Trade Shocks and Firms Hiring Decisions: Evidence from Vacancy Postings of Chinese Firms in the Trade War*

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Abstract

This paper studies the effect of cost shocks on the hiring behavior of firms exposed to the recent China-US trade war. Our analysis leverages a unique dataset of job vacancies from a Chinese online job board, and a firm-level tariff-exposure measure built using custom transactions data. We find that firms more exposed to US tariffs on Chinese goods responded by posting fewer job vacancies and offering lower wages. The decrease in wages is partially balanced out by the increasing non-wage compensations, indicating a shift in employer's hiring decision in favor of a flexible and performance-based pay. We also find a negative relationship between US-tariff exposure and the firm's education requirement in job ads, which is in line with the finding that US tariffs disproportionately targeted relatively skill-intensive products. Evidence on the effects of China's retaliatory tariffs, however, is not found due to statistical insignificance. Our results suggest a negative impact of the trade war on both firms and job-seekers in China.

Keywords: Trade war, tariffs, online job vacancies, firm recruitment

JEL Code: D22, F13, F14, J23

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1 Introduction

Cost shocks to firms typically have an adverse impact on their performance in a competitive environment. In some cases, they can be mitigated by adjusting the factor mix or by switching to alternative production technologies. In the case of a tax or a tariff, the cost shock is unrelated to a firms' production technology or factor mix. Exposed firms' products will become more expensive and face lower demand in markets where the tariff applies. Lower sales and profits might force the firm to downscale, which also affects its labor demand.

We document adjustments in labor demand to a cost shock for a sample of Chinese firms that have been exposed to the recent China-US trade war. Relying on newly collected information from online job-vacancy postings in China, we observe differential responses across firms depending on the degree of their exposure to tariffs in the trade war. Our analysis focuses on the most recent round of US tariff increases and subsequent Chinese retaliation in 2019.[1] Combining this with monthly observations of online job-postings (between May and November 2019), we evaluate within-firm adjustments in labor demand along several dimensions.

The US-China trade war is a suitable setting for analyzing the effects of a cost-shock on firms' hiring behavior. The shock materializes in the form of ad-valorem tariffs that are charged on specific Chinese goods when entering the United States. This means that the cost-shock is exogenous from the perspective of the Chinese firm, assuming that it had no control over the tariff schedules issued by the Trump administration in that period. Moreover, unlike a minimum wage (for instance), US tariffs are the product- and not factor-specific. Accordingly, the impact on labor demand would be less obviously driven by factor substitution, but could rather be modeled as an adverse productivity-shock at the overall firm level. Heterogeneity in exposure to the trade war across firms can still be identified, as their revenues depend to a different degree on sales in the US. Besides their exposure to US tariffs, we also analyze adjustments in response to China's retaliation. This occurred as China imposed own tariffs on US products, which potentially shelter Chinese firms form external competition, but may also be hurtful if retaliation cuts off input supply.

Despite its recency, there are already a number of studies quantifying the short-term effects of the US-China trade war. Most studies focus on the US economy, such as Fajgelbaum et al. (2019) and Amiti et al. (2019), who find that aggregate welfare effects are modest. They might be much larger, however, in particularly exposed regions where Chi-

[1] See Bown and Kolb (2019) for a detailed description and sequence of events.

nese retaliation appeared to depress local consumption and employment (Waugh, 2019; Goswami, 2020). Adverse effects have also been documented in firm-level studies, especially for those relying on global supply chains and production networks that involve trade with China. Huang et al. (2019) find that the new US tariffs on Chinese goods affected stock-market returns and the default risk of firms. Handley et al. (2020) document that US exporters that rely on imported inputs from Chinese perform significantly worse than other exporters since the new tariffs have come into effect. Indeed, a recent study by Meinen et al. (2019) finds that Chinese export revenues from goods subject to the recent tariff hike decreased by 30 percent relative to non-affected products. We contribute to the strand of literature by documenting new evidence regarding the connection between trade policy and the firm's labor demand and hiring decisions.

Our study reveals novel insights on the firm-level effects of this trade war and extends our understanding of its repercussions in the labor market. Different from existing studies, we focus on firm-level demand for labor by analyzing online job-ads. A main advantage of using online job advertisements is its rich information that is typically not observable in firm-level census or survey data. This includes, for instance, the number of open positions and their change over time, the average wage offered for a particular job as well as the envisaged duration of the contract (i.e. fixed-term versus permanent). Besides this, we are able to observe different forms of non-wage compensation (such as special insurances or training) as well as specifications of job-requirements (e.g., previous experience or educational background). To investigate responses along these dimensions, we identify firms' differential exposure to the trade war by using pre-sample period information of their trade relationships documented in official statistics form China Customs. Firms trading more with the US *and* trading goods that were subject to new tariffs will be considered as being more exposed to the trade war.

Our findings suggest that firms exposed to higher US tariffs responded by posting systematically lower numbers of job ads. On average the reduction amounts to about 15 percent. We do not find evidence for substitution between permanent and temporary positions. A minor negative impact is found also for the average wage compensation indicated in the job ads. The decrease takes place uniformly across different job-vacancies of a firm so that the overall wage dispersion remains unchanged. The decrease in wages appears to be balanced out by other forms of compensation, such as bonuses, which points at preferences shifting towards greater flexibility and performance-based compensation among firms facing higher US tariffs. Moreover, we find a robust and negative relationship between US-tariff exposure and required educational background, while requirements on previous job experience (measured in years) do not significantly respond. We explain the reduction in average skill-requirements by showing that US tariffs disproportionately targeted relatively skill-intensive products, which translates into lower skill demand at the firm level.[2]

In contrast to these findings, we do not detect any comparable systematic adjustments for the effect of retaliatory tariffs on US exports entering China. While the sign of the corresponding coefficient tends to be the opposite of that for US tariffs, magnitude and precision of these estimates are substantially lower. This pattern is similar to other findings in the related literature, where import tariffs fail to create new jobs or boost firm performance (e.g. Huang et al., 2019; Goswami, 2020). While part of the explanation could be that the potential producer gains from protection are offset by costlier imported inputs, it is also plausible that missing evidence of job creation is due to the premature nature of these tariffs. While US tariffs reduce sales of Chinese firms immediately and lead to fewer job offers, China's retaliation tariffs do not provide sufficient certainty about the amount (and duration) of protection. Hence, it might be less costly to postpone hiring new personnel to the moment when US tariffs are revoked than to separate from employees that have been hired under (temporary) protection.[3] Overall, our study suggests that the US-China trade war has hurt both firms and job-seekers. Mainly so, because positive effects of protectionist policies do not materialize while the additional costs imposed on firms enforce immediate adjustments that result in slower job growth.

The rest of the paper is organized as follows. Section 2 introduces our new firm-level job vacancy dataset and discusses related research using similar data. In section 3 we provide additional background information on the events during the US-China trade war and lay out some potential channels of adjustment. Section 4 explains the empirical strategy we adopt for the identification of its impact of tariffs on labor demand. Section 5 presents our results, including robustness checks and an exploration of heterogeneous responses across firms. We conclude the paper with section 6.

[2]This interpretation is in line with Atkin (2016); Blanchard and Olney (2017) and also with the notion that US tariffs disproportionately targeted intermediate inputs (Handley et al., 2020).

[3]This is in line with theories on firms' investment behavior under policy uncertainty (e.g. Handley, 2014; Handley and Limão, 2015), where firms opt for delaying new hires until the situation improves. Abowd and Kramarz (2003) document for French firms that the costs associated with hiring are substantially lower than the costs associated with terminating a contract.

2 Online job-vacancy data

2.1 Data collection

We join a growing literature that uses job vacancy data to understand a variety of issues related to the labor market. Since the early study of Kuhn and Skuterud (2004), several papers exploit such information to study, among others, the relationship between firm performance and skill demand (Deming and Kahn, 2018; Kahn and Hershbein, 2018), firm's financial health and its recruiting outcomes (Brown and Matsa, 2016), as well as other demand-side features, such as gender discrimination (Kuhn and Shen, 2013), search effort and search duration (Faberman and Kudlyak, 2016), or labor market concentration for specific types of jobs (Azar et al., 2018). While most job-vacancy datasets stem from English job-ad platforms,[4] Kuhn and Shen (2013) are an exception using vacancy data from the Chinese recruitment website *Zhaopin.com*.

