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Did the 2018 Trade War Improve Job Opportunities for US Workers?

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Abstract

This paper uses data on the near universe of job adverts posted online in the US to study the impact of the 2018 trade war on US job opportunities. We develop measures of labour market exposure to three key channels of impact from the trade war: import protection for US producers, the higher cost of imported inputs for US producers, and exposure of US exporters to retaliatory tariffs. We find evidence that both tariffs on imported inputs and retaliatory tariffs led to a relative decline in online job postings in affected commuting zones. These effects were stronger for lower skilled postings than for higher skill postings. By contrast, we do not find any evidence of positive impacts of import protection on job openings. We estimate that the tariffs led to a combined effect of 175,000 fewer job postings in 2018, or 0.6 percent of the US total, with two thirds of this aggregate decline due to the imported input tariffs and one-third due to retaliatory tariffs.

Keywords: Tariffs, trade barriers, online job adverts, trade war, local labour markets

JEL Classification Number: F14, F15, F16

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1. Introduction

"One by one, the factories shuttered and left our shores, with not even a thought about the millions upon millions of American workers left behind"
- President Trump, Inaugural Address, 2017

In 2018, after many decades of focus on lowering barriers to international trade, the US embarked on a wave of protectionism, unilaterally raising tariffs on imports from many of its major trade partners. Tariffs were levied in several rounds, covering approximately 12 percent of total US imports by the end of 2018. One of the central justifications offered for this unprecedented shift in trade policy was boosting the competitiveness of the US manufacturing sector and protecting US manufacturing jobs. This was a common theme during the Trump Presidency, as is reflected in statements such as that listed above and the promise that 'we will bring back our jobs.'[1] In response to the US tariffs, from April 2018 onward, the US's main import partners, starting with China, then followed by Mexico, Turkey, the European Union, Canada and Russia, all levied retaliatory tariffs on US exports. By the end of 2018, these had covered approximately 8 percent of the US's total exports.[2]

While many of the impacts of this trade war, such as on trade flows, prices and consumption, have now been well documented, research on the labor market consequences of the trade war remains more scarce. Did these tariffs really achieve the goal of improving job opportunities for US workers? In this paper, we aim to shed light on this question by studying how the trade war affected the posting of online job adverts during the immediate aftermath of the tariff hikes in 2018. In contrast to official employment statistics, which capture both labor demand and supply-side factors and provide only total employment counts, online job adverts provide an almost real-time proxy for firms' intentions to hire and include comprehensive and rich information on the characteristics of jobs on offer. This allows us to cleanly pin down the link between trade policy and labor markets.

We investigate three key ways in which the trade war could have affected online job postings in the US: (i) the impact of protection for US firms from import competition ('output tariff exposure'), (ii) the impact of the higher cost of imported inputs for US producers ('in-

[1] https://www.whitehouse.gov/briefings-statements/the-inaugural-address

[2] A detailed overview of the US Trade War timeline is provided by Bown and Kolb (2019), and Crowley, ed (2019) presents a discussion of key elements of the conflict, including its origins, costs, and the challenges it poses for the future.

put tariff exposure') and (iii) the impact of the retaliatory tariffs levied by third-countries on US exports ('export tariff exposure').

To test the impacts of the tariffs, we employ a shift-share estimation strategy that exploits the timing of the tariffs and the *ex ante* reliance of each commuting zone's labor force on trade in tariff-affected products. We measure labor force exposure to the future tariffs by combining commuting zone pre-trade war industry employment shares with the national reliance of each industry's employment on trade in specific products. For output and export tariff exposure, we map the product-level US import tariffs to the industries producing similar goods. For the intermediate import tariff exposure, we use an input-output matrix to measure the reliance of downstream US industries on imported inputs that were affected by the tariffs. A panel data specification with commuting zone fixed effects then allows us to relate the changes in tariffs to changes in postings, removing all time-invariant commuting zone characteristics.

Although lists of targeted tariffs were typically released ahead of implementation, significant uncertainty surrounded the specific dates, products and source countries that would be affected by the tariffs. This meant that the timing and composition of the tariffs by product and country was largely unanticipated, as has been emphasised by several studies on the trade war including Flaaen and Pierce (2021), Amiti et al. (2019) and Fajgelbaum et al. (2020). These papers have also demonstrated that there was little evidence of pre-trends in trade, prices, or employment in the tariff affected products or industries. In terms of of the orthogonality conditions required for our shift-share strategy to be valid, we hence view the case for causal identification as stemming from the plausible exogeneity of the time-varying tariff shocks. The results of robustness checks suggested by Borusyak et al. (2022) provide support for the validity of this strategy.

We find that both the retaliatory export and imported input tariffs had an economically meaningful negative impact on job postings. In contrast, the impact of output tariffs is not statistically significant once imported input tariffs are controlled for. In terms of magnitude, a one-standard-deviation increase in commuting zone input tariff exposure led to a 3.6 percent decrease in online job postings, and a one-standard-deviation increase in commuting zone export tariff exposure led to a 7.3 percent decrease in online job postings. A back-of-the-envelope counterfactual calculation shows that these effects were concentrated in the second half of 2018 as the tariffs started to build up, and led to a estimated combined effect of 175,000 fewer job postings. Just over two thirds of this aggregate decline was due to the imported input tariffs and one third due to retaliatory tariffs. The lost postings represent a 0.6 percent decrease for the whole of 2018 and a 0.9 percent decrease for the second half of the year. These results provide evidence, therefore, of an overall negative impact of the trade war on the advertising of job openings, which could reflect either lower firm employment growth, firm downsizing or closures.

Both higher skilled and lower skilled job postings were affected by the tariffs, but the magnitude and statistical significance of effects is stronger for lower skilled jobs, for both intermediate inputs and retaliatory tariffs. In terms of occupations, the intermediate input tariffs most negatively affected job adverts for farming, fishing and forestry, construction and extraction jobs, but also professional and managerial positions, with postings for managers, engineers, architects and lawyers experiencing strong negative effects. For retaliatory tariffs, job adverts for cleaning, maintenance and repair, and production workers were most negatively affected, along with those in health, education, social services and the sciences.

In an extension of our analysis, we additionally control for the US agricultural subsidies announced in July 2018 as a response to the retaliatory tariffs, finding some evidence of a positive impact on job postings but no evidence that the subsidies were more effective in commuting zones that were more exposed to the retaliatory tariffs. We also conduct various robustness checks, including pre-sample placebo tests and using alternative construction of the exposure measures, both of which support the baseline results. To allay concerns related to possible over-rejection in statistical inference with the use of Bartik measures, we also construct adjusted standard errors following Adao et al. (2019) and Borusyak et al. (2022) and find that our results are robust to this change.

Neoclassical trade theory stemming back to Dixit and Norman (1980) would suggest that the impact of more expensive imported inputs on US firms should depend on the tariff pass-through rate to US producers and the extent to which firms are able to costlessly substitute the tariff-affected imported inputs with other alternatives. Several papers, including Amiti et al. (2019), Cavallo et al. (2021), Fajgelbaum et al. (2020), and Flaaen et al. (2020), have documented a high degree of pass through of the US tariffs to both domestic importers and retail prices. Flaaen and Pierce (2021) have also documented that the tariffs raised producer prices, pointing to a limited degree of substitution. Likewise, Handley et al. (2020) found that the US import tariffs on inputs led to reduced US exports. Through this lens, a high degree of tariff pass-through and low degree of substitution can thus provide an explanation for our results on imported input tariffs.

The theoretical impacts of retaliatory tariffs should also depend on the incidence of the tariffs and demand response of foreign consumers. Empirical evidence to date also shows a high degree of pass-through of retaliatory tariffs, although is somewhat more mixed, with Cavallo et al. (2021) showing that US exporters dropped their prices in the face of retaliatory tariffs, pointing to lower revenues for US exporters. Our results are hence consistent with an explanation of retaliatory tariffs resulting in a negative demand response from foreign consumers and US firms being affected by lower prices or revenues.

But why don't we find any positive effects of output tariffs on job postings? Such tariffs are typically justified on the grounds that they raise the price of imports, increasing the competitiveness of domestic firms and thus boosting domestic employment. Trade theory points to three conditions that are required for this to be the case. The first is that the tariffs are passed through to domestic prices for the affected imports, rather than the incidence of the tariffs falling on foreign exporters. The second is that there is a high trade elasticity, meaning that the higher prices of the affected imports result in consumers purchasing less of them. The third is that consumers substitute these imports with domestically produced varieties, rather than with imports from other countries. The existing research outlined above points to the first two conditions having held, with evidence of a high pass-through rate and trade elasticity. However, the extent to which the third condition held is less clear: Fajgelbaum et al. (2022) have shown, for example, that the tariffs resulted in an increase in US imports from countries not subject to tariffs. A further possibility could be that, despite gaining market share, US producers did not expand by hiring more workers. Alternatively, our short-run analysis may not have picked up longer term positive effects.

Our results thus resonate with a growing literature on the trade war concluding that in an interdependent international economy with global supply chains, the likelihood of trade diversion, retaliation and indirectly raising firms' supply chain costs all render tariffs a blunt instrument for protecting domestic producers. We make several contributions to the growing body of research on the impacts of the trade war. We add new evidence on the labor market consequences of the trade war using a novel outcome – on-line job advertisements – that has not been considered in the trade context before. Our findings are consistent with the conclusions from Flaaen and Pierce (2021), who investigate the impact of the trade war on manufacturing employment at the industry level, finding that the tariffs were associated with relative declines in US manufacturing employment due to the rising imported input costs and export retaliation, which more than offset the gains from import protection. Our findings are also in line with the regional analysis of Waugh (2019), who concentrates specifically on the retaliatory Chinese tariffs, finding that retaliatory tariffs lowered retail employment growth. Finally, our findings echo the results of a working paper by Goswami (2020) that commuting zones subject to higher retaliatory tariffs experienced lower employment growth, with no effects found from import protection.

We demonstrate that a key channel through which employment effects materialised was on the demand side through reduced job openings, particularly for lower skilled workers. We also show that labor market effects were felt more broadly than by the manufacturing sector alone. In addition, our data with detailed geographic, time series and occupational variation allows us to pin down the causal impact of the tariffs more tightly by exploiting actual monthly changes in tariffs and by using a shift-share identification strategy with commuting zone fixed effects, which mitigates potential industry-level confounding effects.

Second, we add further evidence to the broader understanding on the economic consequences of the trade war.[3] In addition to the literature on tariff incidence and trade quantities discussed above, there is a growing literature documenting the impacts of the trade war on firm performance. For example, Huang et al. (2021) and Amiti et al. (2020) show how the trade war affected firms' financial performance, with negative effects for stock returns and investment. On the China side, Chor and Li (2021) also show how the US tariffs lowered industrial activity of Chinese firms. Our results reinforce the conclusions of these papers that the impacts of tariffs in a globally integrated economy are complex, with the possibility that the unintended consequences from the tariffs outweigh the gains from import protection.

Finally, this paper also contributes to a burgeoning literature focusing on the labor market consequences of both trade integration and the recent retreat from global integration. An influential literature has documented the large job-reducing effects of imports from China

[3]For a recent survey on this literature, see Fajgelbaum and Khandelwal (2022).

on the U.S. labor market (e.g. Autor et al. (2013), Pierce and Schott (2016)). On the other side of the coin, the job-creating effects of exports to China have also been documented (e.g. by Feenstra et al. (2019)). A growing literature is also documenting the negative labor market consequences of a retreat from global integration, (e.g. Javorcik et al. (2020) in the context of the UK leaving the European Union). This paper adds to the literature by suggesting that unilaterally raising tariffs does not appear to be an effective solution to remedy the negative labor market consequences of import competition.

