMS dataset, and I sum them to the commuting zone level. Because the OLMS does not indicate the employer or industry sector for each union, there are non-manufacturing union workers included in this outcome variable. There is not a direct method by which import exposure will affect non-manufacturing union workers (such as teachers or nurses), but any changes would be captured by this variable. This does not bias results but does increase variance - it is more difficult to empirically detect changes across diverse industries that may experience contrasting effects. The right-hand side includes the import exposure measure as well as state-level controls for college education and gender at the start of the time period.[23] I include time fixed effects γ_t and state fixed effects λ_s. I progressively add controls in the multiple specifications provided for each model in the Results. Across specifications, I use robust standard errors clustered at the state-level.

I present the summary statistics in Table 1 for left-hand side and right-hand side variables used in the model. There are some large values for each of the variables in their minimums and maximums. For both the U.S. industry import exposure and the instrumental variable import exposure (constructed using trade data with eight countries similar to the U.S.), the average import exposures are positive, which are consistent with a net increase in imports from China. A negative value for the import exposure would indicate that trade decreased in a given commuting zone over a decade. If trade decreased in one sector that constituted a greater percentage of a commuting zone's business, then one commuting zone may have a more negative value for its import exposure. The standard deviations are fairly large, reflecting the diversity of industries across commuting zones in the U.S. There are some union outcomes

[23]Commuting zones may cross state lines. In such instances, I assign a commuting zone to the state in which the majority of the commuting zone population lies. This follows David Dorn's methodology; I apply the E8 commuting zone-state crosswalk at his data page.

Table 1: Summary Statistics

	N	Mean	Std Dev
U.S. Industry Import Exposure	1232	8.42	42.30
Instrumental Variable Import Exposure	1232	9.43	34.92
Percent Male	1232	49.50	0.73
Percent with a College Degree	1232	20.74	4.17
Change in CZ Members (1000)	1232	-1.90	22.01
Change in CZ Dues ($100,000)	1232	17.95	124.92
Change in CZ Union Count	1232	-5.89	21.64
Union Statistics in 2000			
CZ Members (1,000)	616	22.26	77.39
CZ Dues ($100,000)	616	67.50	274.34
CZ Union Count	616	37.01	73.11
Union Statistics in 2010			
CZ Members (1,000)	616	18.84	68.02
CZ Dues ($100,000)	616	77.49	336.27
CZ Union Count	616	28.82	59.11
Manufacturing Union Subset			
Change in CZ Members (1,000)	1006	-1.94	12.57
Change in CZ Dues ($100,000)	1006	7.44	67.74
Change in CZ Union Count	1006	-3.33	9.23

of significant magnitude as well; for example, the maximum change in union members for one commuting zone-year time period is over 371,000. Such an increase more likely reflects multiple large unions that relocate during a ten year time period.[24] It is important to note that the dues are presented for each union as a whole (as opposed to dues per member). These values are then summed up across a commuting zone and computed as a decadal difference in the regression model.[25] The control variables reflect the percentage of a state's population with a college degree in 2000 and in 2010.[26]

[24]If a commuting zone has one or more values for union outcomes over the three observation periods (2000, 2010, 2020), then I replace missing values with zeros. If there is never any union presence in a commuting zone, I drop the commuting zone from the analysis. This is why fewer than 722 commuting zones are presented in the models.

[25]As a robustness check, I also estimate models that removed the most extreme union outcomes (i.e., values with magnitude in the top 1% and top 5% values) and find no differences with my primary estimations. I did this in the event that my initial data cut (removing the largest 1% of unions) left large national unions in the dataset. I explore other alternative specifications in the Appendix.

[26]When ACS data is aggregated to the commuting zone level, there are too many missing observations. I therefore apply state-level controls, so commuting zones in the same state will have the same control variables.