Our data comes from *Qian Cheng Wu You 51job.com* (hereafter, 51job.com), a leading company for human resource services, and also the largest online recruitment platform in China. According to the annual report from 51job.com, there are more than 100 million registered members, with over five million job postings and 40 million applications delivered to potential employers every week. Observations come from 297 prefecture cities in China, which include four centrally-administrated municipalities, 15 vice-provincial cities, and 278 prefecture-level cities across the nation. For each job vacancy, the ad page on the site of 51job.com provides standardized information, including wage and non-wage compensations offered by the employer, job requirements on education level, working experience, language and computer skill-set, detailed occupation information, the working location, ad published date, and unique firm and job identifiers. In addition, each ad provides actual text and keywords of the main tasks for a certain vacancy. The detailed information allows us to implement controls for geographic factors, type of job vacancies and other aggregate-level factors.

We started collecting information systematically in May 2019 and construct a dataset with monthly frequency covering the period through November 2019.[5] Because the job ads are linked to a firm's page, we also have basic information on the firms posting job ads. Firm characteristics consist of firm ownership, the scale of employment, and industry. Using the company name, we matched the firms in our vacancy data to customs data

[4]Examples of job-ad platforms are Craiglist (Kuhn and Skuterud, 2004), the Job Openings and Labor Market Turnover (JOLTS) survey from the BLS (Davis et al., 2012, 2013), Burning Glass (Kahn and Hershbein, 2018; Deming and Kahn, 2018), *indeed.com* (Mamertino and Sinclair, 2016; Turrell et al., 2019), *CareerBuilder.com* (Brown and Matsa, 2016; Marinescu, 2017), or *Snagajob.com* (Faberman and Kudlyak, 2016).

[5]The procedures for collecting the data are discussed in Appendix A.1.

for 189,280 firms that will allow us to measure firm-level exposure to the trade war, as we explain in greater detail below.

2.2 Summary statistics

Table 1 presents summary statistics of the resulting sample. The sample contains 1.2 million unique job vacancies posted by the 0.19 million matched firms from May through November 2019. The annual wage mean per vacancy is around 100,000 RMB, approximately equivalent to 14,500 US dollars. In addition to the basic wage, over half of the vacancies provide non-wage compensations (i.e., subsidies and bonuses). Over 70% of the vacancies provide five insurances and housing compensation as additional welfare benefits for employees.[6]

Table 1: Summary Statistics of Job Vacancies

Variables	Mean	Std.Dev.
Panel A. Job vacancy characteristics		
Number of vacancies per firm per month	6.18	21.73
Wage		
Wage per vacancy - lower bound (1000 USD/year)	11.48	28.82
Wage per vacancy - upper bound (1000 USD/year)	17.64	48.35
Wage per vacancy - mean (1000 USD/year)	14.56	38.42
Non-wage compensation		
Share of vacancies providing subsidies to employee	0.56	0.50
Share of vacancies providing bonus to employee	0.50	0.50
Share of vacancies providing insurances to employee	0.72	0.45
Job requirement		
Working experience required by the job - lower bound (year)	1.58	1.70
Working experience required by the job - upper bound (year)	1.95	2.27
Working experience required by the job - mean (year)	1.77	1.98
Education level required by the job: college or higher	0.77	0.42
Panel B. Firm characteristics		
Share of vacancies posted by mega firms (employment greater than 10000)	0.07	0.25
Share of vacancies posted by small-scale (employment less than 50)	0.07	0.25
Number of firms	189,280	
Number of job vacancies	1,212,982	

Note: Author's calculations based on data collected from 51job.com. Summary statistics for sample of firms matched with China Customs information, May-November 2019.

In terms of job requirements, 77% of the vacancies require a college degree or higher. The bar of working experience is set at 1.77 years on average (i.e., one year and 9 months).

[6]Five insurances include unemployment insurance, endowment insurance, medical insurance, work-related injury insurance, and maternity insurance.

Panel B of Table 1 presents firm characteristics. In our sample, 7% vacancies are posted by mega-firms with more than 10,000 employees. Another 7% represent small firms with less than 50 employees, so that the remaining 86% of firms in our sample are of intermediate size between these two extremes.[7]

Summary statistics of monthly data samples are provided in Table A.2. Over 13 thousand uniquely identified firms are posting job ads each month, and each firm posts around 4-8 job ads per month. Column (1) through (7) contains the mean and standard deviation of the corresponding variable across monthly samples, from May to November, respectively. Steady pattern of the job requirements and firm characteristics can be found across columns, with a gradually decline in the total number of job vacancies since July 2019.

In Figure 1, we present the geographic coverage of our sample, as well as the concentration of job ads and wage levels across regions. While it is not surprising that high-wage jobs are clustered in the coastal and borderline areas of China, a higher density of vacancies appears in the inner-land regions. One explanation could be that modern China has moved its labor-intensive manufacturing base into inner Chinese regions, whereas higher-paid jobs are offered in other, more knowledge-intensive sectors (Mau and Xu (2019)). Indeed, Figure A.1 shows that manufacturing firms posting job-ads during our sample period tend to reside in lower parts of the city wage-rank distribution. Moreover, Table A.1 suggests that more than 40 percent (i.e. the largest single portion) of the job-ads are posted by firms from the primary, manufacturing, and utility industries.[8]

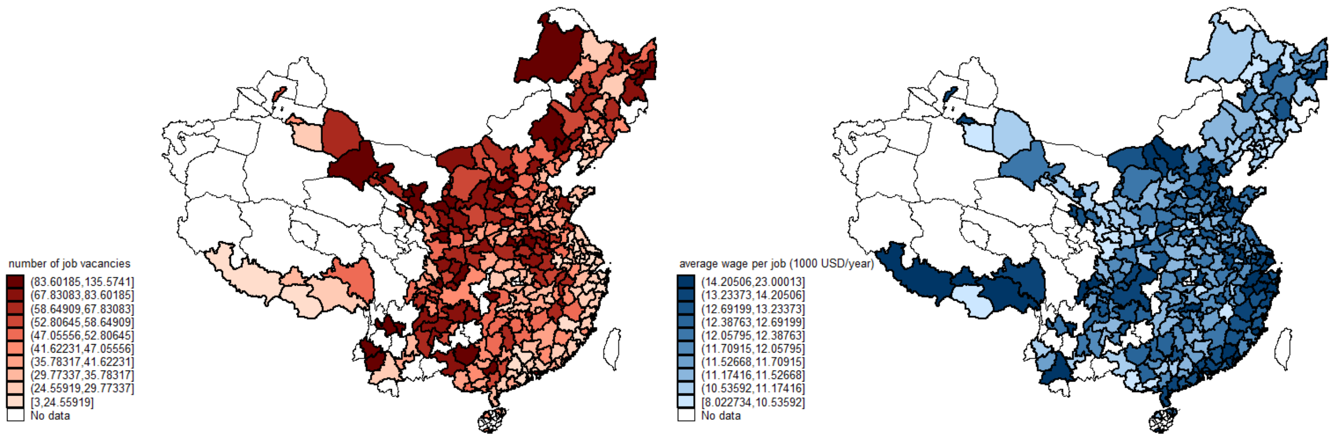
We compare our data to the information from the *Zhaopin.com* sample used in Kuhn and Shen (2013), and the selected urban census population from China's eight highest-income provinces summarized by the same authors (see Table A.1). It provides interesting footage of China's economic transformation over the past 1-2 decades. We note that most job ads (more than 95 percent) in our data offer fairly low monthly wages. Nevertheless, the portion representing high-paying jobs has increased slightly compared to the 2005 urban census data. A striking change can be observed in the requirements of educational background. While less than a quarter of the job ads in the urban census sample required such qualifications, this fraction is three out of four today. Similar patterns can be observed in the fractions of private and state-owned (or state-controlled) enterprises. In terms of industry structure, the expansion of the IT and communications sector is re-

[7] We further note that around 6% of the vacancies are posted by state-owned firms (SOE) and government institutions, and nearly 20% are posted by foreign firms.