The paper proceeds as follows: Section 2 provides background information on the trade war, Section 3 summarises the data sources used and construction of the exposure measures, Section 4 outlines the empirical strategy, Section 5 presents the results, Section 6 the robustness checks, and Section 7 concludes.

2. Background on the 2018 tariffs

This paper focuses on the tariffs introduced in 2018, both by the US on imports from various partners, as well as by these partners on US exports. Table 1 displays a summary of the timeline for the introduction of tariffs.[4] Following Bown and Kolb (2019), we split the trade disputes and associated tariff changes into three key 'battles': solar panel and washing machines; steel and aluminium; and unfair trade practices for technology and intellectual property. We briefly discuss each one in turn in the following subsections but refer the reader to Bown and Kolb (2019) for a more detailed account.

As contextual background, the World Trade Organisation (WTO), and before it the General Agreement on Tariffs and Trade (GATT), had been introduced to provide a rules-based system for international trade, and resulted in dramatic decreases in tariff barriers and greater predictability in global trade policy over the two decades prior to the trade war. The unilateral actions of the US, for which the dispute resolution mechanisms of the WTO were largely sidelined, led to a fast ramping up of tariffs, which were product and source country specific. In order to justify these actions, the US relied on a number of relatively infrequently used articles within US trade law such as those relating to a 'national security threat' and 'global

[4] As summarised by Fajgelbaum et al. (2020).

safeguards', discussed in more detail below.[5]

It is important to note that 2018 was a period of great uncertainty for importers and exporters in the US. Although lists of targeted tariff lines were typically announced in advance of the actual change, these lists were frequently subject to substantial modifications in terms of the specific products included, the rates that those products would face, and which countries would be affected or exempt. Moreover, negotiations were ongoing throughout the period with the aim of halting any future increases in tariffs on both sides, and there were several occasions where changes were delayed or halted at the last minute (see below for examples). The result of this was that firms would have been unable to predict any extra costs or benefits they might experience with any certainty until the actual day of tariff implementation. This is important for the estimation of the effects of tariffs on job postings as discussed in Section 4.

2.1 Solar panel and washing machine import tariffs

In response to two industries' requests for investigation under Section 201 of the Trade Act of 1974, President Trump imposed safeguarding tariffs on $1.8 billion in imports of washing machines, and on $8.5 billion in imports of solar panels on the 22nd January 2018. This was followed, on the 5th February, by China launching anti-dumping and countervailing duty investigations into US exports of sorghum. Although not explicitly retaliatory in nature, the timing implies a link with the US tariff increases. China went on to initiate anti-dumping duties of 178.6 percent on its imports of sorghum from the US, and South Korea followed by filing a dispute at the WTO on the 14th May. On the 18th May, following negotiations between the US and China, China announced the end of their sorghum tariff increases. However, later in the year (14th August 2018), China joined South Korea in filing a dispute at the WTO against US solar panel tariffs.

[5] Section 201 of the Trade Act of 1974 allows protection if an import surge is a substantial cause of serious injury to an industry (invoked for tariffs on imported washing machines and solar panels). Section 232 of the Trade Expansion Act of 1962 allows the United States to impose tariffs when imports threaten to impair national security (invoked for imposing tariffs on imported steel and aluminum). Section 301 of the Trade Act of 1974 allows for protection if a trading partner is deemed to have violated a trade agreement or engages in unreasonable practices that burden US commerce (invoked for tariffs on US imports from China).

Table 1: Timeline of tariff increases

Tariff wave	Date enacted	Products	2017 imports		Tariff (%)	
		(# HS-10)	(mil US$)	(%)	2017	2018
Panel A: Tariffs on U.S. imports enacted by the United States in 2018						
Solar panels	7th Feb, 2018	8	5,782	0.2	0	30
Washing machines	7th Feb, 2018	8	2,105	0.1	1.3	32.2
Aluminum	Mar–Jun, 2018	67	17,685	0.7	2	12
Iron and steel	Mar–Jun, 2018	753	30,523	1.3	0	25
China 1	6th July, 2018	1,672	33,510	1.4	1.3	26.2
China 2	23rd Aug, 2018	433	14,101	0.6	2.7	27
China 3	24th Sep, 2018	9,102	199,264	8.3	3.3	12.9
Total		12,043	302,970	12.7	2.6	16.6
Panel B: Retaliatory tariffs on U.S. exports enacted by trading partners in 2018						
China	Apr–Sep, 2018	7,474	92,518	6	8.4	18.9
Mexico	5th Jun, 2018	232	6,746	0.4	9.6	28
Turkey	21st Jun, 2018	244	1,554	0.1	9.7	31.8
European Union	22nd Jun, 2018	303	8,244	0.5	3.9	29.2
Canada	1st July, 2018	325	17,818	1.2	2.1	20.2
Russia	6 Aug, 2018	163	268	0	5.2	36.8
Total		8,073	127,149	8.2	7.3	20.4

Notes: Reproduced based on Fajgelbaum et al. (2020). Panels display unweighted monthly 10-digit HS country average tariff rates. 2017 tariff rates computed as annual average; 2018 rates computed in December 2018. Total tariff rates represent trade-weighted average of row values. Import/export share denominator is total 2017 annual US$ value of all U.S. imports/exports. US government announced import tariffs on aluminum and steel on March 23 but granted exemptions for Mexico, Canada, and the EU which were later lifted on 1st June. Chinese retaliation dates are 6th April, 2nd July, 23rd August, and 24th September.

2.2 Steel and aluminium tariffs

On the 20th April and 27th April 2017, President Trump asked the Commerce Secretary to initiate investigations into steel and aluminium imports, with a focus on their threat to US national security (Section 232 of the Trade Expansion Act of 1962). On the 16th February 2018, the Department of Commerce concluded that these imports do indeed threaten national security, despite the fact that the vast majority of the imports are sourced from allies such as Canada, the European Union, Mexico, and South Korea. Forthcoming tariffs of 25 percent on steel and 10 percent on aluminium on all trading partners were announced by the US on the 1st March. In response, on the 7th March, the EU threatened to file a WTO dispute, as well as to introduce 25 percent tariffs on a precisely targeted \$3.4 billion of imports from the US including cranberries, Harley Davidson motorcycles, blue jeans, and bourbon.

President Trump temporarily exempted Canada and Mexico from the forthcoming tariffs on the 8th March, whilst waiting to assess the results of the NAFTA renegotiation. This was followed on the 22nd March by exemptions for the EU, South Korea, Brazil, and Australia effective until the 1st May 2018. The steel and aluminium tariffs (25 percent and 10 percent respectively) on the remaining non-exempt countries then went into effect on the 23rd March, with no clear guidance for if, how, or when the tariffs would be removed. Five days later, on the 28th March, South Korea received a permanent exemption from the steel tariffs in exchange for capping its steel exports at a 21.2 percent reduction from 2017 levels.

On the 2nd April, China retaliated by imposing tariffs on US exports of products such as aluminium waste and scrap, pork, and fruits and nuts totalling \$2.4 billion in 2017 export value (as compared to US tariffs covering \$2.8 billion of Chinese exports). At the last minute, on the 30th April, the US extended the tariff exemptions for the EU, Canada and Mexico until the 1st June 2018 but not for South Korea's aluminium exemption. Indefinite exemptions were awarded to Argentina, Australia and Brazil while finalising 'alternative means' to address the issue of national security. On the 1st June, tariff exemptions for the EU, Canada and Mexico finally ended, leading to the imposition of 25 percent on steel and 10 percent on aluminium. Argentina agreed to quotas on both metals, while Brazil agreed to quotas on steel but faced a 10 percent tariff on aluminium. The only country not facing restrictions at this point was Australia.

In retaliation, on the 22nd June the EU implemented tariffs on \$3.2 billion of US exports from the initial list defined on the 7th March, with steel and aluminium making up about a third of this value. On the 1st July, Canada also retaliated with tariffs on $12.8 billion of US exports covering steel and aluminium, as well as a range of agricultural goods and consumer goods. The US went on to escalate the exchange on the 16th July by filing disputes at the WTO challenging the tariffs levied by Canada, China, the EU, Mexico, and Turkey.

In order to compensate American farmers for lost export sales resulting from what the US Department of Agriculture termed 'unjustified retaliatory tariffs', the US administration announced agricultural subsidies worth up to $12 billion on the 24th July.[6] In response to the depreciation of the Turkish Lira, on the 10th August, President Trump announced an increase from 25 percent to 50 percent on the steel tariff faced by Turkey, along with an increase from 10 percent to 20 percent for aluminium. Turkey responded on the 14th August by announcing new tariffs on imports of cars, alcohol and tobacco from the US.

2.3 Unfair trade practices for technology, intellectual property

On 18th August 2017, the US Trade Representative (USTR) initiated an investigation into whether any of China's laws, policies, practices, or actions may be unreasonable or discriminatory and may be harming American intellectual property rights, innovation, or technology development (Section 301 of the Trade Act of 1974). The results were released on 22nd March 2018 finding evidence of unfair trade practices with respect to intellectual property, technology transfer, and innovation. President Trump followed up by announcing a forthcoming response including new tariffs, new rules on investment, and a WTO dispute.

The new list of products was published on the 3rd April with a threat of up to 25 percent tariff rates on $46.2 billion of imports from China and included products such as machinery, mechanical appliances, and electrical equipment. Bown and Kolb (2019) estimate that approximately 85 percent of these imports would be intermediate inputs and capital goods with the possibility of increasing costs for American firms. In response, one day later, China published its own list of products for retaliatory tariffs covering $50 billion of US exports in products such as vehicles, aircraft, vessels and soybeans. Again escalating the confrontation, the US started to consider tariffs on an additional $100 billion of imports from China on the 5th April.

[6] https://www.usda.gov/media/press-releases, 24th July 2018, discussed further in the Data section.

A revised list of products was released by the USTR on the 15th June, splitting the implementation into two phases, the first starting on the 6th July and covering $34 billion in imports from China (the second phase was to cover $16 billion in imports). The new list included even more intermediate inputs and capital equipment, this time totalling 95 percent of targeted products by 2017 import value. On the same day, China also released its revised retaliatory list, also including a two-phase approach, and covering vehicles as well as agricultural and food products. New products on the list included mineral fuels, medical equipment and some consumption goods whilst aircraft were removed.

Three days later, in response to China's retaliatory tariff list, President Trump directed the USTR to identify an additional $200 billion of imports from China to potentially face a rate of 10 percent, along with threatening yet another $200 billion if China was to retaliate again.

As planned, the 6th July saw the implementation of the first phase of the tariff lists defined on the 15th June, representing $34 billion for both Chinese and US tariffs. This was followed four days later by the USTR releasing the list of $200 billion of imports from China to be subject to a 10 percent tariff after public hearings in August. Approximately half of the products on this list were intermediate goods with a larger proportion of consumer goods relative to the previous lists. On the 20th July, President Trump indicated he would be willing to go even further and introduce tariffs on the remaining $262 billion of imports from China, therefore including all $504 billion of 2017 imports. On top on this, he instructed the USTR to consider 25 percent tariffs on the July 10th list of $200 billion, rather than the initial proposal of 10 percent. In response, China warned of another $60 billion of US exports that could be covered by new tariffs, ranging from 5-25 percent.

The USTR released an updated list on the 7th August for the second phase of the $50 billion list announced on the 15th June. Only 5 out of the 284 products initially identified were removed, and the tariff rate was increased from 10 percent to 25 percent on the remaining $16 billion. China also revised its second phase list the following day, covering a similar value of US exports, and removing crude oil and introducing a few other products. Both lists were then implemented on the 23rd of August as planned.