5 Results

5.1 Full Time Period Results

In Table 2, I present the primary specification for the effect of the change in imports from China to the U.S. per worker on union membership. Column (1) presents a baseline instrumental variables model that only includes the trade exposure variable. There are no fixed effects or demographic controls in (1). I then add fixed effects, which include state fixed effects and a time period fixed effect (since there are only two time periods in the model), in specification (2). In column (3), I add demographic controls at the state-level.[27] All three models present that increasing manufacturing trade exposure leads to a decrease in the number of union members. Across specifications, the effect of import exposure per worker is not statistically significant. In column (4), I present a simple OLS association between U.S. import exposure and the change in union membership per commuting zone. Note that the OLS coefficients are not causal but reflect a negative association between changes in trade exposure and union membership. To understand the practical significance of these results, consider that a one standard deviation increase in import exposure reduces union membership by approximately 60 members per commuting zone over a decade (Column 3). Comparing these results to the summary statistics, there are an average of 22,263 union members in 2000 and 18,842 in 2010, so a decrease of 60 union members in a commuting zone translates to approximately a 0.27% decrease in 2000 and 0.32% decrease in 2010. These values represent aggregate changes across all unions in a given commuting zone over a ten year time period.

In Table 3, I explore the effects of import exposure on union dues collected

[27] Commuting zones in the same state will have the same demographic controls. I attempted to aggregate ACS demographic data at the commuting zone level, but there were sufficient missing observations that I prefer state-level controls.

(in thousands of USD). I follow the same column specifications as before. In column (3), the model with full controls and fixed effects, there is an increase in dues significant in a 90% confidence interval. In 2000, unions collected an average of $7,749,000 within a given commuting zone. A one standard deviation increase in import exported increases union dues collected within a commuting zone over the course of a decade by approximately $82,063 (column 3), which translates to a 1.06% increase.[28]

Finally, there is also a possibility that union membership declines while individual members shift between locals that consolidate. For this reason, I consider the possibility that trade with China consolidates unions, leading to fewer union locals reporting to the OLMS. I present these results in Table 4. In the first specification without fixed effects or controls (column 1), there is a negative relationship significant at the 10% significance level. The relationship remains negative as controls are added, but the coefficient is no longer statistically significant as controls are added. In the full model (column 3), a one standard deviation increase in U.S. import exposure leads to a decrease of 0.19 unions per commuting zone over a decade. This amounts to a 0.51% decrease over the 2000-2010 time period and a 0.66% decrease over the 2010-2020 decade, both of which are small effects.

Overall, at an aggregate level, unions appear relatively unaffected over the entire 2000-2020 time period, but I consider a subgroup consisting of manufacturing unions in the following section in light of recent union research, particularly Ahlquist and Downey (2019), who find that unionization within manufacturing declined by 12.3 percentage points from 1990 to 2014. Regarding manufacturing employment, Acemoglu et al. (2016) find manufacturing job losses attributable to increases in import exposure to Chinese goods from 1999

[28]The calculated change is $\frac{7666937-7749000}{7749000} * 100 = 1.05901\%$

to 2011. I explore whether these trends differ over time by extending the period of analysis to 2020 in my Split Time Period Results.

Table 2: Change in Union Members and Import Exposure, 2000-2020

	(1)	(2)	(3)	(4)
U.S. Import Exposure	-107.1188	-57.1705	-60.6285	-4.0512
	(99.8169)	(86.3332)	(88.9124)	(6.1714)
College Degree			3078.7943	2869.8778
			(3184.7338)	(3049.1159)
Male			1177.3105	1423.7194
			(3849.4128)	(3936.9778)
N	1232	1232	1232	1232
Fixed Effects	N	Y	Y	Y
Controls	N	N	Y	Y
Specification	IV	IV	IV	OLS

Standard errors in parentheses; standard errors are clustered at the state-level

Sample includes 616 commuting zones, 2000-2020

Model implements IV estimation for columns (1)-(3) in which controls are progressively added.

Col (4) presents an OLS estimation using U.S. trade as an explanatory variable.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 3: Change in Union Dues Collected and Import Exposure, 2000-2020

	(1)	(2)	(3)	(4)
U.S. Import Exposure	62.1928	82.7590*	82.0631*	8.8576
	(38.5482)	(46.2050)	(46.3619)	(5.8413)
College Degree			579.2114	849.5287
			(1405.7040)	(1298.2952)
Male			261.4841	−57.3447
			(1810.5097)	(1588.5520)
N	1232	1232	1232	1232
Fixed Effects	N	Y	Y	Y
Controls	N	N	Y	Y
Specification	IV	IV	IV	OLS

Standard errors in parentheses; standard errors are clustered at the state-level

Sample includes 616 commuting zones, 2000-2020

Model implements IV estimation for columns (1)-(3) in which controls are progressively added.