[8] Figure A.1 (a) further shows that service sector firms posting job-ads are fairly evenly distributed across most regions with occasional outliers in higher ranked cities. Panel (b) of Figure A.1 shows that large-scale firms take a larger proportion of posted job ads in cities with a higher wage rank. No such pattern is detected from the startup firms. Lastly, the proportion of SOEs and foreign firms, shown in part (c), reveal no significant concentration across the city wage rank.

Figure 1: Geographic distribution of job vacancies, May-Nov. 2019

(a) Number of Job Vacancies (b) Annual Average Wage



markable, while construction and transportation are less represented in our data.

Overall, it appears that compared to the urban employment census, both 51job and Zhaopin's job ads are skewed towards well-educated workers that are employed in the private sector and in IT-related industries.[9] While parts of these structural differences may be due to selection effects into online job-advertisement, we find that certain attributes, like the wage distribution or coverage of manufacturing jobs, are fairly representative in our data. We draw similar conclusions from our comparison of labor markets across Chinese regions in Figure A.2, where we plot the number of job-ads observed per city against the corresponding number of urban employment reported for the year 2018 in the *China City Statistics Year Book*. While our 51job.com data fits well on average, recent comparable data from the online platform *Zhaopin.com* seems to understate cross-regional variation in job ads.

[9]Similar differences have been noticed before in other studies. Samples based on online job vacancy data often over-represent certain areas of an economy (e.g. Davis et al., 2013).

3 The US-China trade war

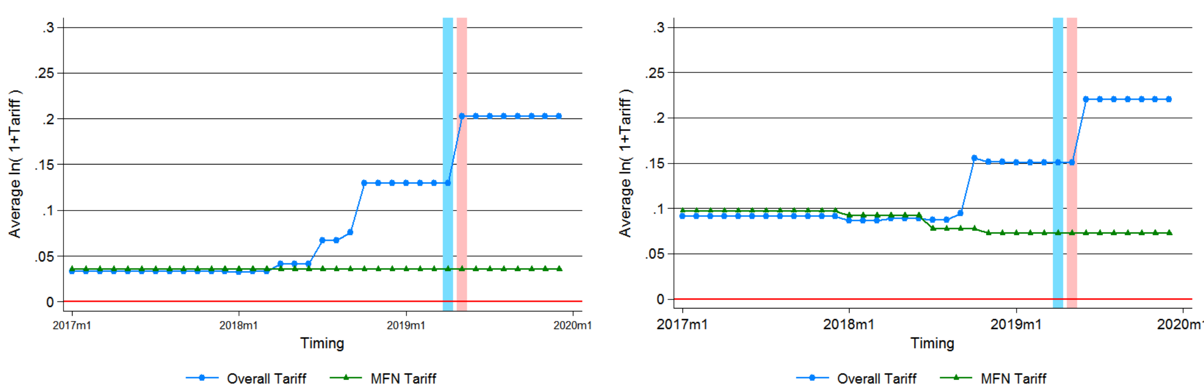
3.1 Stages of escalation

The U.S. administration under President Trump has implemented new trade policies against free trade in several rounds, using various justifications. The first round of trade barriers imposed were global safeguard tariffs on imports of washing machines and solar panels in January 2018. These were followed by tariffs on steel and aluminum, in March 2018, which the US justified with national security concerns. Several major US trading partners were affected by these measures and imposed retaliatory tariffs on US goods, claiming that the measures taken by the Trump administration violated WTO trade law.

China became the main target of US trade policy following investigations on the abuse of US companies' intellectual property rights. Since then, the US government imposed several rounds of tariffs on Chinese products. China retaliated by imposing its own tariffs on US products. Figure 2 presents average tariff rates applied by the US and China on their respective imports, before and during the trade war. They are benchmarked against the most-favored-nations (MFN) tariff rates both countries continue to apply on imports from (most) other trade partners.[10]

Figure 2: Average U.S. and Chinese Tariffs (Industry Level)

(a) US Tariff on Chinese Goods (b) Chinese Tariff on the US Goods



Note: Authors' calculations based on data from Fajgelbaum et al. (2019), Li (2018), and own updates.

The first major round of US tariffs on China became effective in July and August 2018 and targeted 818 and 279 product categories, specified according to the 8-digit harmo-

[10]See Bown and Kolb (2019) for a detailed time-line of the events. Also see Benguria et al. (2020).

nized tariff schedule (HTS), respectively with an additional 25% increase on the existing rates. China's retaliation to this first round targeted an equivalent value of US goods and covered 545 and 333 products, respectively, with a 25% rate.[11] In September 2018, the US applied another 10% tariff rate on products valuing $200 billion in imports. China's response entailed a simultaneous tariff increase by 5 and 10 percentage points targeting 5,207 US products worth $60 billion in imports. At the same time, the US administration announced to increase tariffs on the same goods by another 25 percentage points at a later stage, and China announced to do the same. In fact, following a meeting in December 2018, the governments agreed to postpone these measures, and China eliminated some of its retaliatory tariffs on US cars and car parts in early 2019. Another stage of the escalation followed in May 2019, when the US began to apply the previously announced additional tariffs. China followed a month later. Despite ongoing threats over the months that followed, no further tariffs have been imposed since then. In December 2019, the two parties announced a so-called "Phase-one Deal" in which China committed to purchasing major amounts of US products, while leaving unchanged all other measures taken before. The agreement was signed in mid-January 2020 and came into effect a month later.[12] As our sample with monthly job-vacancy data begins only in May 2019 (as indicated by the vertical bars in Figure 2), our analysis will focus on the last round of tariff increases.

3.2 Potential effects on firms' hiring behavior

Empirical research on the US-China trade war documents an abrupt and major impact of the tariffs on export revenues of the two countries (e.g. Fajgelbaum et al., 2019; Meinen et al., 2019). While Chinese exporters may pass on the tariffs to its US customers, it might be rational to (at least partially) absorb some of the burden to avoid excessive reductions in sales. To absorb the tariff burden, firms have to lower their prices, which can be achieved by lowering mark-ups or production costs. Regardless of which strategy a firm adopts, employees are likely to suffer. Lower sales translate into lower labor demand and charging a lower price per unit sold exerts pressure on wages.

Our job vacancy data prevents us from observing adjustments in the number or com-

[11] Note that earlier, in April 2018, China had imposed tariffs on a small set of products amounting to $2.4 billion in imports from the US in response to the steel and aluminum tariffs discussed at the beginning of this section. Those tariffs applied additional 15% and 25% ad-valorem rates targeting 91 HS6 products (or 104 8-digit HTS categories). 6-digit Harmonized System (HS6) product categories represent to the most disaggregated internationally harmonized classification of goods and are administered by the World Customs Organization. Further disaggregation, such as 8-digit HTS categories are typically country-specific and not internationally comparable.

[12] See www.piie.com for the most recent up-to-date time line of events.

pensation of existing employees. However, we observe characteristics of a firm's potential future employees, which can be interpreted as an intended investment. As previous research has shown that firms may postpone investments when facing economic and political uncertainty (Handley, 2014; Handley and Limão, 2015), we expect that the number of job vacancies posted by firms subject to US tariffs will decline.[13] Moreover, we may expect adjustments in the announced compensation of labor. While lower wages could help firms to lower their prices, they face the risk of deterring good candidates from applying to their posted positions. Major reductions in the offered wage may therefore be counterproductive if no other forms of compensation substitutes for them. Substitution away from rigid to more flexible (performance-based) wage schedules could help firms in finding high-quality employees. Hence, firms might be expected to offer lower wages while shifting to flexible compensation, such as bonuses. Other observable forms of non-wage compensation (e.g., insurances, training, or subsidies) may also become more prominent among exposed firms.