The 17th September saw the finalization of the $200 billion list of imports from China that would face a 10 percent tariff from the 24th September onwards. President Trump also added that this rate would increase to 25 percent on the 1st January 2019. In the end, 50 percent of this list were intermediate goods and 24 percent were consumer goods. Several products were dropped from the earlier list, including bedsheets, gloves, and smartwatches. China responded with its own finalized list of $60 billion of US exports, with tariffs ranging from 5-10 percent, down from the originally presented 5-25 percent. Both sets of tariffs then went into action on the 24th September.

Finally on the 1st December 2018, the US and China agreed to halt the next increase in tariffs that was due in January while they negotiate a solution. At the end of 2018, the US faced retaliation on 8 percent of its total exports whilst covering approximately 12 percent of its total imports with tariffs, largely on intermediate inputs and capital goods.

3. Data

3.1 Online job adverts

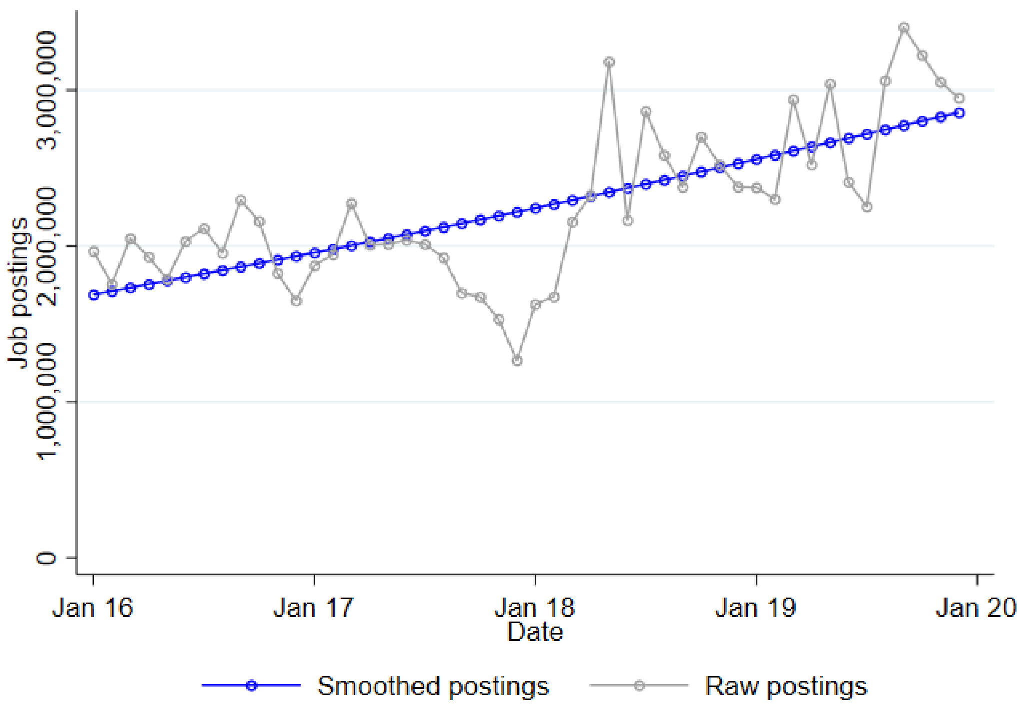
This paper uses data collected by Burning Glass Technologies (BGT), a company that scrapes what they identify to be the quasi-universe of US online job postings on a daily basis. BGT estimate that these postings are sourced from approximately 40,000 online job boards and company websites. This data has now been widely used to study US labor markets (e.g. recent examples include Acemoglu et al. (2022) and Bloom et al. (2021)).

Hershbein and Kahn (2018) provide a detailed analysis of the industry-occupation mix of vacancies in BGT relative to other detailed US data sources, such as JOLTS, and how this mix has changed over time. They find that the BGT postings are disproportionately concentrated in occupations and industries that typically require higher skill levels, but that the distributions are relatively stable across time and the aggregate and industry trends in the quantity of vacancies track official sources reasonably closely. Therefore, while online job adverts do not provide a complete picture of the entire labor market, they can provide a useful barometer of labor market demand.

BGT classify the job adverts along a range of dimensions; this paper makes use of the classification by county and Standard Occupational Classification (SOC) codes. They also clean the data and remove duplicate postings.[7] The postings cover 3,228 counties across the US, with 98.6% of total job postings being classified by county.

[7]Duplicates are recorded as a single posting in the first period in which the posting occurs.

Figure 1: Total monthly online job postings, US



Notes: This figure displays both the unsmoothed raw monthly total postings, and a trend line which is smoothed using the Hodrick-Prescott time-series filter, removing cyclical components.

Over the period considered in the analysis, January 2017 to December 2018, a total of 50,818,695 postings are included in the dataset. Figure 1 displays the upward trend in the time series of US monthly job postings over the period of the analysis. The raw postings are aggregated up to the month-commuting zone (CZ) level as discussed in Section 3.2.

3.2 Local labor markets

The empirical approach used in this paper builds on the literature on local labor markets (e.g. Autor et al. (2013)). Although both the BGT and regional employment data (see Section 3.3) required for the analysis are provided at the administrative county level, county boundaries are not generally considered adequate confines for the local economy or labor markets. In response to this, 'commuting zones' were developed (originally in 1980) with the intention of providing a spatial measure of the local labor market with boundaries that are only rarely crossed by commuters.

In order to convert between counties and commuting zones, we use a crosswalk provided by the Penn State Commuting Zones/labor Markets Data Repository.[8] This crosswalk uses the commuting zone methodology devised by the Economist Research Service (ERS) at the US Department of Agriculture, updated to 2010 zones and modified to correct for some discrepancies by Fowler et al. (2016).[9]

3.3 Local labor market exposure

We proxy for local labor market exposure using the pre-trade war sectoral employment composition of commuting zones. The employment data are originally produced by the US Census Bureau in the form of the County Business Pattern (CBP) database, and consists of employment per county and sector at the North American Industry Classification (NAICS) 6-digit level, representing the most detailed view of the United States' industrial structure available to the public. The CBP data are extracted from the US Census Bureau's Business Register, consisting of administrative tax records of all private US non-farm employer establishments, supplemented by additional information from sources such as the Economic Censuses, Annual Surveys, Current Business Surveys, and Company Organization Surveys, as well as the Bureau of Labor Statistics and the Social Security Administration.[10]

We then aggregate the county-level variables up to the commuting zone level using the crosswalk discussed in Section 3.2. This leads to 625 commuting zones, with total postings over the period ranging from 98 to 277,0274 per commuting zone, and total employment (excluding farm employment) ranging from 279 to 6,830,871.

In order to analyse the relationship between job postings and tariff exposure at the local labor market level, we weight national sectoral exposure measures using baseline employment shares within a local labor market for each industry. The regional (commuting zone) tariff exposure measure is defined as:

$$\text{tariff measure}_{rt} = \sum_j \text{empl share}_{rj2015} \times \text{tariff exposure}_{jt} \quad (1)$$

[8] https://sites.psu.edu/psucz/data/

[9] The term 'labor-shed' is used in this data repository as analogous to commuting zones. Fowler et al. (2016) establish a set of metrics for comparing different labor market delineations and provide an overview of these differences.

[10] We use the modified version of the CBP produced by Eckert et al. (2020), which aims to address the fact that employment is suppressed for the majority of county-industry cells in order to protect confidentiality (see http://www.fpeckert.me/cbp/). The authors use 'a linear programming method that exploits the large set of adding-up constraints implicit in the hierarchical arrangement of the data to impute missing employment'.

where empl share$_{rj2015}$ is industry j share of CZ r employment in 2015, and tariff exposure$_{jt}$ is defined in the following sections. Pre-sample employment shares (2015) are used for exogeneity.

The CBP excludes farm employment, consisting of Crop Production (3-digit NAICS 111) and Animal Production and Aquaculture (3-digit NAICS 112), but includes Support Activities for Agriculture and Forestry (3-digit NAICS 115). Following Blanchard et al., we therefore allocate farm-related tariffs to employment in the associated support activities. Specifically, we calculate the average tariff across 3-digit NAICS sector 111 and allocate this to total employment in 4-digit NAICS sector 1151. We then calculate the average tariff across 3-digit NAICS sector 112 and allocate this to total employment in 4-digit NAICS sector 1152.[11]

3.4 Sectoral tariff exposure

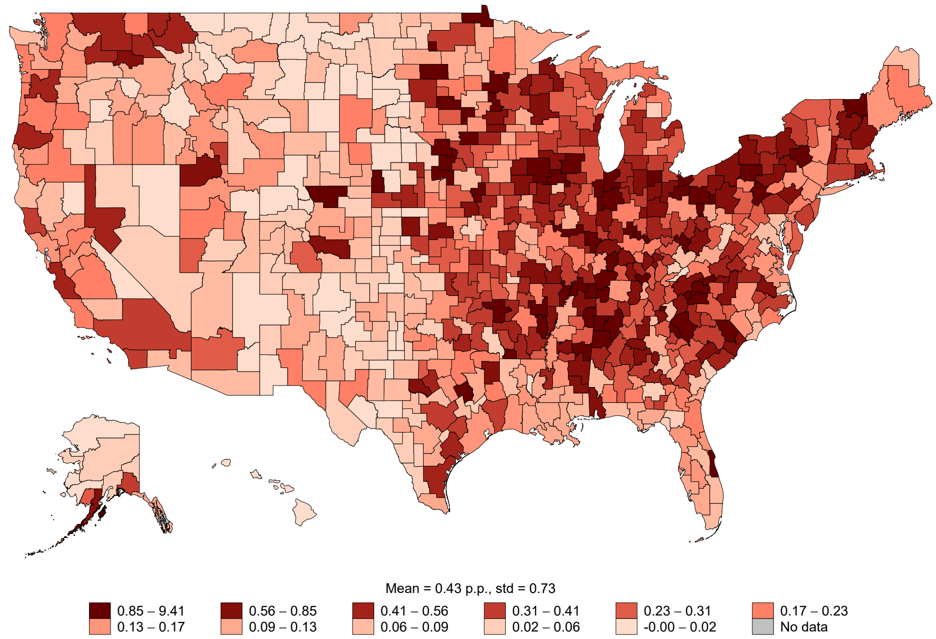
The following sections describe the construction of the sectoral tariff exposure measures used to generate local labor market exposure in equation 1: output exposure, input exposure, and export exposure. The three measures focus on tariff barriers specifically and do not take into account any changes in quotas, in the form of import quotas or voluntary export restraints, and hence could be seen as a lower bound estimate of the exposure to new trade barriers.

3.4.1 Exposure to reduced competition through import tariffs

One channel through which imposing or increasing import tariffs could affect US businesses is by increasing the price of imports that compete with US products, hence rendering US firms more competitive in the domestic market. As in Blanchard et al. (2019), the sectoral exposure used in this paper creates an average dollar value of exposure to the tariff per worker in that sector, based on US imports in 2016:

[11]We do not remove sectors 111 and 112 from the BGT data for two reasons. First, the measure described in the text still accounts for the tariffs in these sectors, even if they are allocated to slightly different NAICS codes when conducting the employment weightings. Second, the coverage and accuracy of the sector classifications in the BGT data is much weaker than the county classification and hence it's unclear that we would be able to convincingly isolate and remove postings within these particular sectors. The classification issue comes from the challenge of assigning a sector to the data scraped from a job posting (i.e. job postings will almost never provide NAICS codes inside the associated text).