Col (4) presents an OLS estimation using U.S. trade as an explanatory variable.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 4: Change in Number of Union Locals and Import Exposure, 2000-2020

	(1)	(2)	(3)	(4)
U.S. Import Exposure	−0.2548*	−0.1840	−0.1902	−0.0092
	(0.1352)	(0.1192)	(0.1235)	(0.0106)
College Degree			3.3818	2.7135
			(3.1953)	(2.9860)
Male			3.4507	4.2389
			(5.1260)	(5.2053)
N	1232	1232	1232	1232
Fixed Effects	N	Y	Y	Y
Controls	N	N	Y	Y
Specification	IV	IV	IV	OLS

Standard errors in parentheses; standard errors are clustered at the state-level

Sample includes 616 commuting zones, 2000-2020

Model implements IV estimation for columns (1)-(3) in which controls are progressively added.

Col (4) presents an OLS estimation using U.S. trade as an explanatory variable.

* $p < .10$, ** $p < .05$, *** $p < .01$

5.2 Split Time Period Results

I separate results by decade to consider how the effects of import exposure differ over my two decades of observation: 2000-2010 and 2010-2020. In Table 5, I report the effects of import exposure from 2000-2010 (columns 1-2) and 2010-2020 (columns 3-4). The results indicate a highly different effect in each time period.[29] A one standard deviation increase in import exposure leads to 107 fewer union members per commuting zone in 2000-2010, but this trend reverses in the second time period. An increase in import exposure by one standard deviation causes 52 more workers to join a union within each commuting zone.

More recent years have been relatively underexamined in the literature, which makes it more difficult to compare my results to the existing literature. Ahlquist and Downey (2019) examine changes in CPS union membership from 1990-2014, and Charles, Johnson, and Tadjfar (2021) study changes in NLRB elections from 1990-2007, following the same time period as Autor, Dorn, and Hanson (2013). It may be possible that U.S. industries and unions have faced less competitive pressure over time, or that unions have adapted into a new trade environment. The closest analysis to my own results is that of Acemoglu et al. (2016), who consider changes in manufacturing jobs over 2000-2007. I find decreases in union members over 2000-2010 in columns (1) and (2) of Table 5. However, the trend completely changes over 2010-2020, evidenced in columns (3) and (4), which suggest that increases in import exposure cause a predicted increase in union members.

In contrast to the opposing trends in membership, union dues appear to increase in both time periods, evidenced in Table 6. There is a statistically significant increase in union dues by $92,379 within the 2000-2010 time period for

[29] China joined the World Trade Organization in December 2001. See the World Trade Organization for details.

Table 5: Change in Union Members and Import Exposure, 2000-2020

	(1)	(2)	(3)	(4)
U.S. Import Exposure	−131.6875	−107.1711	59.9061	51.6301
	(139.1814)	(136.0938)	(84.6467)	(74.8434)
College Degree		−70.7670		95.3992
		(290.6584)		(194.9562)
Male		2820.1979		−983.8912
		(2404.7397)		(1440.6222)
N	616	616	616	616
Years	2000-2010	2000-2010	2010-2020	2010-2020
Fixed Effects	N	N	N	N
Controls	N	Y	N	Y
Specification	IV	IV	IV	IV

Standard errors in parentheses; standard errors are clustered at the state-level

Sample includes 616 commuting zones, 2000-2020

Note that time periods are split

* $p < .10$, ** $p < .05$, *** $p < .01$

a one standard deviation increase in trade exposure (column 2). This increases to $136,009 from 2010-2020 (column 4), although a wider variance makes the result not statistically significant.

In Table 7, the changes in the count of union locals is separated by time period. There appears to be a decrease in the union count within each commuting zone over both time periods. In column (1), the instrumental variable regression for 2000-2010 without controls reports that a one standard deviation increase in import exposure causes a decrease of about 0.2861 union locals within each commuting zone. Based on the summary statistics, this corresponds to a 1.29% decrease. Even though total membership has a positive relationship with import exposure over the 2010-2020 time period, the relationship between union count and import exposure remains negative. This suggests that existing unions in industries that were more exposed to trade over the second decade may have experienced membership growth within existing unions, rather than through the creation of new union locals.