Predictions of possible adjustments become less obvious when we consider the required skill-profile or previous work experience indicated in job ads. For skill-demand, they might depend on firms' efforts to shifting sales towards products that are less exposed to US tariffs, which might translate into relative skill demand (Atkin, 2016; Blanchard and Olney, 2017). If such a strategy is relevant, we might observe relatively less demand for skilled workers in our job ads, as products shipped to the US belong to the most skill-intensive goods in China's exports.[14] An alternative channel could be that exposed firms respond to lower sales and the pressure of reducing their costs by seeking to attract workers that are willing accept lower wages (and less certain working conditions), which might lead firms to request lower minimum standards in work experience and education in their job vacancy postings.

Since the trade-war denotes an event of reciprocally applied tariffs, Chinese firms might also be affected by the measures their own government took to retaliate US tariffs. Indeed, this might protect some firms from external competition by US firms and potentially result in increasing market shares. However, it is questionable that this is sufficient reason for firms to adjust labor demand and compensation. As pointed out earlier,

[13]Obviously, decreasing sales should be sufficient reason to expect that firms will hire less. The uncertainty effect comes on top of this and will be relevant for our expected adjustments to China's retaliation, as we explain further below.

[14]See Figure A.4 for the relative skill-intensity of products facing US tariff increases. The bias towards skill-intensive goods is much less pronounced in China's retaliatory tariffs, as shown in Figure A.5. Skill-intensity is measured by the industry-employment share of skilled workers, as documented in the Annual Survey of Industry Production (ASIP) for the year 2004. A similar pattern is obtained if we measure skill-intensity based on the Indonesian manufacturing census, as used by Amiti and Freund (2010).

the US-China trade war results in substantial uncertainty about the future economic environment of exposed firms' operations. Once these tariffs are revoked, firms would find themselves with too many employees and struggle to separate from them. Empirical evidence from Abowd and Kramarz (2003) suggests that separation costs are considerably higher than the cost of hiring workers. Hence, a major positive effect on labor demand should be expected to materialize only in the case of a sustained increase in market shares. Another argument against such an effect is the lack of evidence in related studies on the US labor market adjustments (Waugh, 2019; Goswami, 2020), where US tariffs failed to create jobs (although they might have prevented some from disappearing). Moreover, since goods exported from the US to China might also serve as intermediate inputs for Chinese firms, China's retaliatory tariffs might actually hurt its own firms. Handley et al. (2020) document patterns along these lines for US exporters which rely on imported inputs from China. Overall, we expect that the negative effects of the trade war dominate.

4 Empirical framework

4.1 Firm-level exposure to the trade war

4.1.1 Sample selection

As already indicated in section 2, we analyze the impact of the trade war on the hiring behavior for a subpopulation of firms that are engaged in international trade. The reasons for doing so are threefold. First, many firms in our job-vacancy data might be unaffected by the trade war, simply because they do not engage in international trade (directly or indirectly). Second, even if they are affected indirectly, it is impossible for us to measure their exposure to the trade war, as we do not observe such information. This may imply that we miss out adjustments to the trade war in parts of the Chinese economy and, hence, that our estimates indicate the lower-bound of its actual impact. Third, since typically only a fraction of firms in a country are involved in international transactions, and as such firms are quite distinct from non-trading firms, we do not believe that non-trading firms constitute an appropriate control group. One reason for this skepticism is differences in firm size that typically prevail between trading and non-trading firms. Another reason is the different market environments in which such firms operate. While trading firms operate at a global scale in highly competitive markets, non-trading firms may be shielded from such competition if they produce and sell exclusively in domestic (niche) markets. Nevertheless, we are confident that our sample of firms will convey economically meaningful information, as large exporting and importing firms often account for the single largest fraction of local and industry level output and employment.

4.1.2 Measurement and identification

By focusing on trading firms, we can construct two measures of firm-level exposure to the trade war and discuss their interpretation. The first measure captures exposure to US tariffs, which mainly affects exporters. The second measure captures exposure to China's retaliatory tariffs on US products and mainly affects importers. We denote $\text{Tariff}_f^{\text{US}}$ as the US-tariff exposure of firm f, which is constructed as follows:

$$\text{Tariff}_{ft}^{\text{US}} = \sum_{j \in J_f^e} \left[\frac{X_{fj0}^{\text{US}}}{\sum_i X_{fj0}^i} \tau_{jt}^{\text{US}} \right], \tag{1}$$

where τ_{jt}^{US} is good j's *ad valorem* tariff imposed by the US at time (i.e. month) t, X_{fj0}^{US} is firm f's exports of good j to the US in a pre-sample base-period $t = 0$ (i.e. 2016), which we divide by firms' total export revenues from good j, as indicated in the denominator. J_f^e is the set of goods exported by firm f. By interacting the US tariff rate with a measure of the relative importance of the US market for each exporter, we obtain our measure of exposure as a weighted average of the US tariff rate faced by firm f.

Likewise, based on China's retaliation tariffs on US goods and firms' imports data, we construct our measure of firm f's exposure to import tariffs:

$$\text{Tariff}_{ft}^{\text{CHN}} = \sum_{j \in J_f^m} \left[\frac{M_{fj0}^{\text{US}}}{\sum_i M_{fj0}^i} \tau_{jt}^{\text{CHN}} \right], \tag{2}$$

where τ_{jt}^{CHN} is good j's *ad valorem* tariff imposed by China on the US goods at time t (i.e. month), M_{fj0}^{US} is firm f's average imports of good j from the US in a pre-sample base-period $t = 0$ (i.e. 2016), which we divide by firms' total imports of good j, as indicated in the denominator. J_f^m is the set of goods imported by firm f. By interacting the Chinese tariff rate on US products with a measure of their relative importance for each importer, we obtain our firm-level measure of exposure to import tariffs.

Since we can directly observe US and Chinese applied tariffs, as well as firms' relative "specialization" in US trade relations, our measure denotes an accurate quantification of tariff exposure. Indeed, our approach is similar to related research that studied the impact of the trade war on local US labor markets (e.g. Waugh, 2019; Goswami, 2020). Furthermore, by employing custom data in 2016 to construct our pre-period weights, we are able to address endogeneity concerns that could potentially bias our estimates.[15] However, we also face one caveat for identification, as our pre-sample period weight does not take into account firms' domestic sales and purchases. As a result, it is possible that a firm with a high degree of specialization in US trade relations, according to our measure, is actually specialized in domestic transactions. We would overstate the degree of such a firms' exposure and may likewise understate the exposure of highly export-oriented firms. Although we cannot rule out such a possibility, we expect that such measurement error would lead to an attenuation bias and loss of precision in our point estimates.

4.1.3 Tariff and trade data

To construct our measures of firm-level exposure, we combine information from two datasets. The first is the China Customs Dataset, in which we observe export and import values at the product-firm-destination (or source) country level for all international transactions in 2016. We use this information to compute the firm-specific weights that capture their relative reliance on US trade relations. We combine this data with a detailed dataset of US tariffs imposed upon China, as well as Chinese retaliatory tariffs on the US, which is reported at a monthly frequency for the years 2016-2019. The evolution of these tariffs has already been discussed in Section 3 (Figure 2).[16]

We collected the reciprocal Chinese and US tariffs from several data sources, including official communications by the US Trade Representative, the CARD Trade War Tariffs Database (Li, 2018), as well as data provided by Fajgelbaum et al. (2019) and Bown and Kolb (2019). US and Chinese MFN tariff rates were collected from the WTO (World Trade Organization) *Tariff Download Facility* database. Chinese MFN tariffs were further complemented with data from Bown and Kolb (2019), which includes more recent changes in Chinese tariffs based on official Chinese government communications. Detailed numbers for our tariffs in 2018 and 2019 are provided in Table A.3 in Appendix B. Starting with MFN rates of 3.6% and 9.2% in an average (6-digit HS) product category, both the US and China increased tariffs up to 23.2% and 25.1% respectively in just two years. Taking into

[15] Note that the year of 2016 pre-date the years of Donald Trump's presidency. Although he threatened to impose new trade policy measures against China already during his electoral campaign, his victory in late 2016 was a surprising outcome that is unlikely to have driven anticipatory behavior among Chinese firms. See Amiti et al. (2019) for further discussion on this issue. Also note that any major anticipation effects in firms' hiring behavior would induce a downward bias on our estimated coefficients.