Figure 2: Exposure of commuting zones: output tariffs



Notes: This map displays the change in the baseline employment-weighted output tariff exposure for each commuting zone between December 2017 and December 2018. Darker colours represent more exposed areas.

$$\text{output tariff exposure}_{jt} = \frac{\sum_{cp\in j} \text{US imports}_{pc2016} \times \text{US tariff}_{pct}}{\text{L}_{j2015}} \tag{2}$$

where US tariff$_{pct}$ is the percentage tariff rate applied to imports of product p (HS-10) from country c in month t, US imports$_{pc2016}$ is the value of imports of product p from country c in 2016, and L_{j2015} is the number of workers employed in sector j nationally in 2015. We use pre-trade war imports and employment to avoid capturing any changes that may occur to both of these in response to the tariffs. The measure, along with the two following measures, can be interpreted in units of $1,000 per worker exposure.

Figure 2 provides a map of the output tariff exposure measure once weighted by employment composition of commuting zones as discussed in Section 3.3. The map shows a concentration of exposure in the East of the United States, including large sections of the Midwest, Northeast and South. There is relatively little, although nonzero, exposure in the Great Plains with pockets of highly exposed commuting zones in the West.

3.4.2 Exposure to increased cost of imported inputs

Alongside potential protection of US industries, tariffs may have the additional negative impact of increasing the cost of inputs to these or other US industries. We calculate this exposure by taking the output measure from above and, using US input-output tables, weighting it by the share this 'input' industry makes up in all of the 'output' industry's inputs.[12] Specifically, the measure is calculated as follows:

$$\text{input tariff exposure}_{kt} = \tfrac{1}{\mathrm{L}_{k2015}} \textstyle\sum_j S_{jk} \sum_{cp\in j} \text{US imports}_{pc2016} \times \text{US tariff}_{pct} \tag{3}$$

where k is the output sector, j is the input sector (6-digit BEA level), and S_{jk} is the inputs from sector j as a share of total inputs used by sector k sourced from input-output tables. In other words, this variable captures the cost of tariffs on inputs per worker employed in the output industry.

Figure 3 provides a map of the input tariff exposure measures once weighted by employment composition as discussed in Section 3.3. As for the output tariffs, the map shows a concentration in the East with lower exposure in the Great Plains and West, but with a different pattern of variation within these regions.

3.4.3 Exposure to retaliatory tariffs

In response to the imposition of US tariffs, a number of countries implemented retaliatory tariffs on US exports to their countries (see Table 1 for an overview). A sectoral exposure measure can be constructed as for output tariffs, but using foreign tariffs and US exports instead of imports:

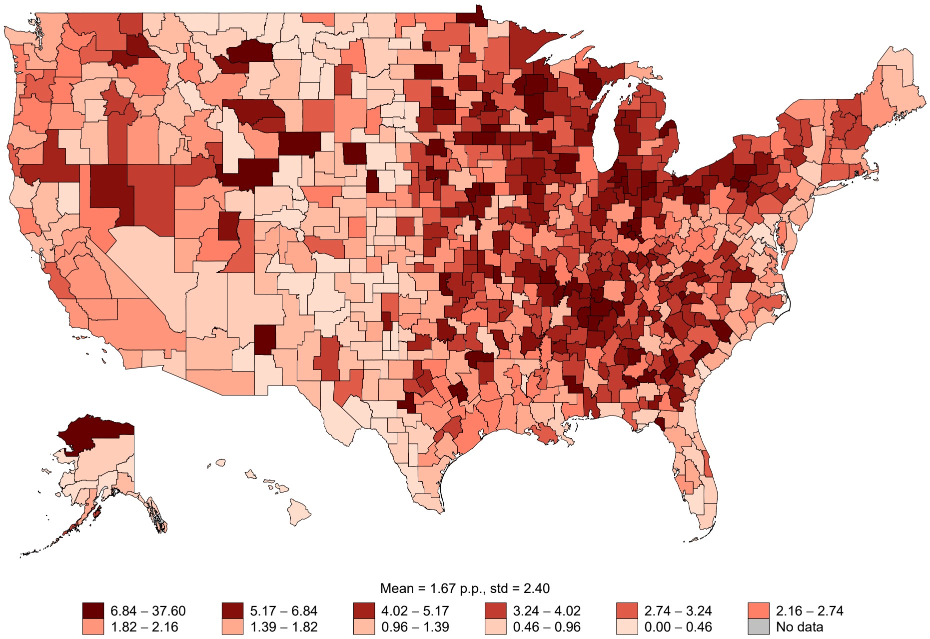
$$\text{export tariff exposure}_{jt} = \frac{\sum_{cp\in j} \text{US exports}_{pc2016} \times \text{Foreign tariff}_{pct}}{\mathrm{L}_{j2015}} \tag{4}$$

where US exports_{pc2016} is the value of US exports of product p (HS-6) to destination country c in 2016, and Foreign tariff_{pct} is the tariff levied by country c on its imports of product p from the US in month t.

Figure 4 provides a map of the export tariff exposure measures once weighted by employ-

[12] Here US Bureau of Economic Analysis (BEA) input-output tables are used, as in Amiti et al. (2019), along with concordances between NAICS and BEA industry codes.

Figure 3: Exposure of commuting zones: input tariffs



Notes: This map displays the change in the baseline employment-weighted input tariff exposure for each commuting zone between December 2017 and December 2018. Darker colours represent more exposed areas.

ment composition as discussed in Section 3.3. Relative to the other two exposure measures, export tariff exposure shows a much greater concentration in the Great Plains and West, likely reflecting the concentration of agricultural products included in the retaliatory tariffs.

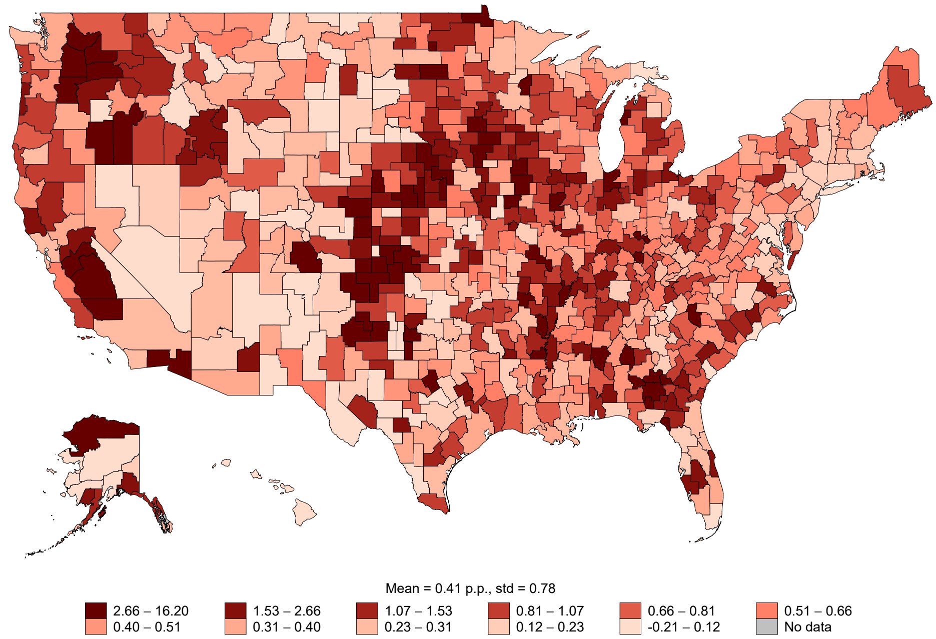
3.5 Classifying job adverts by occupation and skill

The BGT job postings data provide information on the US SOC code of each of the postings (96% coverage). Examples at the 2-digit level include 'Business and Financial Operations' or 'Food Preparation and Serving Related'; the full range is presented in Table 6 in the Appendix.

In order to investigate the impact of the tariffs on job postings by skill level, it is necessary to allocate postings into skill categories. Although the BGT data includes a variable for the minimum education level required in each job advert, the coverage is relatively low: only approximately 51 percent of postings have positive assigned minimum values of education.[13] In order to include the widest possible range of postings in the skill classification, we therefore instead use the available minimum education data to classify each SOC code by skill

[13]This could be due to challenges in scraping this type of information from online adverts, or because many adverts do not explicitly name a minimum education level.

Figure 4: Exposure of commuting zones: export tariffs



Notes: This map displays the change in the baseline employment-weighted export tariff exposure for each commuting zone between December 2017 and December 2018. Darker colours represent more exposed areas.

level. This allows us to allocate a skill level to each job advert using its SOC code, with 96 percent of postings including a SOC code in the dataset (rather than only the 51 percent with a non-missing education requirement).

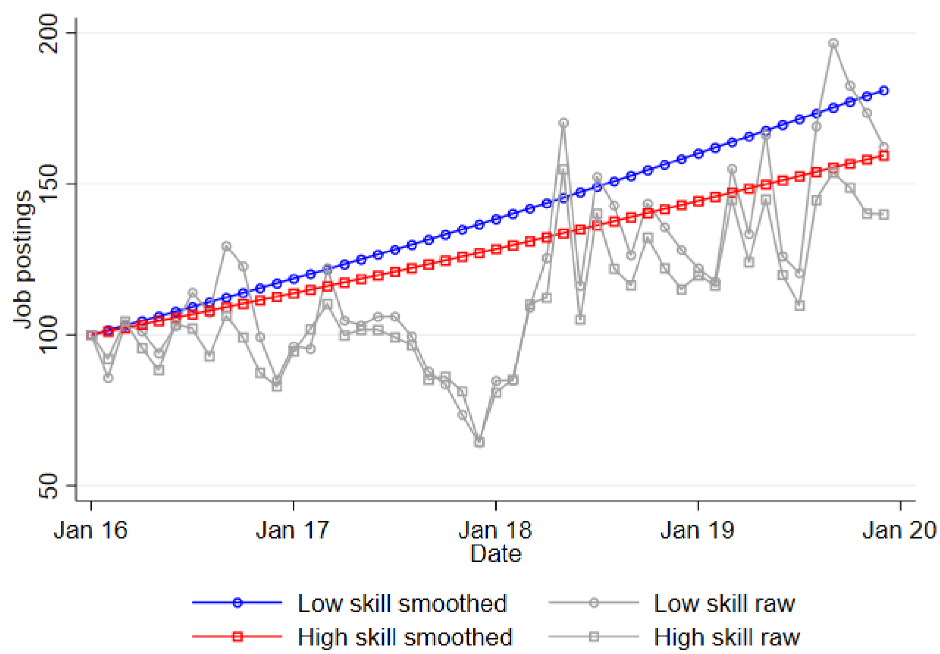
We classify each SOC code as 'high skilled' if the average number of years of education for the occupation across the whole dataset is greater than or equal to 14 years; the equivalent of an associate's degree in the US. All of the analysis in the main body of the paper uses the categorisation based on 2-digit SOC codes (as presented in Table 6), but the analysis is also repeated in the Appendix for 6-digit SOC codes.

Figure 5 displays the evolution of high skilled and low skilled job postings over time. Although both are increasing over time, a gap can been seen between the progression of the two types with high skill postings increasing more slowly than low skill postings over the period.