Table 6: Change in Union Dues Collected and Import Exposure, 2000-2020

	(1)	(2)	(3)	(4)
U.S. Import Exposure	75.5221	92.3788*	130.8019	136.0091
	(50.9585)	(54.0508)	(115.8057)	(120.4633)
College Degree		59.3822		−35.1374
		(165.5311)		(169.7556)
Male		1499.5158		554.0554
		(919.1862)		(1680.9925)
N	616	616	616	616
Years	2000-2010	2000-2010	2010-2020	2010-2020
Fixed Effects	N	N	N	N
Controls	N	Y	N	Y
Specification	IV	IV	IV	IV

Standard errors in parentheses; standard errors are clustered at the state-level

Sample includes 616 commuting zones, 2000-2020

Note that time periods are split

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 7: Change in Number of Union Locals and Import Exposure, 2000-2020

	(1)	(2)	(3)	(4)
U.S. Import Exposure	−0.2861*	−0.2466	−0.0445	−0.0401
	(0.1633)	(0.1544)	(0.0686)	(0.0586)
College Degree		0.0207		0.1394
		(0.3677)		(0.1784)
Male		3.9947		0.0322
		(2.5749)		(1.2812)
N	616	616	616	616
Years	2000-2010	2000-2010	2010-2020	2010-2020
Fixed Effects	N	N	N	N
Controls	N	Y	N	Y
Specification	IV	IV	IV	IV

Standard errors in parentheses; standard errors are clustered at the state-level

Sample includes 616 commuting zones, 2000-2020

Note that time periods are split

* $p < .10$, ** $p < .05$, *** $p < .01$

6 Subgroup Analysis

6.1 Manufacturing Unions

One difficulty with the OLMS dataset is that unions are not linked to employers or industries, making industry identification difficult. One possible solution is to identify union locals by their parent organization, and then apply the broad industry classification of the parent (national) union to the local. In the following analysis, I identify national unions in the OLMS dataset that are associated with industries more likely to be affected by trade competition.[30] I list these specific unions and their main industry in Table 11. Counting all union locals in the main sample (i.e., excluding the largest 1% and keeping those in Washington, D.C.), there are 69,217 unions in 2000, 2010, and 2020 combined. Within this sample of 17 national (primarily) manufacturing unions, there are 22,869 unions; this represents 33% of entire the sample consisting of manufacturing and non-manufacturing unions.

I estimate the effects of import exposure on this subgroup. I include D.C. unions and exclude the largest 1% in models for members, dues, and union count, respectively.

In Table 8, I estimate the effect of import exposure on union members within manufacturing. A one standard deviation increase in U.S. import exposure decreases manufacturing union members by 54.5 members per commuting zone over a decade, using the full specification in column (3). Compared to baselines of over 22,263 in 2000 and 18,842 in 2010, this is still practically insignificant. Furthermore, in comparison to Table 2, the decreases in union membership are comparable. Based on results from the literature, it is possible

[30]To clarify, this analysis still focuses on union locals and excludes the large national union observations, but union locals are identified by their national affiliate. I use this identifier to infer which union locals are comprised mainly of manufacturing workers.

that these national unions remain too broad to identify specific industry-based changes. For example, one manufacturing union may be nearly unaffected by changing trade patterns with China while another suffers from the trade; the net result may be approximately zero in the change in membership across a commuting zone.

In Table 9, I report low, but positive, coefficients for import exposure in affecting union dues among manufacturing union locals. These are substantially smaller than for the overall sample, about 23.6% the size of the dues increase predicted for all unions in Table 3. In Table 10, I note small and insignificant decreases in the total union count per commuting zone as a result of increased trade exposure. These coefficients are strictly less than those in Table 4. These results are qualitatively consistent with the existing literature.

Table 8: Manufacturing Δ Union Members and Import Exposure

	(1)	(2)	(3)	(4)
U.S. Import Exposure	−71.7785	−44.8606	−47.3101	−3.0856
	(50.8023)	(42.6278)	(43.4444)	(4.9564)
College Degree			966.9247	768.4819
			(1795.0500)	(1737.4514)
Male			1614.1549	1933.9523
			(2682.1036)	(2699.4316)
N	1006	1006	1006	1006
Fixed Effects	N	Y	Y	Y
Controls	N	N	Y	Y
Specification	IV	IV	IV	OLS

Sample includes only union locals that affiliated with manufacturing unions.
Standard errors in parentheses; standard errors are clustered at the state-level
Sample includes 503 commuting zones, 2000-2020
Model implements IV estimation for columns (1)-(3) in which controls are progressively added.
Col (4) presents an OLS estimation using U.S. trade as an explanatory variable.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 9: Manufacturing Δ Union Dues Collected and Import Exposure