[16] Although we do not exploit MFN tariffs in our empirical analysis, we collected this information for illustrative purposes. They reflect applicable tariffs to most other trade partners of the two countries. Since the trade war took place mostly between these two countries, we abstained from collecting corresponding information for all other trade partners and assume that the majority of trade flows were subject to (stable and predictable) MFN tariff rates.

account firms' specialization in US trade relations, we observe increases in similar orders of magnitudes (see Figure A.3 and Table A.4). In the period we observe in our empirical analysis (i.e., between May and November 2019) firms faced an average increase of tariffs on their exports by about eight percentage points and an about seven percentage-point increase on imported goods.

4.2 Estimation

4.2.1 Empirical baseline specification

To investigate the effect of tariffs on firms' recruiting behavior, we adopt a simple linear panel regression model:

$$y_{ft} = \beta_1 \ln(1 + \text{Tariff}^{\text{US}}_{f,t-1}) + \beta_2 \ln(1 + \text{Tariff}^{\text{CHN}}_{f,t-1}) + \mathbb{X}'_{ct}\gamma + \eta_f + \eta_t + \varepsilon_{ft}, \tag{3}$$

where $\text{Tariff}^{\text{US}}_{f,t-1}$ and $\text{Tariff}^{\text{CHN}}_{f,t-1}$ are US and Chinese tariffs faced by firm f, lagged by one month. We employ lagged tariff exposure since we count vacancies as monthly totals, while actual implementation and responses could have taken place on different dates during the same month. By using lags, we avoid potential problems arising from different order of events and also allow firms a limited amount of time to adjust to the tariffs.[17] In line with the empirical trade literature we employ tariff exposure as an iceberg trade-cost term by adding one to the tariff rate and taking logs (e.g., a 5 percent of firm tariff exposure measure would enter the equation as $\ln[1.05]$).

As β_1 and β_2 denote our main coefficients of interest, we attempt to control for potentially confounding factors and implement firm fixed effects (η_f) and time fixed effects (η_t) into our baseline estimation equation. Time fixed effects control for aggregate trends or shocks that are correlated with both our dependent variable and our main variables of interest. This includes, for example, seasonal fluctuations in hiring which might happen to coincide with tariff changes. Firm fixed effects are included to control for unobservable time-invariant characteristics of a firm. This is of particular importance in our context, as we do not observe many firm-level characteristics, including its hiring history. However, as we can observe firms' location (at the city level c), we employ time-varying control variables along these dimensions in vector $\mathbb{X}_{ct}$ to capture aggregate developments in local labor markets. Specifically, we include the total number of firms posting job vacancies as well as the total number of job vacancies available in city c and at time t.[18] Finally, ε_{ft}

[17] Meinen et al. (2019) show that the effects of the trade war on US imports from China started to materialize in the last quarter of 2018, i.e. in the quarter after the first tariffs had come into effect.

[18] Since every firm f resides only in a single location, we suppress city subscripts c in our dependent

denotes an i.i.d. error term which we cluster at the city-month level.

4.2.2 Dependent variables and sample structure

We employ a number of different dependent variables y_{ft} to analyze alternative outcomes of the US-China trade war. These include broadly (i) the number of online job vacancies posted by a firm; (ii) measures of the nominal wage offered in a firms' average job-ad; (iii) indicators of other forms of compensation, such as bonuses, subsidies, or insurances; and (iv) job requirements as indicated by previous work experience and educational background. A detailed overview of these variables, along with further descriptions, is provided in Table A.5.

Table 2: Descriptive Statistics by Duration of Job Posting

Sample Statistics	Variable						
	No. Jobs	Wage	SOE	Foreign	Startup	Mega	Small
Sample: 1 months							
Mean	0.52	12.36	0.06	0.27	0.01	0.01	0.31
Std.Dev.	2.82	13.82	0.24	0.44	0.08	0.09	0.46
N firms	30,492						
Sample: 2 months							
Mean	1.24	12.65	0.05	0.32	0.00	0.01	0.27
Std.Dev.	3.98	8.77	0.23	0.47	0.07	0.12	0.44
N firms	21,868						
Sample: 3 months							
Mean	2.47	12.65	0.04	0.31	0.00	0.01	0.24
Std.Dev.	8.33	8.44	0.20	0.46	0.07	0.10	0.43
N firms	23,492						
Sample: 4 months							
Mean	3.56	13.50	0.05	0.30	0.00	0.01	0.21
Std.Dev.	7.87	26.90	0.22	0.46	0.05	0.11	0.41
N firms	23,772						
Sample: 5 months							
Mean	4.79	13.07	0.05	0.28	0.00	0.02	0.16
Std.Dev.	9.01	12.19	0.22	0.45	0.05	0.12	0.36
N firms	23,618						
Sample: 6 months							
Mean	6.82	13.49	0.05	0.27	0.00	0.02	0.13
Std.Dev.	11.22	8.79	0.21	0.44	0.05	0.12	0.34
N firms	25,501						
Sample: 7 months							
Mean	17.23	14.48	0.04	0.23	0.00	0.03	0.08
Std.Dev.	42.61	8.86	0.21	0.42	0.06	0.16	0.27
N firms	40,530						

variable and in the tariff measures to avoid confusion about the dimensions of their variation.

Table 2 provides an overview of the variation in our data, showing descriptive statistics of vacancy and firm characteristics by sub-samples of firms with varying lengths of posting job ads. In the first panel, *Sample: 1 month*, corresponds to summary statistics for firms that post job ads in only one of the seven months we observe in our sample, while the next panel, *Sample: 2 months*, features firms posting jobs for two months, and so on. Not only does the number of firms differ across these sub-samples, characteristics such as the number of vacancies posted, average wage and scale of firms also vary over those samples. Both the number of job vacancies and average wages have an upward trend as the duration of job posting increases. Firms with larger numbers of employees are more likely to continuously post job-ads, while small-scale firms post jobs for a shorter duration. Ownership of firms posting jobs across months and the proportion of startup firms are relatively stable across posting lengths. Overall, our data set appears to feature sufficient within- and across-firm variation to exploit for the purposes of this study.

5 Results

5.1 Main findings

5.1.1 Number of Job Vacancies

Our first dependent variable measures the absolute number of job vacancies posted by a firm f at time t. Since this is a count variable which features zeros and otherwise discrete positive values, we present results for a linear regression approach, as introduced in the previous section, and for a Poisson regression model (Wooldridge, 2010; Marinescu and Rathelot, 2018).

Table 3 reports our results. Throughout all specifications, we find a negative and statistically significant effect of increasing US tariffs on job postings of exposed firms. As shown in columns (2) and (4), city-level control variables tend to exert a downward correction of the absolute size of the coefficient, and the deterring effect of increasing US tariffs remains statistically significant. In contrast to the US tariffs, coefficients estimated for the effect of China's retaliation are generally statistically insignificant. Also the signs of the coefficients differ between the linear model and the Poisson regression, while the inclusion of city-controls leads to a general downward correction of the estimated coefficient. If we were to interpret specifications that include such control variables as being more reliable, China's retaliation appears to have either a negative effect on firms' labor demand (in the linear case) or almost no effect at all (in the Poisson case).

Table 3: Effect of Tariffs on the Number of Job Vacancies

Dept var: N^{v}_{ft}	Linear Models (1) FE	(2) FE	Poisson Regression (3) FE	(4) FE
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1})$	-2.692	-3.088	0.339	0.068
	(2.698)	(2.423)	(0.245)	(0.185)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1})$	-5.661***	-3.745***	-0.863***	-0.427*
	(1.458)	(0.920)	(0.303)	(0.248)
Observations	189,279	189,279	189,272	189,272
R-squared	0.761	0.763		
City Control	-	Y	-	Y
Firm FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y

Notes: Regressions use firm online job vacancy data from May 2019 to Nov 2019. City controls include city-month specific number of firms posting online vacancies and the total number of vacancies posted online. For linear models, robust standard errors are clustered at the city and month level; for Poisson fixed effect model, bootstrapped standard errors are used. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. .