3.6 Agricultural subsidies

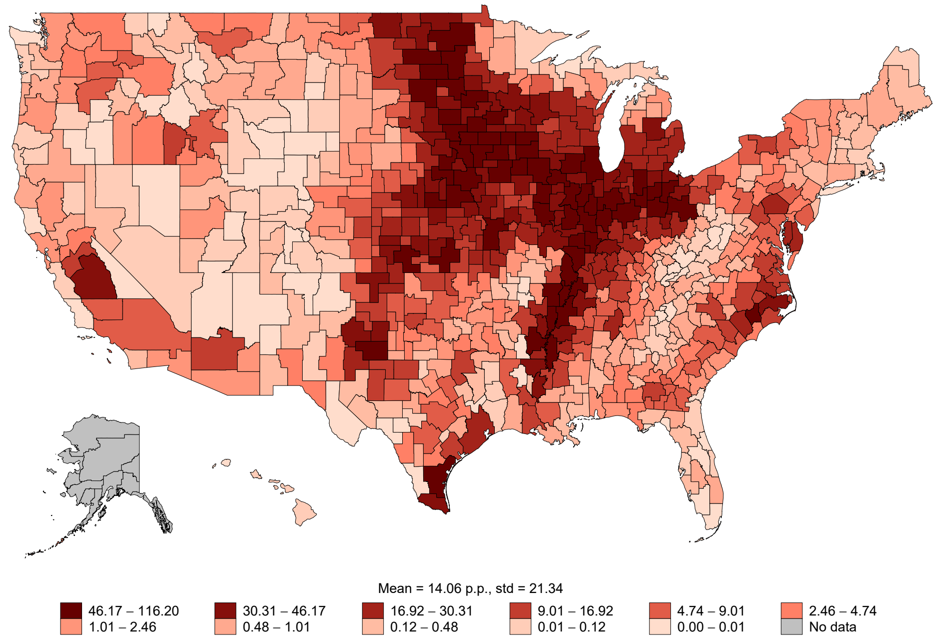
As discussed in Section 2, significant proportions of the retaliatory tariffs were directed toward US agriculture exports. In response, on the 24th July 2018 the US administration announced plans to provide subsidies to American farmers of up to $12 billion under the 2018

Figure 5: High and low skilled job postings over time



Notes: This figure displays both the unsmoothed raw monthly total postings, and a trend line which is smoothed using the Hodrick-Prescott time-series filter, removing cyclical components, for high skill and low skill postings. Here high skill is defined by greater than or equal to an average of 14 years of education for the associated 2-digit SOC occupation.

Figure 6: Map of MFP agricultural subsidies



Notes: This map displays the total estimated agricultural subsidies, under the Market Facilitation Program of 2018, for each commuting zone in the US. Darker colours represent more exposed areas.

Market Facilitation Program (MFP). The explicit justification for these subsidies was 'to assist farmers in response to trade damage from unjustified retaliation' and involved the application of a 1933 law devised to support farmers hit by the Great Depression. Products specifically mentioned for the subsidy include soybeans, sorghum, wheat, dairy, and hogs.

Blanchard et al. (2019) calculate estimates of county-specific total subsidy values combining the announced subsidy rates for key commodities with preceding years production or inventory values.[14] We use their values and aggregate them up to the commuting zone level using the crosswalk discussed in Section 3.2.[15] As can be seen in Figure 6, the main recipients of agricultural subsidies were located in the Midwest and to a degree the Great Plains, with very little in the East and West.

Table 2 displays summary statistics for monthly job postings and all other key variables used in the paper.

[14] See the Appendix in Blanchard et al. (2019) for more details on the full set of commodities included and the data sources.

[15] These measures are in total dollars (units of $1,000,000) per commuting zone rather than being expressed in per worker terms. The reason for this is that the CBP excludes farm employment and hence the resulting measure would be agricultural subsidies per non-farm worker which does not capture the desired effect. The average size of the agricultural sector is also controlled for, in principle, by the CZ fixed effects.

Table 2: Summary statistics

Variables	Mean	Median	Min.	Max.	Std Dev.
Job postings:					
Monthly postings	656	71	0	103,542	3,022
Monthly postings low skilled	300	40	0	48,651	1,268
Monthly postings high skilled	357	29	0	55,248	1,800
Exposure Measures:					
Output tariff exposure	0.43	0.21	0	9.41	0.73
Input tariff exposure	1.67	0.84	0	37.6	2.40
Export tariff exposure	0.41	0.24	0	16.2	0.78
Other:					
Agricultural subsidies	16	3.72	0	143	25.1

Notes: This table displays summary statistics for all of the key variables used in the analysis. The dataset includes a total of 625 commuting zones, across 24 months (Jan 2017 - Dec 2018), totalling 15,000 observations. Summary statistics are taken across all CZ-time observations. Agricultural subsidy data is only available for 610 CZs. All tariff exposure measures can be interpreted in units of $1,000 per worker average exposure, and agricultural subsidies in units of $1,000,000.

4. Empirical strategy

4.1 Baseline specification

The baseline specification estimates the impact of tariffs, as a function of commuting zone exposure to these tariffs through industrial employment composition, on monthly online job postings from January 2017 to December 2018. We estimate the following model:

$$\log(\text{postings}_{rt}) = \beta_0 + \beta_1 \text{export tariff exposure}_{rt} + \beta_2 \text{output tariff exposure}_{rt} + \beta_3 \text{input tariff exposure}_{rt} + \gamma_t + \gamma_r + \epsilon_{rt} \quad (5)$$

where postings_{rt} are the total number of online job adverts posted in month-year t and commuting zone r, output tariff exposure_{rt} is a measure of the exposure of CZ r to protection through US import tariffs, input tariff exposure_{rt} is a measure of CZ exposure to US tariffs on imported inputs, and export tariff exposure_{rt} is a measure of CZ exposure to retaliatory tariffs on US exports.[16] The specification controls for time-invariant CZ-specific factors with the inclusion of CZ fixed effects, γ_r, and common time trends are controlled for with year-month fixed effects, γ_t.

We am also interested in the impact of trade policy for different skill groups and occupations, and so we run the specification in (5) separately for each category of job postings, with these categories defined in Section 3.

The tariff rates included in the tariff exposure measures are the rates that applied to trade in month-year t. In an ideal experiment, the tariff changes would be unexpected and randomly allocated for the measured effects to approach a causal interpretation. One concern in out setup could be that the tariffs were not unexpected: in several cases lists of targeted products were published by both the US and trade partners in advance of implementation. However, the nature of the negotiations meant that firms faced large uncertainty about the likelihood of tariffs up until the moment that these tariffs were actually implemented, as discussed in Section 2. Products were routinely both added and taken away from these tariff lists in the gap between announcement and implementation. The implementation of the tariffs was also delayed in several occurrences. Firms may also not have expected such a large and

[16]The varying measures of exposure are discussed in more detail in Section 3.

rapid increase in tariff barriers given how long it had been since this type of unilateral tariff action had been adopted by a major advanced country. An additional concern could also be that the tariffs targeted products with declining job opportunities. The existing literature on the trade war has established that this doesn't appear to have been the case and there is little evidence of pre-trends in the trade performance, revenues or prices of targeted products or industries. Nevertheless, we further investigate this possibility in Section 5.4.

5. Results

5.1 Baseline results

The baseline results are presented in Table 3. The specifications in columns (1), (2) and (3) include each of the output, input and export tariff exposure measures in turn, with the remaining columns displaying combinations of these measures. The estimated effect of the output tariff measure is negative across all specifications, but becomes insignificant as soon as the imported input tariff exposure is included. The simple correlation between these measures is 0.48, and it appears that the dominant effect is that of the imported input tariff exposure. The negative sign, along with the lack of significance, suggests that the import tariffs did not have a positive impact on the posting of job adverts as might have been expected if they increased the competitiveness of US producers.

The estimated effect of imported input tariff exposure is significant and negative across the board. This is in line with expectations, as more costly imported inputs represent a negative shock for firms, consistent with a reduction in hiring. The magnitude is fairly consistent across specifications; taking column (7) as the preferred specification, a one-standard-deviation increase in exposure ($2,400 per worker) led to a 3.6 percent decrease in job postings.

The estimated effect of export tariff exposure is also consistently negative and significant across specifications, showing that retaliatory tariffs had a negative impact on US job postings. A one-standard-deviation increase in exposure ($780 per worker) led to a reduction of 7.3 percent in job postings.

The baseline results for these three tariff exposure measures point to an overall negative effect of the trade war on online job postings in the US during 2018. These are, however, short

Table 3: Baseline results

Dep. var. ln(postings+1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Output tariff exposure	-0.048***			-0.020		-0.039***	-0.016
	(0.014)			(0.013)		(0.013)	(0.014)
Imported input tariff exposure		-0.019***		-0.017***	-0.016**		-0.015**
		(0.006)		(0.006)	(0.006)		(0.006)
Export tariff exposure			-0.112***		-0.096***	-0.105***	-0.094***
			(0.029)		(0.032)	(0.028)	(0.032)
Observations	15,000	15,000	15,000	15,000	15,000	15,000	15,000
Adjusted R-squared	0.976	0.976	0.976	0.976	0.976	0.976	0.976
FE	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM
Cluster	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM

Notes: This table displays the results from the regressions of the log of monthly job postings in each commuting zone on the associated trade barrier exposure measures. All specifications include CZ and month-year (YM) fixed effects, and standard errors (in parentheses) are two-way clustered at the CZ and month-year level. Tariff exposure measures should be interpreted in units of $1,000 dollars per worker. *** p<0.01, ** p<0.05, * p<0.1.

term effects and it remains possible that, over time, the effects could be stronger or weaker. For example, if individuals in the US believe they will receive longer term protection from foreign competition they may begin to establish new firms to produce products which would otherwise have been produced almost entirely abroad, and hence increase hiring. Similarly, if it becomes clear that the long term tariff rates are actually lower than those implemented during the trade war then there could be some reversal of the short term negative effects. It is also unclear to what extent the observed effects are due to uncertainty around future costs, as opposed to the direct costs themselves. As discussed in Section 2, there was a significant lack of clarity regarding the likely duration, scope and intensity of the trade war throughout 2018.

5.2 Agricultural subsidies

Table 4 presents the baseline results with additional controls for both the value of agricultural subsidies in a CZ, as defined in Section 3.6, and the interaction of these subsidies with the export tariff exposure. Both of these variables are interacted with a dummy taking the value 1 from August 2018 onwards, as the subsidies were announced in July 2018.

The main results are robust to the inclusion of both the subsidies term and its interaction with the export tariff exposure.[17] The coefficient of the imported input tariff exposure does not change at all, while the export tariff exposure coefficient is marginally reduced in magnitude. There is some weak evidence that the subsidy directly had a positive impact on job postings when included alongside the interaction term in column (3), but this effect does not appear to be any stronger for commuting zones that were more exposed to retaliatory tariffs as was the declared intention of the US Administration.[18] Here a one-standard-deviation increase in subsidies ($25,100,000), led to a 2.5 percent increase in postings.

The weakness of the subsidy results may be due to several factors. The first is that the effect is small and difficult to identify, especially given the few months included in the sample after the announcement of the subsidies. The second is that the online job adverts data may insufficiently capture farm labor, and particularly informal farm labor. Third, due to the construction of the export tariff exposure measure using CBP data, which excludes farm labor, the results may insufficiently capture the part of retaliatory tariff exposure which affected farm labor. Hence, the agricultural subsidies would be less effective at pushing back against this negative impact in this specification.

5.3 Impact on different skill groups and occupations

Table 5 displays the baseline regressions run separately for high skilled and low skilled job adverts. The classification here categorises 2-digit SOC codes into skill levels based on whether the average number of years of education required is greater than or equal to 14 (discussed further in Section 3). Panel A shows the results for low skilled job adverts, while Panel B shows the results for high skilled job adverts.