	(1)	(2)	(3)	(4)
U.S. Import Exposure	6.4327	20.2004	19.5764	4.0221
	(12.0451)	(13.5742)	(13.6507)	(2.5999)
College Degree			302.8614	372.6558
			(802.4342)	(777.3066)
Male			335.9572	223.4812
			(1232.0280)	(1192.4923)
N	1006	1006	1006	1006
Fixed Effects	N	Y	Y	Y
Controls	N	N	Y	Y
Specification	IV	IV	IV	OLS

Sample includes only union locals that affiliated with manufacturing unions.
Standard errors in parentheses; standard errors are clustered at the state-level
Sample includes 503 commuting zones, 2000-2020
Model implements IV estimation for columns (1)-(3) in which controls are progressively added.
Col (4) presents an OLS estimation using U.S. trade as an explanatory variable.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 10: Manufacturing Δ Union Locals and Import Exposure

	(1)	(2)	(3)	(4)
U.S. Import Exposure	-0.0945^{**}	-0.0751^{*}	-0.0779^{*}	-0.0063
	(0.0466)	(0.0406)	(0.0420)	(0.0073)
College Degree			0.9065	0.5853
			(1.3680)	(1.2893)
Male			2.0969	2.6146
			(2.1722)	(2.1859)
N	1006	1006	1006	1006
Fixed Effects	N	Y	Y	Y
Controls	N	N	Y	Y
Specification	IV	IV	IV	OLS

Sample includes only union locals that affiliated with manufacturing unions.
Standard errors in parentheses; standard errors are clustered at the state-level
Sample includes 503 commuting zones, 2000-2020
Model implements IV estimation for columns (1)-(3) in which controls are progressively added.
Col (4) presents an OLS estimation using U.S. trade as an explanatory variable.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 11: Manufacturing Unions

Union	Industries
International Brotherhood of Boilermakers (BBF)	Shipbuilding, Manufacturing, & Metalwork
Building and Construction Trades Department(BCTD/NABTU)	Construction
Carpenters IND (CJA)	Construction
Glass, Molders, Pottery, Plastics and Allied Workers International Union (GMP)	Manufacturing
International Association of Machinists and Aerospace Workers (IAM)	Aerospace, Manufacturing, & Automotive
International Brotherhood of Electrical Workers (IBEW)	Computers & Telecommunications
International Brotherhood of Teamsters (IBT)	Warehousing, Distribution, & Manufacturing
International Union of Operating Engineers (IUOE)	Construction
Operative Plasterers' and Cement Masons' Intl. Association (OPCM)	Concrete & Plaster Construction
Paper, Allied-Industrial, Chemical and Energy Workers International Union (PACE)	Chemical Manufacturing
United Auto Workers (UAW)	Automobile Manufacturing
United Electrical, Radio and Machine Workers of America (UE)	Manufacturing & Service Sector
United Food and Commercial Workers International Union (UFCW)	Grocery, Retail, & Chemical
United Mine Workers of America (UMW or UMWA)	Mining
United Steelworkers (USW)	Mining & Manufacturing
United Workers Union (UWU)	Farming, Distribution, & Health
Association Of Western Pulp And Paper Workers Union (WPPW)	Paper Manufacturing

6.2 Health and Education Unions

To complement the manufacturing subgroup analysis, I also consider a subgroup consisting of workers in healthcare and education. This sample constitutes 5.2% of all total union locals and 10.32% of all union members. All union locals used in this analysis are affiliated with the parent organizations listed in Table 15. I follow the same empirical specification as used in the manufacturing union subgroup analysis; namely, excluding the largest 1% of unions and including D.C. unions. The sample size (175 commuting zones x 2 time periods) is much smaller than in the manufacturing subgroup (503 commuting zones x 2 time periods) and the overall sample (616 commuting zones x 2 time periods). This is possibly because the teachers that unionize are more concentrated, such as in large cities, whereas manufacturing workers may unionize in rural and urban commuting zones in the U.S.

In Table 12, I examine the first outcome, the decadal change in union members, among the subgroup of health and education unions. The magnitudes of coefficients appears highly similar to the results for the manufacturing subgroup, estimated in Table 8. While the initial estimates in column (1) diverge as education and health unions report about half the member losses over a decade in a commuting zone as a result of a one standard deviation increase in import exposure (-71.78 vs. -34.01). However, after including controls and fixed effects, the magnitudes are highly similar in columns (2) and (3) - unions in the education and health professions actually show a slightly larger decrease in union members. These results are not statistically significant.