To give the estimated coefficients a quantitative interpretation, we can infer from column (2) that a doubling in the applied US tariffs — i.e., an increase by 100 percent — results in 3.75 fewer job vacancies posted on average per firm per month. Tariffs increased by about 46 percent during our sample period, and by a factor of about 7.52 since the beginning of the trade war. While this implies about 12.12 fewer jobs offered by an average firm between May and November 2019 ($3.75 \times 0.46 \times 7$ months), due to higher US tariffs, the implied future monthly reduction since the beginning of the trade war amounts to about 28.19 job ads per firm on average (3.75×7.52).[19] Poisson estimates in column (4) report the implied job-tariff elasticity, which amounts to 19.69 percent fewer job-ads between May and November 2019 ($42.7\% \times 0.46$). This is a more conservative result than the estimated 12.12 reduction in vacancy numbers based on the linear model in column (2). Using this number together with an average number of 43.26 (6.18×7 months) vacancies per firm in our sample (see Table 1), we obtain about 28.02 percent fewer job offers.

[19]Calculations based on information about monthly firm-level tariff exposure as documented in A.4, where trade-weighted US tariffs increased from 16.9 to 24.7 percent between May and November 2019, and from 2.9 to 24.7 percent since January 2018.

5.1.2 Average Wage per Vacancy

We next study how firms' wage schedules responded to the tariff changes. To do so, we compute for each firm f the average wage w_{ft} offered in the vacancies it had posted at time t. Since job ads (v) typically indicate a wage range, i.e. a minimum and a maximum wage (or salary) level, we analyze responses in both of these wages separately and in addition responses in the average of two ($w_{fvt}^{mean} \equiv (w_{fvt}^{\min} + w_{fvt}^{\max})/2$). In all specifications, we measure wage rates in logs.

Table 4: Effect of Tariffs on Average Wage per Vacancy (one-period lagged tariff)

Dept var:	Minimum Wage		Maximum Wage		Mean Wage		Wage Dispersion	
	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE	(8) FE
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1})$	0.009	0.009	0.027	0.026	0.036	0.035	0.026	0.026
	(0.045)	(0.048)	(0.045)	(0.047)	(0.046)	(0.048)	(0.014)	(0.014)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1})$	-0.085*	-0.085*	-0.077*	-0.077*	-0.073*	-0.073*	0.012	0.013
	(0.035)	(0.036)	(0.033)	(0.034)	(0.033)	(0.034)	(0.012)	(0.011)
Observations	107,800	107,800	107,800	107,800	107,800	107,800	107,800	107,800
R-squared	0.738	0.738	0.734	0.734	0.732	0.732	0.736	0.736
City Control	-	Y	-	Y	-	Y	-	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Average wages in column (1) to (6) are in logs $\ln w_{ft}$; wage dispersion in column (7) and (8) is measured as $\ln w_{ft}^{max} - \ln w_{ft}^{min}$. Regressions use firm online job vacancy data from May 2019 to Nov 2019. City controls include city-month specific number of firms posting online vacancies and the total number of vacancies posted online. Robust standard errors are clustered at the city and month level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. .

Table 4 presents our results. As in our previous table, we do not find any significant responses to Chinese retaliation tariffs on US goods, so we focus in our discussion on the US tariffs. Columns (1) and (2) suggest that the lower bound of annual wages offered in our observed job ads decreased among firms that were more exposed to the trade war. The same can be found for the upper bound of annual wages and for the average of the two, in columns (3)-(4) and (5)-(6), respectively. Throughout, the estimated coefficients suggest a fairly low elasticity of wages with respect to faced tariffs among Chinese firms. Yet, given the major increase in tariff levels during the trade war, the coefficients imply about $([24.7/16.9 - 1] \times \hat{\beta}_1) \approx$ 3-4 percent lower wages offered by affected firms (which corresponds to about $500 less per year, if average wage compensation is $14,560 as stated in Table 1). The last two columns confirm that the size of the indicated wage intervals does not change significantly among firms.

5.1.3 Non-wage compensation

A lower offered wage does not necessarily imply the labor costs would decrease. Non-wage compensation can account for major portions of total labor costs (Woodbury, 1983; Liu et al., 2019). Indeed, it might be convenient for firms to offer alternative forms of compensation if they have different means to providing such benefits. To evaluate such adjustments, we focus on three different forms of alternative compensation schemes: bonuses, subsidies, and insurances. With bonuses firms can avoid early commitments to paying higher wages when the actual performance of the future employee (but also of the firm as a whole during the trade war) is uncertain. Subsidies include the provision of overtime pay or transportation, communication, and meal allowances by the employer, whereas insurances include the provision of a "five-insurances" package that is part of China's social security system.[20] To evaluate whether firms increasingly advertise the provision of such alternative forms of compensations, we compute the share of a firm's job ad including such components.

That is, the share of jobs offering bonus payments to employees ($Share_{ft}^{Bonus}$) is defined as follows:

$$Share_{ft}^{Bonus} = \frac{\sum_{v \in \Omega_{ft}} \mathbf{1}_{fvt}(\text{the advertisement explicitely offers bonus})}{N_{ft}} \tag{4}$$

where Ω_{ft} denotes the mass of all vacancies posted by firm f in month t, N_{ft} is the number of job vacancies posted by firm f in month t, and $\mathbf{1}_{fvt}$ is an indicator variable that equals to one if job-ad v explicitly mentions that the job will be offered with performance-based bonus payment. We compute shares of jobs offering subsidies, $Share_{ft}^{Sub}$, and insurances, $Share_{ft}^{Ins}$, in the same fashion.

Table 5 reports our results. Columns (1) and (2) suggest that firms exposed to higher US tariffs also increasingly offer bonuses payments as a form of compensation. This is in line with our earlier conjectures that such payment schemes offer greater flexibility to employers. They may also provide adequate financial incentives to employees as wage growth has been shown to slow down and might otherwise deter qualified candidates from applying to these jobs (e.g. Luft, 1994). The corresponding coefficients for China's retaliation tariffs are very similar in terms of their magnitude, but much less precisely estimated.[21] The results in columns (3) and (4) suggest that there is somewhat weaker,

[20]The five insurances include unemployment, pension, medical, work-related injury, and maternity insurances. While being mandatory in principle, it is not implemented throughout the country and some foreign enterprises might be eligible for exemptions from it. See www.china-briefing.com/news/social-insurance for an overview.

[21]The positive sign might suggest that higher tariffs on US goods may have harmed Chinese firms more

Table 5: Effect of Tariffs on None-wage Compensation (one-period lagged tariff)

Dept var	Bonus		Subsidy		Insurance	
Share of Firm Vacancies with	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1})$	0.046	0.051*	0.006	0.012	0.020	0.016
	(0.028)	(0.026)	(0.042)	(0.043)	(0.027)	(0.026)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1})$	0.047**	0.050**	0.040*	0.046*	0.010	0.016
	(0.018)	(0.017)	(0.020)	(0.020)	(0.020)	(0.020)
Observations	109,158	107,800	109,158	107,800	109,158	107,800
R-squared	0.854	0.855	0.863	0.863	0.863	0.864
City Control	-	Y	-	Y	-	Y
Firm FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y

Notes: Regressions use firm online job vacancy data from May 2019 to Nov 2019. City controls include city-month specific number of firms posting online vacancies and the total number of vacancies posted online. Robust standard errors are clustered at the city and month level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. .

but still positive evidence for increasing provision of subsidies among exposed firms. Firms do not appear to respond by offering different insurance packages to their future employees, as we can see from columns (5) and (6).