Relative to the aggregate baseline coefficients, presented for reference in column (6), the low skilled results remain significant and increase slightly in magnitude for both imported input and export tariff exposure measures. The opposite is seen for high skilled results, with coefficients that are smaller in magnitude than the aggregate results. It therefore appears that it is lower skilled workers that are disproportionately affected by both the imported input

[17]All specifications use the slightly reduced dataset with non-missing subsidy values which covers 615 instead of 625 CZs

[18]If anything, the coefficient on the interaction term is negative although it has a p-value of 0.135. If the coefficient were significant, it would lead to a negative overall effect for export tariff exposures of over 2.69, is the case in only 164 CZ-year-month observations spread across 21 out of 615 commuting zones.

Table 4: Regression results including agricultural subsidies

Dep. var. ln(postings+1)	(1)	(2)	(3)
Output tariff exposure	-0.005	-0.009	-0.006
	(0.015)	(0.014)	(0.015)
Imported input tariff exposure	-0.020***	-0.020***	-0.020***
	(0.007)	(0.007)	(0.007)
Export tariff exposure	-0.126***	-0.131***	-0.120***
	(0.035)	(0.036)	(0.036)
Total ag subsidy		0.001	0.001*
		(0.001)	(0.001)
Ag subsidy * Export tariff exposure			-0.000
			(0.000)
Observations	14,640	14,640	14,640
Adjusted R-squared	0.977	0.977	0.977
FE	CZ YM	CZ YM	CZ YM
Cluster	CZ YM	CZ YM	CZ YM

Notes: This table displays the results from the regressions of the log of monthly job postings in each commuting zone on the associated trade barrier exposure measures, with the addition of controls for agricultural subsidies. Only observations with non-missing values of agricultural subsidies are included, hence the small differences between column (1) and the baseline results. All specifications include CZ and month-year (YM) fixed effects, and standard errors (in parentheses) are two-way clustered at the CZ and month-year level. Tariff exposure measures should be interpreted in units of $1,000 dollars per worker and agricultural subsidies in units of $1,000,000. *** p<0.01, ** p<0.05, * p<0.1.

tariffs and the export tariffs.[19]

Table 8 in the Appendix displays the results for different occupations. Job adverts for production workers (SOC 51) are negatively affected via the export tariff channel, while postings for in Installation, maintenance and repairs jobs (SOC 49) are negatively affected by both tariffs on exports and intermediate inputs. But the impact of these tariffs extends to other occupations as well. The intermediate input tariffs also negatively influenced adverts for farming, fishing and forestry, construction and extraction jobs as well as postings for managers, engineers, architects and lawyers. The negative impact of retaliatory tariffs additionally extended to adverts for jobs in cleaning, health, education, social services and the sciences.

5.4 Aggregate counterfactual effects

In order to evaluate the plausible effects of these results for the full sample, we carry out a basic counterfactual exercise on the baseline results. For each commuting zone, we consider what the predicted values for monthly postings would have been if the tariff rates had stayed the same as January 2017 throughout the period of analysis. This approach follows closely that from Chodorow-Reich (2014).

Specifically, we take the fitted values of the specification in column (7) of Table 3 and then subtract the difference in exposure between any given month and that at the start of the period (January 2017), multiplied by the relevant estimated coefficient. Using the exponential function we return the fitted value and the estimated counterfactual to a count measure of postings and then calculate the estimated difference in postings for each month and each CZ.

First focusing only on the counterfactual of zero changes to tariffs on imported inputs, we estimate a total of 121,571 fewer postings occurred over the period than would have been the case in this counterfactual world. Figure 7 shows how these were spread out over time, with month 1 being January 2017. All of the changes are concentrated in the period after February 2018, getting more severe month by month.

A similar calculation can be made for export tariff exposure leading to an estimated total

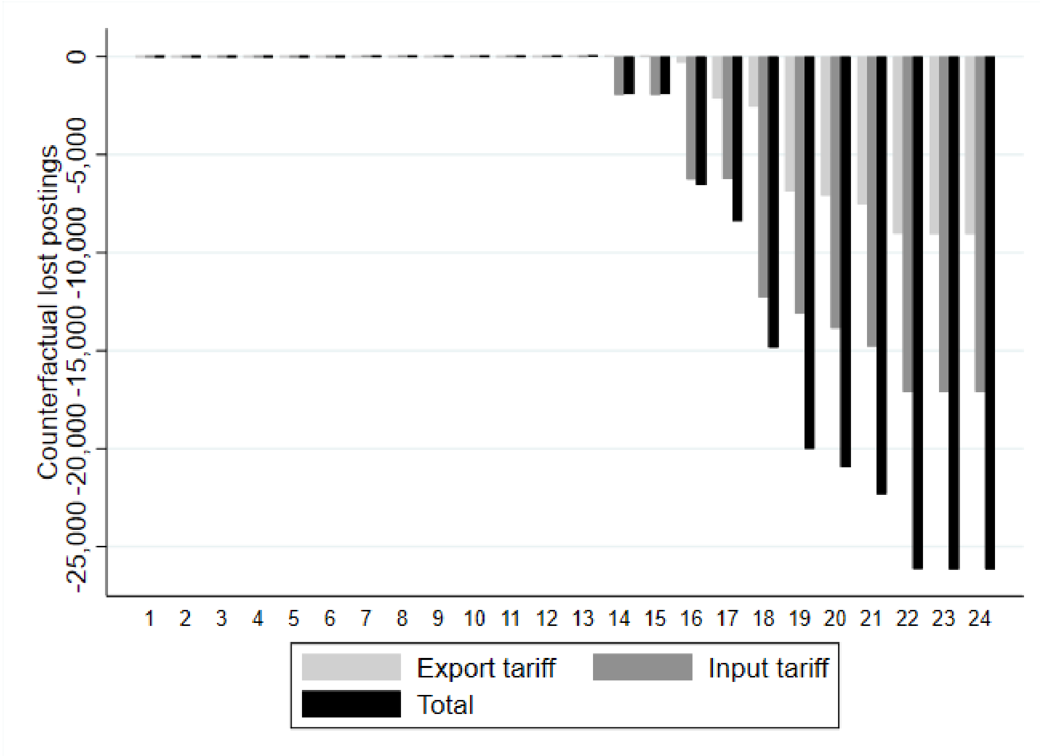
[19]The agricultural subsidies only have a positive and significant impact for high skilled workers (see column (5)), perhaps contrary to expectations. This could be because the online job postings data captures high skilled agricultural jobs more effectively than the more informal lower skilled agricultural jobs that are less likely to be published online.

Table 5: Impact by skill group

Dep. var. ln(postings+1)	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Low skill			Baseline
Output tariff exposure	-0.052***			-0.006	-0.007	-0.006
	(0.016)			(0.016)	(0.016)	(0.015)
Imported input tariff exposure		-0.024***		-0.022***	-0.022***	-0.020***
		(0.007)		(0.007)	(0.007)	(0.007)
Export tariff exposure			-0.152***	-0.140***	-0.133**	-0.120***
			(0.046)	(0.046)	(0.049)	(0.036)
Total ag subsidy					0.001	0.001*
					(0.001)	(0.001)
Ag subsidy * Export tariff exposure					-0.000	-0.000
					(0.000)	(0.000)
Adjusted R-squared	0.964	0.964	0.964	0.964	0.964	0.977
			Panel B: High skill			Baseline
Output tariff exposure	-0.038**			-0.008	-0.010	-0.006
	(0.016)			(0.017)	(0.016)	(0.015)
Imported input tariff exposure		-0.016**		-0.014**	-0.015**	-0.020***
		(0.006)		(0.006)	(0.006)	(0.007)
Export tariff exposure			-0.110***	-0.102***	-0.099***	-0.120***
			(0.033)	(0.032)	(0.034)	(0.036)
Total ag subsidy					0.001**	0.001*
					(0.001)	(0.001)
Ag subsidy * Export tariff exposure					-0.000	-0.000
					(0.000)	(0.000)
Adjusted R-squared	0.964	0.964	0.964	0.964	0.964	0.977
Observations	14,640	14,640	14,640	14,640	14,640	14,640
FE	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM
Cluster	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM

Notes: This table displays the results from the regressions of the log of monthly job postings in each commuting zone on the associated trade barrier exposure measures, with the addition of controls for agricultural subsidies. The postings variables are broken down into high and low skill postings using the average education level (threshold of 14 years of education) of their associated 2-digit SOC occupations. All specifications include CZ and month-year (YM) fixed effects, and standard errors (in parentheses) are two-way clustered at the CZ and month-year level. Tariff exposure measures should be interpreted in units of $1,000 dollars per worker and agricultural subsidies in units of $1,000,000. *** p<0.01, ** p<0.05, * p<0.1.

Figure 7: Counterfactual change in job postings



Notes: Counterfactual postings calculated using the difference in predicted postings when tariff values are set to those of January 2017, before the 2018 tariff hikes. Output tariffs not shown as the baseline results are not significant. Counterfactual predicted values are based on the specification presented in column (7) of Table 3

of 53,544 fewer postings, again concentrated in 2018 as shown in Figure 7. Adding these two components together we see a counterfactual impact of 175,115 job postings fewer as a result of the increases in both import and retaliatory tariffs during 2018 (also displayed in Figure 7). This represents 0.6 percent of the aggregate postings for 2018 (28,555,238) and 0.9 percent for the second half of the year, with no sign of reducing into 2019.

6. Robustness checks

6.1 Pre-trade war placebo

The baseline specification controls for time-invariant CZ-specific factors with the inclusion of CZ fixed effects, and common time trends are controlled for with year-month fixed effects. However, one may still be concerned by CZ-time varying factors that affect job postings and are correlated with the exposure variables. More broadly, there may be global sectoral trends which happen to correlate with exposure to US and retaliatory tariffs. We attempt to address this concern by running a placebo test on the pre-trade war period. To do this, we keep only the 2017 data and lag the 2018 tariff exposures by one year to see whether job postings respond to these changes in 2017 when there were in fact no tariff changes. If the baseline results capture medium-term trends that are not related to tariff exposure then we would expect to see similar results in this placebo test. Insignificant results would support the claim that it is in fact the tariff changes that matter.[20]

Table 9 in the Appendix presents the results of this placebo test. The resulting coefficients are not significant across all specifications, suggesting that this impact was not observed prior to the start of the trade war.

6.2 Alternative tariff exposure measures

The particular form of the exposure measures used in this paper follows examples such as Blanchard et al. (2019) and Autor et al. (2013), but there are a range of ways in which tariff exposure can be calculated. We additionally consider five other formulations to check robustness, and the results are presented in Table 10 in the Appendix along with full definitions of the measures. Column (1) repeats the main measure used in the paper, while column (2) adjusts this measure applying the weighting to $ln(1 + \text{tariff rate}_{pc,t})$ rather than directly to the US or retaliatory tariff rates. Column (3) takes a similar approach but applies the log transformation to the measure after the trade and employment weighting is already applied. Column (4) weights only by import shares rather than incorporating sectoral labour.

Columns (5) and (6) weight by sectoral output rather than employment. For example, the sectoral output tariff exposure (later weighted by CZ employment shares) for the specification in column (5) is constructed as follows:

$$\text{output tariff exposure}^{(D)}_{j,t} = \frac{\text{US imports}_{j,2016}}{\text{Output}_{j,2016}} \times \frac{\sum_{c,p\in j} \text{US imports}_{cp,2016} \times \ln(1\text{+import tariff}_{cpt})}{\text{US imports}_{j,2016}} \tag{6}$$

where c is the county of origin, and p is the 10-digit HS product. Column (5) is similar but

[20] It may be worth nothing that an alternative interpretation of this placebo test is that tariff changes were not anticipated 12 months in advance of their implementation.

additionally multiplies by the sectoral share of imports in output, where output is defined as domestic shipments plus imports minus exports as in Amiti et al. (2019). Finally, column (6) instead applies the log transformation after the import weighting and then multiplies again by the import share.