In Table 13, I estimate the change in union dues over a commuting zone-decade, and I find slightly positive increases, although these are not statistically significant. The coefficient for trade exposure is comparable to that in the manufacturing subgroup model. Table 14 shows a smaller decrease in the union count among health and education unions compared to the manufacturing subgroup, presented in Table 10, which had a larger decrease of -0.078 that was statistically significant at the 10% level.

This subgroup analysis complements the work of Ahlquist and Downey (2019), who find that import exposure pushed unionized retail workers into jobs in health and education while manufacturing workers were more likely to shift into service jobs. Outside of manufacturing, where Ahlquist and Downey find a decrease in unionization, they find large increases. I do not find these results - my manufacturing and education subgroups have highly similar results. There are multiple explanations for such disparities. First, there could be consequential differences in samples. I use OLMS data while Downey measures unionization from the CPS, and I measure unionization from 2000-2020 while Downey studies changes from 1990-2014. It could be that the most significant changes in unionization occurred when China first joined the WTO in December 2001; I do not have the 1990 data to measure such a change. Finally, it is possible that I miss a critical share of manufacturing or health and education union members in my categorizations.[31] Linking union names to businesses remains an important next research task to optimize the OLMS data.

[31] For aforementioned reasons, I cannot measure the exact employers or positions of union members in the union locals I include in my sample. I can only leverage the general industry representation of the umbrella/parent affiliated union.

Table 12: Health-Education Δ Union Members and Import Exposure

	(1)	(2)	(3)	(4)
U.S. Import Exposure	−34.0068	−47.0310	−48.3000	−6.3966
	(50.8563)	(59.7229)	(61.4393)	(6.5524)
College Degree			1458.2696	1344.2809
			(2514.8302)	(2555.7172)
Male			−770.4403	−260.3938
			(3190.4505)	(3271.5842)
N	350	350	350	350
Fixed Effects	N	Y	Y	Y
Controls	N	N	Y	Y
Specification	IV	IV	IV	OLS

Sample includes only locals in health and education unions.
Standard errors in parentheses; standard errors are clustered at the state-level
Sample includes 175 commuting zones, 2000-2020
Model implements IV estimation for columns (1)-(3) in which controls are progressively added.
Col (4) presents an OLS estimation using U.S. trade as an explanatory variable.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 13: Health-Education Δ Union Dues Collected and Import Exposure

	(1)	(2)	(3)	(4)
U.S. Import Exposure	12.4750	20.6858	20.4978	0.8500
	(10.4154)	(21.3960)	(21.5310)	(1.7453)
College Degree			193.5993	247.0465
			(861.7535)	(839.9328)
Male			−266.1094	−505.2607
			(1390.5743)	(1314.1420)
N	350	350	350	350
Fixed Effects	N	Y	Y	Y
Controls	N	N	Y	Y
Specification	IV	IV	IV	OLS

Sample includes only locals in health and education unions.
Standard errors in parentheses; standard errors are clustered at the state-level
Sample includes 175 commuting zones, 2000-2020
Model implements IV estimation for columns (1)-(3) in which controls are progressively added.
Col (4) presents an OLS estimation using U.S. trade as an explanatory variable.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 14: Health-Education Δ Union Locals and Import Exposure

	(1)	(2)	(3)	(4)
U.S. Import Exposure	-0.0061	-0.0166	-0.0168	0.0021
	(0.0099)	(0.0156)	(0.0160)	(0.0019)
College Degree			0.5484	0.4971
			(0.9586)	(0.9299)
Male			1.9617	2.1914
			(1.9437)	(1.8131)
N	350	350	350	350
Fixed Effects	N	Y	Y	Y
Controls	N	N	Y	Y
Specification	IV	IV	IV	OLS

Sample includes only locals in health and education unions.

Standard errors in parentheses; standard errors are clustered at the state-level

Sample includes 175 commuting zones, 2000-2020

Model implements IV estimation for columns (1)-(3) in which controls are progressively added.