5.1.4 Job Requirement

Besides adjustments in wage compensation, there might also be changes in the requirements firms impose on their applicants. In fact, changes in wages and in the number of posted vacancies could be associated with changes in job requirements. Deming and Kahn (2018), for example, document a positive correlation between average wages offered and the required number of years of schooling. As we found fewer job offers overall, as well as slightly lower wage compensation in our data, we might expect that also the required educational background will be lower.[22]

Like in the previous subsection, we analyze effects on firms' job requirements by measuring the fraction of vacancy posting that explicitly require applicants to have a college degree (or higher):

$$Share^{College}_{ft} = \frac{\sum_{v\in\Omega_{ft}} \mathbf{1}_{fvt}(\text{the advertisement explicitly require college degree})}{N_{ft}} \tag{5}$$

than it has served, although such an interpretation would require further scrutiny in light of lacking evidence in all other specifications.

[22]This would also be in line with our previous notion that US tariffs targeted mainly goods that were relatively skill-intensive from the viewpoint of Chinese firms (see Figure A.4).

where Ω_{ft} denotes the mass of all vacancies posted by firm f in month t, N_{ft} is the number of job vacancies posted by firm f in month t and $\mathbf{1}_{fvt}$ is an indicator variable that equals to one if the advertisement v explicitly mention that the qualified applicants will require a college degree.

In addition to the potential change in the education requirement, firms may also adjust their requirement of age-dependent skills (Cai and Stoyanov (2016)), such as working experience (i.e., the number of working years). We also analyze adjustments in the corresponding upper and lower bounds of these indicated intervals, as well as their means, and take the average value of those observations in a given firm-month observation. The results are reported in columns (1)-(6) of Table 6 and suggest that neither US nor Chinese tariffs had any impact on the required working experience in the advertised job vacancies. However, we observe in column (7) and (8) that higher US tariffs on Chinese products significantly decreased the fraction of job ads that require a college degree. We find no significant impact of China's retaliation again, despite a positive sign that might indicate a tendency for increasing needs of skilled personnel to substitute for skill-intensive imports.

Table 6: Effect of Tariffs on Job Requirement (one-period lagged tariff)

	Experience Requirement (yrs)						Share of Jobs Requiring	
Dept var:	Minimum Experience		Maximum Experience		Mean Experience		College Degree	
	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE	(8) FE
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1})$	0.020	0.007	-0.005	-0.024	0.008	-0.009	0.044	0.027
	(0.102)	(0.092)	(0.128)	(0.130)	(0.114)	(0.110)	(0.039)	(0.038)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1})$	-0.188	-0.067	-0.226	-0.068	-0.207	-0.068	-0.088***	-0.070**
	(0.106)	(0.070)	(0.147)	(0.097)	(0.126)	(0.083)	(0.023)	(0.021)
Observations	108,877	107,544	108,877	107,544	108,877	107,544	109,158	107,800
R-squared	0.697	0.745	0.694	0.744	0.696	0.745	0.696	0.712
City Control	-	Y	-	Y	-	Y	-	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Regressions use firm online job vacancy data from May 2019 to Nov 2019. City controls include city-month specific number of firms posting online vacancies and the total number of vacancies posted online. Robust standard errors are clustered at the city and month level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. .

5.2 Robustness checks

Our findings suggest that the US-China trade war had a mostly one-sided impact on the labor demand and hiring behavior of Chinese firms that were directly exposed to higher tariffs. While exporters facing higher US tariffs reveal lower labor demand, wages and skill demand (as well as a tendency to adopt more flexible and non-wage compensation schemes), importing firms do not show comparable adjustments. In this subsection, we address potential concerns of identification by carrying out two robustness checks that should corroborate our previous results.

5.2.1 Placebo experiment with randomly assigned tariff exposures

For our first robustness check, we perform a placebo experiment in which we randomly assign the Chinese and US tariff exposures to firms. The purpose of doing this is to ensure that our baseline findings are not the results of coincidental correlations, which appear to be nevertheless likely enough to reveal in our empirical analysis.[23] By assigning randomly to the firms in our sample, we expect our earlier findings to disappear if our envisaged mechanism is correctly identified.

Hence, firm f's "fictional" tariff exposure can be written as:

$$\widetilde{\text{Tariff}}_{f,t}^{\text{Type}} = \text{Tariff}_{s,t}^{\text{Type}}, \qquad \text{Type} \in \{\text{US}, \text{CHN}\}, \tag{6}$$

where s indexes a firm that is randomly drawn from our original estimation sample. That is, f adopts the level of exposure that we have actually measured for any random firm s we draw from a pool of about 190 thousand firms in our sample. Provided with these randomly assigned fictional tariff exposure measures, we repeat our previous analysis and report the results in Appendix Tables A.6-A.9. None of our previously significant estimates can be reproduced in our placebo estimation, which lends support our baseline results and their economic interpretation.

5.2.2 Control for pre-trends

Due to our short sample period, we are unable to directly observe any firm-level trends before they receive treatment by tariffs. This raises concerns about the interpretation of our results as a causal relationship. While it is plausible that firms that are exposed to higher tariffs may exhibit lower labor demand, firms' exports and import structure might as well be correlated with their labor demand through other predetermined economic trends. The validity of our research design depends on whether the exposure of firms to tariffs was exogenous to other determinants of their labor demand and hiring behavior.

[23] A similar placebo test has been employed by Beverelli et al. (2017) to study the effect of restriction on service trade.

To address this concern, we draw on an alternative data source that allows us to observe *actual* employment and average wages paid for a small subset of our firms. We obtain this information from the ASIP firm-level data set where we observe such variables for the years 2012 and 2013, long before the trade war and the election of Donald Trump for US president.[24] Our inference relies on a falsification exercise in which we estimate the observed firm-level change in (log) employment and (log) average wage payments between 2012 and 2013. A statistically significant coefficient for our measures of firm-level tariff exposure would reveal an underlying long-term trend in our data and challenge our identification.

Table A.10 presents the results of our test. Columns (1) and (2) suggest that exposure to US tariffs during the recent trade war is positively, yet not significantly, related to employment growth. Hence, Chinese exporters that face higher US tariffs today tended to have grown relatively faster than other firms, which is the opposite of our results for their labor demand after the US tariff had been increased. In columns (3) and (4), we find that wages grew slower among the more exposed firms, which is similar to our original findings. However, also here the relationship is not statistically significant. China's retaliation against the US does also not suggest any underlying pre-trends in this subsample.

5.3 Firm Heterogeneity

In this last subsection, we explore the existence of heterogeneous responses across firms. Based on their observed trade volumes in 2016 (i.e., exports plus imports), we allocate each firm to one of three groups — small, medium and large. For each of these subsamples, we re-run our main specification as displayed in equation (3). Point estimates and corresponding 95% confidence intervals are reported for each firm group in Figures A.6-A.8.

Figure A.6 presents fixed effect estimates for labor demand, by firm-group for increasing the US and Chinese tariffs respectively in panels (a) and (b). While the latter does not reveal any systematic impact, as in our baseline results, we observe a clear tendency of smaller and intermediate-sized exporters to respond to the US tariffs. While small firms appear to post substantially fewer job-ads, large firms reveal only a marginal response.

These patterns are somewhat different for wages as displayed in Figure A.7. Although we find again that large firms tend to be fairly resilient to the trade war, also small firms do not reveal any statistically significant response. Only medium-sized exporters indi-

[24] As before, we matched firms based on the reported information of their company name and location. The matched sample consists of 4,669 firms.

cate major downward adjustments, which exceed the originally found effects from the pooled sample. Figure A.9, panels (a)-(c), report results for our three alternative forms of compensation. The fraction of jobs offering performance-based bonus payments increases mostly among the small firms, but confidence intervals are larger suggesting that this is a fairly heterogeneous group of firms. This is similar for their response in terms of subsidies and insurance provisions, although the latter is significant for small firms. Medium-sized and large firms seem to be similarly willing to offer bonuses and also more willing to offer subsidies than smaller firms. This tendency is reversed in panel (c), where medium-sized and large firms are essentially unresponsive to tariffs in terms of insurance provision.