The results suggest that these different formulations of the exposure measure do not significantly change the conclusions from the baseline. The estimated effects of both the imported input and export tariff exposure are negative and highly significant in all specifications. There is some evidence of positive and significant coefficients for the output tariff exposure, but only in two out of the six cases.[21]

The estimated effects of the agricultural subsidies remain positive and significant across the board with the interactions remaining insignificant in all but one specification. Taken together these results provide confidence in the main conclusions that firms did appear to be adjusting hiring significantly in response to tariff changes but only when exposed through exports or imported inputs.

6.3 Shift-share robustness

The exposure variables used in the main empirical specification are constructed in the shift-share or 'Bartik' style. Here the 'shares' are commuting zone employment shares by industry, and the 'shocks' are national industry-time varying aggregations of trade-weighted product level tariffs (measured in units of $1,000 exposure per worker). Recent literature (e.g. Borusyak et al. (2022), Goldsmith-Pinkham et al. (2020), Adao et al. (2019)) has pointed to the need for additional robustness checks to ensure exogeneity of these variables as well as the use of appropriate standard errors. In our setup, we view the case for causal identification as stemming from the plausible exogeneity of the time-varying tariff shocks, following Borusyak et al. (2022). As discussed above, this approach builds upon several other papers in the field (e.g., Amiti et al. (2019), Fajgelbaum et al. (2022)), that have treated the tariffs as plausibly exogenous due to the uncertain timing of the tariff waves and exact composition of products and countries targeted.[22]

[21] It is possible that the positive results for the output tariff measure are an indication that these particular formulations more accurately capture tariff exposure but it is not clear a priori why this would be the case.

[22] Amiti et al. (2019) treat tariff changes as exogenous, while Fajgelbaum et al. (2022) find only quantitatively small anticipatory effects for importers and exporters.

Step one follows Table 1 of Borusyak et al. (2022) which applies their approach in the context of Autor et al. (2013) (hereby ADH). Table 11 in the Appendix reports summary statistics for the tariff shocks computed with the importance weights generated by applying the *ssaggregate* Stata command. Given that service sectors do not have associated tariff shocks, we start with columns (1), (4) and (7) (one for each of our exposure variables) which includes the "missing" service shock of zero in each period. As in ADH, we see that the shock distribution is unusual as evidenced by a zero interquartile range, which reflects the large fraction of total employment accounted for by the service industry. We also see a high concentration of industry exposure as measured by the inverse Herfidahl index (HHI), which corresponds to the "effective sample size of our equivalent regression", here only 39. This value is even lower (1.6) if we compute the HHI at the level of 4-digit NAICS codes (as opposed the 6-digits in the main regression), which suggests that even less industry-variation is available when shocks are allowed to be clustered by groups or serially correlated. Additionally, the mean of our shocks is significantly different from the zero shock of the missing service industry. As for ADH, these elements point to the need to exclude the service industry shocks from the identifying variation.

Columns (2), (5) and (8) therefore report the same statistics with the service industry excluded, which results in a more regular distribution of shocks and a relatively high inverse HHI of 2,536 in the 6-digit NAICS case and 44 in the 4-digit aggregation. The largest shock weights are 0.14% at the 6-digit and 6.4% at the 4-digit level which suggests a good degree of variation. Columns (3), (6) and (9) summarise the within-period distribution, confirming that there remains a sizable residual shock variation.[23]

Table 12 in the appendix recreates the robustness check suggested by Borusyak et al. (2022) in their Table 4, where the coefficients are estimated using an equivalent industry-level regression which obtains valid exposure-robust standard errors. Standard errors are clustered at the NAICS 4-digit level in column (1) and the 6-digit level in column (2). Our results remain robust and significant after undergoing this transformation.

Taken together, these checks, as well as others presented earlier, allay some of the key potential concerns surrounding our analysis and demonstrate that these findings continue

[23]Table 2 in Borusyak et al. (2022) analyses the correlation patterns of shocks across industries through intraclass coefficients. While their model does not converge for our specification, we explore different levels of clustering by sector and find no major differences in our results. Table 3 in Borusyak et al. (2022) looks at correlations between shocks and the controls included in ADH which are not included in our specification.

to hold with adjustments to measurement of the key variables.

7. Conclusion

This paper uses data on the near universe of US online job postings from January 2017 to December 2018 to analyse how the 2018 tariff hikes by both the US and its trading partners affected US labor market opportunities. We calculate three measures of tariff exposure to account for: (i) the protection of US industries by tariffs on their output products; (ii) the increased cost for US producers due to tariffs on their imported inputs; and (iii) foreign tariffs on US exports in retaliation to the US import tariff increases. We employ a shift-share estimation strategy that exploits the timing of the tariffs and the *ex ante* reliance of each commuting zone's labor force on trade in tariff-affected products.

We find that both the retaliatory export and imported input tariffs had an economically meaningful negative impact on job postings. In contrast, the impact of output tariffs is not statistically significant once imported input tariffs are controlled for. In terms of magnitude, a one-standard-deviation increase in commuting zone input tariff exposure led to a 3.6 percent decrease in online job postings, and a one-standard-deviation increase in commuting zone export tariff exposure led to a 7.3 percent decrease in online job postings. A back-of-the-envelope counterfactual calculation shows that these effects were concentrated in the second half of 2018 as the tariffs started to build up, and led to a estimated combined effect of 175,000 fewer job postings. Just over two thirds of this aggregate decline was due to the imported input tariffs and one third due to retaliatory tariffs. The lost postings represent a 0.6 percent decrease for the whole of 2018 and a 0.9 percent decrease for the second half of the year.

Both higher skilled and lower skilled job postings were affected by the tariffs, but the magnitude and statistical significance of effects is stronger for lower skilled jobs, for both intermediate inputs and retaliatory tariffs. In the lower-skilled category, adverts for production jobs were negatively affected by retaliatory tariffs, while adverts for farming, forestry, fishing, construction and extraction jobs were negatively affected by the input tariffs and installation, cleaning, maintenance and repair jobs were hit by both retaliatory and input tariffs. In the higher-skilled category intermediate input tariffs most negatively affected job adverts for professional and managerial positions, while retaliatory tariffs most negatively affected those in health, education, social services and the sciences. A battery of robustness checks confirm the validity of these results, including pre-sample placebo tests, alternative construction of the exposure measures, as well as checks of validity of Bartik measures suggested by Borusyak et al. (2022).

Taken together, our results paint an overall negative picture on the implications of the trade war for the job opportunities for US workers. They support a growing body of research documenting that, in a globally integrated economy, the likelihood of trade diversion, retaliation and indirectly raising firms' supply chain costs, may render tariffs a blunt instrument in terms of protecting domestic producers.

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Online Appendix (Not for publication)

Alternative tariff measure definitions

This section presents the full definitions of the alternative tariff measures discussed in Section 6.2. For simplicity we present only the output tariff exposure measures, but the other measures are analogous. The superscripts link these definitions to the columns in Table 10.

The first alternative measure adjusts the sectoral tariff exposure by log-transforming the tariff rate:

$$\text{output tariff exposure}_{j,t}^{(A)} = \frac{\sum_{c,p\in j} \text{US imports}_{pc,2016} \times \ln(1 + \text{US tariff}_{pc,t})}{\text{L}_{j,2015}} \tag{7}$$

The second measure instead applies the log transformation to the baseline sectoral exposure measure after weighting by trade values and national employment:

$$\text{output tariff exposure}_{r,t}^{(B)} = \ln\left(1 + \frac{\sum_{c,p\in j} \text{US imports}_{pc,2016} \times \text{US tariff}_{pc,t}}{\text{L}_{j,2015}}\right) \tag{8}$$

The third measure is also presented in the main text and weights by trade shares instead of national employment as follows:

$$\text{output tariff exposure}_{j,t}^{(C)} = \frac{\sum_{c,p\in j} \text{US imports}_{cp,2016} \times \ln(1\text{+import tariff}_{cpt})}{\text{US imports}_{j,2016}} \tag{9}$$

The fourth measure additionally multiplies by the the sectoral share of imports in output, where output is defined as domestic shipments plus imports minus exports as in Amiti et al. (2019):

$$\text{output tariff exposure}_{j,t}^{(D)} = \frac{\text{US imports}_{j,2016}}{\text{Output}_{j,2016}} \times$$
$$\frac{\sum_{c,p\in j} \text{US imports}_{cp,2016} \times \ln(1\text{+import tariff}_{cpt})}{\text{US imports}_{j,2016}} \tag{10}$$

Finally, the fifth measure applies the log transformation after the import weighting and then multiplies again by the import share:

$$\text{output tariff exposure}_{j,t}^{(E)} = \frac{\text{US imports}_{j,2016}}{\text{Output}_{j,2016}} \times$$

$$\ln\left(1+\frac{\sum_{c,p\in j} \text{US imports}_{cp,2016} \times \text{import tariff}_{cpt}}{\text{US imports}_{j,2016}}\right) \tag{11}$$

Additional tables

Table 6: Posting occupations and skill levels

Occ. #	Occupation name	Postings per occ.	Ave. years educ.	Frac. with $\geq$ degree
11	Management	7,635,603	15.5 (H)	0.84
13	Business and Financial Operations	4,590,688	15.5 (H)	0.87
15	Computer and Mathematical	6,519,437	15.7 (H)	0.94
17	Architecture and Engineering	2,095,270	15.3 (H)	0.83
19	Life, Physical, and Social Science	719,991	16.5 (H)	0.88
21	Community and Social Service	852,672	15.8 (H)	0.81
23	Legal	261,428	17.5 (H)	0.83
25	Education, Training, and Library	1,674,570	15.8 (H)	0.80
27	Arts, Design, Entertainment, Sports, and Media	1,228,772	14.4 (H)	0.61
29	Healthcare Practitioners and Technical	7,736,250	15.1 (H)	0.86
31	Healthcare Support	1,086,065	12.1 (L)	0.06
33	Protective Service	816,851	12.6 (L)	0.14
35	Food Preparation and Serving Related	1,068,079	12.4 (L)	0.11
37	Building and Grounds Cleaning and Maintenance	509,504	12.1 (L)	0.04
39	Personal Care and Service	541,215	12.7 (L)	0.19
41	Sales and Related	5,718,844	13.6 (L)	0.41
43	Office and Administrative Support	5,886,668	13.0 (L)	0.29
45	Farming, Fishing, and Forestry	26,328	13.2 (L)	0.34
47	Construction and Extraction	336,449	12.4 (L)	0.12
49	Installation, Maintenance, and Repair	1,521,031	12.3 (L)	0.12
51	Production	1,290,258	12.6 (L)	0.16
53	Transportation and Material Moving	1,359,333	12.2 (L)	0.05
55	Military Specific	63,610	12.8 (L)	0.18
-	Not specified	2,320,844	14.3	0.58

Notes: Occupations labeled as high skill are indicated by '(H)' and low skill occupations are indicated by '(L)'.
Source: US Standard Occupational Classification.