Col (4) presents an OLS estimation using U.S. trade as an explanatory variable.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 15: Health and Education Unions

Union	Industries
National Nurses United (NNU)	Nursing
Service Employees International Union (SEIU)	Healthcare & Public Employees
Association of American Educators (AAE)	Education
American Association of University Professors (AAUP)	Education
American Federation of State, County, and Municipal Employees (AFSCME)	Education, Healthcare, & Public Employees
American Federation of Teachers	Education
American Nurses Association	Nursing
National Education Association	Education
Professional Association of Teachers (PAT)	Education

7 Conclusion

In this study, I conduct an instrumental variable analysis to examine the role of trade with China on unions from 2000-2020 using an OLMS dataset on union membership, dues, and locals. Such analysis has previously been conducted on employment, CPS estimates of unionization, and NLRB elections, but had not been extended to administrative data on union workers.[32] While the OLMS dataset is valuable in presenting new dimensions to union behavior such as the change in number of members over time for each local and the changes in dues and union assets, one weakness that restricted my analysis was the lack of industry identification in the dataset.

As Ahlquist and Downey (2019) note, Chinese manufacturing contributed to slight declines in unionization within manufacturing from 1990-2014, but import exposure actually increased union membership outside of manufacturing. In the OLMS data, it is only possible to separate union industries based on the industry of their national affiliation. I find similar outcomes for a sample of manufacturing unions compared to a sample of health and education unions; it is possible that this is because my period of analysis differs from the existing literature, or that union members even within a broad sector such as education or health are experiencing heterogeneous downstream effects from changes in import exposure.

Regarding the creation of new unions, Charles, Johnson, and Tadjfar (2021) find that import exposure reduced union certification elections by 4.5% within manufacturing industries and by 8.8% in adjacent industries over 1990-2007. This also suggests there should have been a negative relationship between import exposure and union count. My results support such a result, albeit at a much smaller quantity that can be attributed to challenges in OLMS industry

[32]See the descriptions of relevant papers in the literature review.

identification. Overall, the signs of coefficients in my analyses match results in the relevant literature. Another contribution of this paper includes an analysis of union dues, which has not been previously studied, and which I find to have increased in line with greater import exposure. That increases were not statistically significant or particularly large in magnitude suggests that unions either did not perceive competitive challenges from trade exposure, or that raising dues may have alienated members. Qualitative research into unions or an analysis of available collective bargaining agreements may offer insights into this decision problem.

I also conduct a split time period analysis, in which I examine changes in union outcomes solely from 2000-2010 and then from 2010-2020. These results suggest that papers that examine earlier time periods may need to be extended. Other studies adjacent to my own end their analysis at 2014, due to the difficulties in acquiring and constructing trade exposure data. However, I offer some evidence that dynamics may have shifted after 2014. Considering the evidence in columns (3) and (4) of Table 5, I find that a one standard deviation increase in trade exposure causes a 107 union member decrease per commuting zone in 2000-2010, but the coefficient flips to a 52 union member increase from 2010-2020. Additionally, the magnitude of trade import exposure in affecting union dues increases significantly in the second decade, seen in Table 6. My analysis extends the current literature by six years from the previous standard of 2014, although more work remains on disaggregating these changes by industry. As the types of goods exchanged between the U.S. and China vary over time, the consequences may similarly shift for workers across different industries.

8 Appendix

8.1 First Stage Results

I provide first stage results in the following table. I use the instrumental trade exposure variable to predict U.S. trade exposure due to the simultaneity concerns addressed in the Empirical Methods section. I cluster standard errors at the state level. Column (1) is a simple bivariate regression, column (2) adds a decadal fixed effect (since there are only two time periods) and state fixed effects, and column (3) adds two controls. This mirrors the regressions reported in the results section.

All predictors are significant. The p-values are 0.027, 0.056, and 0.057, respectively, for columns (1)-(3). This suggests the instrument is valid. I use standard errors clustered at the state level in my IV regressions presented in the paper. This follows Ahlquist and Downey (2019). While my instrument is weaker than that used in Autor, Dorn, and Hanson (2013), there are several possible explanations, including that I do not include as many commuting zones, include an additional decade after the initial trade shock stabilized, and do not have data on the 1990-2000 time period.