Table 7: Impact by skill group - 6-digit SOC level

Dep. var. ln(postings+1)	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Low skill					Baseline
Output tariff exposure	-0.057***			-0.010	-0.010	-0.006
	(0.016)			(0.017)	(0.017)	(0.015)
Imported input tariff exposure		-0.025***		-0.023***	-0.023***	-0.020***
		(0.007)		(0.008)	(0.008)	(0.007)
Export tariff exposure			-0.158***	-0.145***	-0.141***	-0.120***
			(0.046)	(0.046)	(0.049)	(0.036)
Total ag subsidy					0.001	0.001*
					(0.001)	(0.001)
Ag subsidy * Export tariff exposure					-0.000	-0.000
					(0.000)	(0.000)
Adjusted R-squared	0.966	0.966	0.966	0.966	0.966	0.977
	Panel B: High skill					Baseline
Output tariff exposure	-0.034**			-0.005	-0.006	-0.006
	(0.015)			(0.017)	(0.016)	(0.015)
Imported input tariff exposure		-0.015**		-0.013**	-0.014**	-0.020***
		(0.006)		(0.006)	(0.006)	(0.007)
Export tariff exposure			-0.107***	-0.100***	-0.092**	-0.120***
			(0.036)	(0.035)	(0.037)	(0.036)
Total ag subsidy					0.001**	0.001*
					(0.001)	(0.001)
Ag subsidy * Export tariff exposure					-0.001	-0.000
					(0.000)	(0.000)
Adjusted R-squared	0.976	0.976	0.976	0.976	0.976	0.977
Observations	14,640	14,640	14,640	14,640	14,640	14,640
FE	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM
Cluster	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM

Notes: This table displays the results from the regressions of the log of monthly job postings in each commuting zone on the associated trade barrier exposure measures. The postings variables are broken down into high and low skill postings using the average education level (threshold of 14 years of education) of their associated 6-digit SOC occupations. All specifications include CZ and month-year (YM) fixed effects, and standard errors (in parentheses) are two-way clustered at the CZ and month-year level. Tariff exposure measures should be interpreted in units of $1,000 dollars per worker and agricultural subsidies in units of $1,000,000. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Occupation regressions

Dep. Var. ln(postings+1)	(1) Total	(2) SOC 51: Production	(3) SOC 53: Transportation and Material Moving	(4) SOC 55: Military Specific
Output tariff exposure	-0.016	-0.002	-0.042	0.004
	(0.014)	(0.018)	(0.030)	(0.014)
Input tariff exposure	-0.015**	-0.005	-0.028**	-0.022***
	(0.006)	(0.007)	(0.012)	(0.006)
Export tariff exposure	-0.094***	-0.067*	-0.116	-0.095**
	(0.032)	(0.035)	(0.071)	(0.035)
	(5) SOC 43: Office and Administrative Support	(6) SOC 45: Farming, Fishing, and Forestry	(7) SOC 47: Construction and Extraction	(8) SOC 49: Installation, Maintenance, and Repair
Output tariff exposure	-0.040*	0.004	0.026	-0.013
	(0.021)	(0.017)	(0.017)	(0.017)
Input tariff exposure	-0.016**	-0.017***	-0.026***	-0.013*
	(0.007)	(0.005)	(0.007)	(0.007)
Export tariff exposure	-0.041	-0.009	-0.001	-0.094**
	(0.042)	(0.023)	(0.042)	(0.043)
	(9) SOC 35: Food Preparation and Serving Related	(10) SOC 37: Building and Grounds Cleaning and Maintenance	(11) SOC 39: Personal Care and Service	(12) SOC 41: Sales and Related
Output tariff exposure	0.001	0.003	0.016	-0.015
	(0.024)	(0.029)	(0.044)	(0.015)
Input tariff exposure	-0.017*	-0.020**	-0.021**	-0.012**
	(0.008)	(0.008)	(0.008)	(0.006)
Export tariff exposure	-0.032	-0.112**	-0.097*	-0.011
	(0.046)	(0.048)	(0.055)	(0.038)
	(13) SOC 27: Arts, Design, Entertainment, Sports, and Media	(14) SOC 29: Healthcare Practitioners and Technical	(15) SOC 31: Healthcare Support	(16) SOC 33: Protective Service
Output tariff exposure	-0.025	-0.022	0.009	0.001
	(0.026)	(0.017)	(0.027)	(0.017)
Input tariff exposure	-0.015*	-0.003	-0.005	0.001
	(0.007)	(0.006)	(0.009)	(0.006)
Export tariff exposure	-0.052	-0.086**	-0.023	-0.069*
	(0.032)	(0.031)	(0.025)	(0.034)
	(17) SOC 19: Life, Physical, and Social Science	(18) SOC 21: Community and Social Service	(19) SOC 23: Legal	(20) SOC 25: Education, Training, and Library
Output tariff exposure	-0.026	-0.032	0.019	-0.065**
	(0.031)	(0.021)	(0.015)	(0.027)
Input tariff exposure	-0.012*	-0.003	-0.021***	-0.012
	(0.006)	(0.008)	(0.005)	(0.009)
Export tariff exposure	-0.062**	-0.085**	-0.057*	-0.194***
	(0.030)	(0.035)	(0.032)	(0.043)
	(21) SOC 11: Management	(22) SOC 13: Business and Financial Operations	(23) SOC 15: Computer and Mathematical	(24) SOC 17: Architecture and Engineering
Output tariff exposure	-0.032	0.006	-0.019	-0.009
	(0.021)	(0.018)	(0.022)	(0.019)
Input tariff exposure	-0.017***	-0.005	-0.014**	-0.027***
	(0.005)	(0.005)	(0.006)	(0.006)
Export tariff exposure	-0.035	-0.075**	-0.010	-0.041
	(0.036)	(0.032)	(0.043)	(0.029)
Observations	15,000	15,000	15,000	15,000
FE	CZ YM	CZ YM	CZ YM	CZ YM
Cluster	CZ YM	CZ YM	CZ YM	CZ YM

Notes: This table displays the results from the regressions of the log of monthly job postings of each SOC code in each commuting zone on the associated trade barrier exposure measures. All specifications include CZ and month-year (YM) fixed effects, and standard errors (in parentheses) are two-way clustered at the CZ and month-year level. Tariff exposure measures should be interpreted in units of $1,000 dollars per worker and agricultural subsidies in units of $1,000,000. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Pre-trade war placebo for 2017

Dep. var. ln(postings+1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Output tariff exposure	-0.011			-0.022		-0.009	-0.021
	(0.014)			(0.013)		(0.014)	(0.013)
Imported input tariff exposure		0.005		0.007	0.006		0.007
		(0.006)		(0.007)	(0.006)		(0.007)
Export tariff exposure			-0.017		-0.023	-0.016	-0.021
			(0.021)		(0.022)	(0.021)	(0.022)
Observations	7,500	7,500	7,500	7,500	7,500	7,500	7,500
Adjusted R-squared	0.986	0.986	0.986	0.986	0.986	0.986	0.986
FE	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM
Cluster	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM

Notes: This table displays the results from the regressions of the log of monthly job postings in each commuting zone on 12-month leads of the associated trade barrier exposure measures. The objective is a placebo test of whether tariff changes in 2018 also led to changes in postings in 2017. All specifications include CZ and month-year (YM) fixed effects, and standard errors (in parentheses) are two-way clustered at the CZ and month-year level. Tariff exposure measures should be interpreted in units of $1,000 dollars per worker. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Alternative tariff measures

Dep. var. ln(postings+1)	(1) Baseline	(2) Measure A	(3) Measure B	(4) Measure C	(5) Measure D	(6) Measure E
Output tariff exposure	-0.006	-0.006	321.573**	18.308**	60.336	55.491
	(0.015)	(0.017)	(115.224)	(8.002)	(38.180)	(36.786)
Imported input tariff exposure	-0.020***	-0.023***	-537.423***	-26.251***	-179.449***	-167.469***
	(0.007)	(0.008)	(136.898)	(7.395)	(59.739)	(56.295)
Export tariff exposure	-0.120***	-0.134***	-901.142***	-24.485**	-316.631***	-293.994***
	(0.036)	(0.043)	(265.394)	(8.866)	(90.154)	(81.838)
Total ag subsidy	0.001*	0.001*	0.002**	0.002*	0.002*	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ag subsidy * Export tariff exposure	-0.000	-0.001	-1.982**	-0.120	-0.899	-0.808
	(0.000)	(0.001)	(0.867)	(0.081)	(0.769)	(0.579)
Observations	14,640	14,640	14,640	14,640	14,640	14,640
Adjusted R-squared	0.977	0.977	0.977	0.977	0.977	0.977
FE	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM
Cluster	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM	CZ YM

Notes: This table displays the results from the regressions of the log of monthly job postings in each commuting zone on the associated trade barrier exposure measures. The definitions of each of the tariffs measures are presented in Section 6.2. All specifications include CZ and month-year (YM) fixed effects, and standard errors (in parentheses) are two-way clustered at the CZ and month-year level. Tariff exposure measures should be interpreted in units of $1,000 dollars per worker and agricultural subsidies in units of $1,000,000. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Shock Summary Statistics

	Output tariff exposure shocks			Intput tariff exposure shocks			Export tariff exposure shocks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean	428	1,973	0	1,722	7,933	0	410	1,890	0
Standard deviation	6,728	14,334	14,321	18,372	38,799	38,505	3,953	8,317	8,303
Interquartile range	0	599	645	0	4,257	4,681	0	867	680
Specification									
Excluding service industries		YES	YES		YES	YES		YES	YES
Residualizing on period FE			YES			YES			YES
Effective sample size (1/HHI of $s_{n,t}$ weights)									
Across industries and periods	39	2,536	2,536	39	2,536	2,536	39	2,536	2,536
Across NAICS4 groups	1.6	44	44	1.6	44	44	1.6	44	44
Largest $s_{n,t}$ weight									
Across industries and periods	0.033	0.0014	0.0014	0.033	0.0014	0.0014	0.033	0.0014	0.0014
Across NAICS4 groups	0.78	0.064	0.064	0.78	0.064	0.064	0.78	0.064	0.064
Observation counts									
# of industry-period shocks	10,680	10,656	10,656	10,680	10,656	10,656	10,680	10,656	10,656
# of industries	445	444	444	445	444	444	445	444	444
# of NAICS4 groups	113	112	112	113	112	112	113	112	112

Notes: This table summarizes the distribution of tariff shocks across industries n and periods t. All statistics are weighted by the average industry exposure shares $s_{n,t}$ as calculated in Borusyak et al. (2022). Columns (1), (4), and (7) include the nonmanufacturing industry aggregates in each period with a shock of 0, while columns (2), (3), (5), (6), (8) (9) restrict the sample to agricultural and manufacturing industries. Columns (3), (6), (9) residualize manufacturing shocks on period indicators. We report the effective sample size (the inverse renormalized Herfindahl index of the $s_{n,t}$ weights) with and without the non-manufacturing industry, at the industry-by-period level and at the level of NAICS4 groups (aggregated across periods), along with the largest $s_{n,t}$. *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Baseline regression incorporating exposure-robust standard errors

Dep. Var. ln(postings+1)	(1)	(2)
Output tariff exposure	-0.016	-0.016
	(0.011)	(0.010)
Intput tariff exposure	-0.015***	-0.015***
	(0.005)	(0.004)
Export tariff exposure	-0.094***	-0.094***
	(0.034)	(0.033)
Constant	-0.000	-0.000
	(0.000)	(0.000)
Observations	10,656	10,656
Adjusted R-squared	0.026	0.026
FE	CZ YM	CZ YM
Cluster	CZ YM	CZ YM

Notes: This table reports our baseline regression with Exposure-robust standard errors (reported in parentheses) obtained from equivalent industry-level IV regressions, as described in Borusyak et al. (2022), allowing for clustering of shocks at the level of four-digit NAICS codes (column (1)) and six-digit NAICS codes (column (2)). *** p<0.01, ** p<0.05, * p<0.1.