Table 16: First Stage Results

	(1)	(2)	(3)
Instrumental Variable Import Exposure	0.1561**	0.1381*	0.1387*
	(0.0682)	(0.0703)	(0.0710)
College Degree			3.5611
			(3.7017)
Male			−6.0067
			(9.6518)
N	1232	1232	1232
Fixed Effects	N	Y	Y
Controls	N	N	Y

Standard errors in parentheses
Sample includes 616 commuting zones, 2000-2020
Col (1) is a simple bivariate regression
Col (2) adds fixed effects
Col (3) adds two control variables
Standard errors are clustered at state level
* $p < .10$, ** $p < .05$, *** $p < .01$

8.2 Results Excluding D.C. Unions

In the robustness model for union members, Table 17, I remove all unions in the D.C. location because these are national headquarters rather than manufacturing unions. The vast majority have already been removed after eliminating the top 1% largest unions for the primary specification, so these results are highly similar.[33] I report results for the three outcomes: union membership, union dues collected, and the count of unions in a commuting zone.

The results in Table 17 are highly similar to those in the main specification, Table 2. Coefficients are comparable in magnitude and statistical significance; the standard deviations are quite large on the import exposure coefficients across columns (1)-(3). The same is true when comparing Table 18 to Table 3 and Table 19 to Table 4.

Removing the D.C. unions likely has little effect for several reasons. First, the unions that list a location in D.C. are, in the vast majority of cases, reporting a national headquarters. These unions will therefore report the national number of union workers in their organization, which typically places them in the top 1% of unions by membership size and therefore excludes them from the primary analysis. Second, the number of commuting zones remains the same in these alternate models because the D.C. unions are combined with unions in Alexandria, VA and Arlington, VA.[34] Removing the entire commuting zone (not shown, available upon request) has no effect on results. It is worth noting that these national union organizations that report to the OLMS are just aggregating numbers from their many locals that can be found throughout the U.S. The national union observations should therefore reflect broader national trends.

[33] I also explore removing the top 5%, and there are no meaningful changes.

[34] See the USDA website for more information on commuting zone classifications and the cities encompassed within a given region.

Table 17: Change in Union Members and Import Exposure, 2000-2020

	(1)	(2)	(3)	(4)
U.S. Import Exposure	−105.4039	−57.0604	−60.6843	−3.8392
	(99.5016)	(86.2403)	(88.8455)	(6.1045)
College Degree			2972.1380	2762.2325
			(3177.2531)	(3041.3385)
Male			1388.8374	1636.4128
			(3815.6517)	(3905.3042)
N	1232	1232	1232	1232
Fixed Effects	N	Y	Y	Y
Controls	N	N	Y	Y
Specification	IV	IV	IV	OLS

Standard errors in parentheses; standard errors are clustered at the state-level
Sample includes 616 commuting zones, 2000-2020
Model implements IV estimation for columns (1)-(3) in which controls are progressively added.
Col (4) presents an OLS estimation using U.S. trade as an explanatory variable.
Excludes D.C. unions
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 18: Change in Union Dues Collected and Import Exposure, 2000-2020

	(1)	(2)	(3)	(4)
U.S. Import Exposure	63.2311	82.8786*	82.1242*	9.0517
	(38.6448)	(46.2616)	(46.4169)	(5.9094)
College Degree			541.3964	811.2225
			(1404.3199)	(1296.8246)
Male			336.2415	17.9921
			(1800.5314)	(1577.6877)
N	1232	1232	1232	1232
Fixed Effects	N	Y	Y	Y
Controls	N	N	Y	Y
Specification	IV	IV	IV	OLS

Standard errors in parentheses; standard errors are clustered at the state-level
Sample includes 616 commuting zones, 2000-2020
Model implements IV estimation for columns (1)-(3) in which controls are progressively added.
Col (4) presents an OLS estimation using U.S. trade as an explanatory variable.
Excludes D.C. unions
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 19: Change in Number of Union Locals and Import Exposure, 2000-2020

	(1)	(2)	(3)	(4)
U.S. Import Exposure	-0.2553^{*}	-0.1838	-0.1898	-0.0090
	(0.1354)	(0.1193)	(0.1236)	(0.0105)
College Degree			3.5139	2.8464
			(3.2076)	(2.9986)
Male			3.1876	3.9750
			(5.1662)	(5.2455)
N	1232	1232	1232	1232
Fixed Effects	N	Y	Y	Y
Controls	N	N	Y	Y
Specification	IV	IV	IV	OLS

Standard errors in parentheses; standard errors are clustered at the state-level

Sample includes 616 commuting zones, 2000-2020

Model implements IV estimation for columns (1)-(3) in which controls are progressively added.

Col (4) presents an OLS estimation using U.S. trade as an explanatory variable.

Excludes D.C. unions

* $p < .10$, ** $p < .05$, *** $p < .01$

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