An interesting pattern reveals from differential responses in job requirements across firms as shown in Figure A.8. The negative effect of the US tariffs on skill demand, reported in our main findings above, appears to be almost entirely driven by medium-sized exporters. This group also responds with *increasing* skill demand to China's retaliation tariffs. Moreover, medium-sized firms reveal a substantial increase in their demand for experienced workers as China's retaliation came into effect. While small and large firms are merely unresponsive along these dimensions, these results suggest that medium-sized firms may have been most exposed to the US-China trade war. They adjust their hiring behavior not only due to fewer revenues from US sales, but also due to fewer access to US products. Their response to increasingly investing in skilled and experienced employees may indicate that they switch to producing themselves the goods they used to import from the US.

6 Concluding remarks

In this paper, we present novel micro-level evidence regarding the connection between trade policy and the firm's labor demand and hiring decisions. This article is one of only a few studies that have examined this issue at the firm level and which are based on panel data and hence able to follow individual firms through time. To the best of our knowledge, it is the first study to address the effect of export and import tariff shocks on firm-specific labor demand by leveraging the rich information from online job advertisements that is typically obscure in the firm-level census or survey data.

The results show that firms responded to adverse cost shocks by lowering labor demand and offering lower-paid salaries, and the effect is mostly driven by the cost shocks to the final product. In contrast, cost shocks to using intermediate inputs are not found to affect firm's hiring decision significantly. The reduced wage is partially compensated by the bonuses based on performance and non-wage compensations such as subsidy. We argue this is in line with the mechanism of substitution away from rigid to more flexible (performance-based) wage schedules that could help firms in finding high-quality employees to mitigate the impact of adverse cost shocks.

The results also suggest that cost shocks also impose a distributional effect on firm's labor demand, as captured by the negative relationship between US-tariff exposure and firm's education requirement in job ads. By investigating the skill intensity of products exported to and imported from the US by Chinese firms, we find it is explained by the reduction in skill-demand embodied in tariff shocks and show that US tariffs disproportionately targeted relatively skill-intensive industries.

This paper makes a positive contribution to our understanding of how employment responds to cost shocks. Overall, our study suggests that the US-China trade war has hurt both firms and job-seekers. Mainly so, because positive effects of protectionist policies do not materialize while the additional costs imposed on firms enforce immediate adjustments that result in slower job growth. Building on this notion, our empirical evidence also suggests a route forward in trying to understand the forces behind the heterogeneous labor adjustment induced by import and export tariff shocks.

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Appendix

A Data Appendix

A.1 Vacancy Data

Our data of job vacancies are collected from 51job.com. By using a web crawler that automatically search for job vacancies posted on 51job.com, we collect information of job vacancies and firms on a regular basis. An illustrative example is as following. For a certain month, we initiate a scraping program at 8:00AM on Day 8 to collect job ads posted during Day 1 to Day 7. All the job ads listed on 51job.com during the time frame are excerpted and stored by the collected date. Job vacancies characteristics are collected from the html file of each job. Firm characteristics are extracted from the linked firm's page of each job. On the subsequent rounds, we repeat all the procedures at the same time for consistency on Day 15, Day 23 and Day 30, respectively, and capture all listed job ads, including reposted jobs. Because of the large online storage of historical information on 51job.com, this retrospective method is able to cover every job posted or renewed on the site within the time span. After gathering the data for the whole month, we delete the duplicated job ads that have exact same context.

A.2 Firm Survey Data

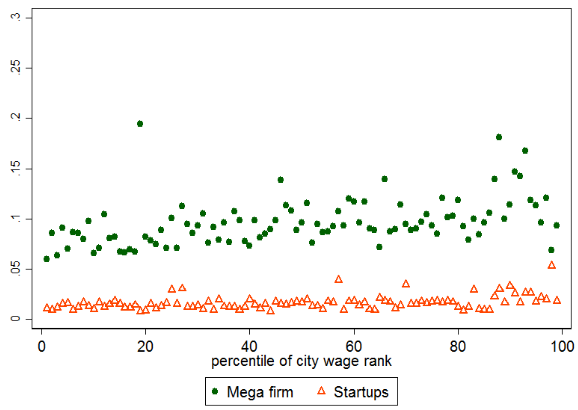
The annual city-industry specific employment sources from the Annual Survey of Industrial Production (ASIP) conducted by the National Bureau of Statistics of China (1998 to 2013). The dataset surveys all types of firms (state-owned / non-state owned) whose revenue is more than five million RMB each year in the manufacturing sector. The sample size varies from 165,119 in 1998 to 336,768 in 2007. ASIP provides us with the employment at the firm level.

B Figure Appendix

Figure A.1: Firm distribution over City Wage Rank

(a) By industry

(b) By scale



(c) By Onwership

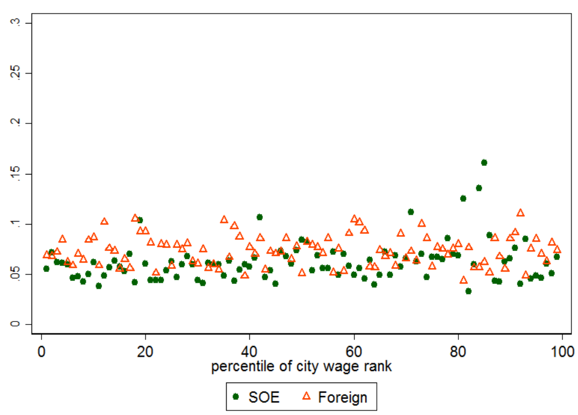
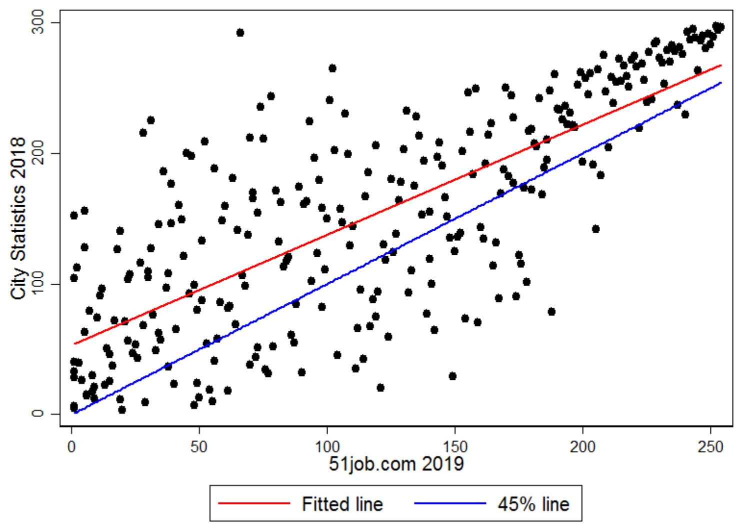
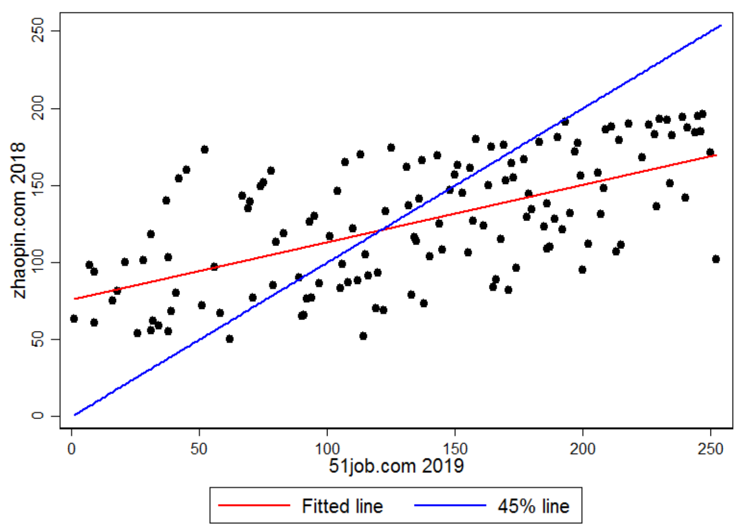


Figure A.2: City rank of job vacancies

(a) vs. 2018 City Statistics



(b) vs. 2018 Zhaopin.com

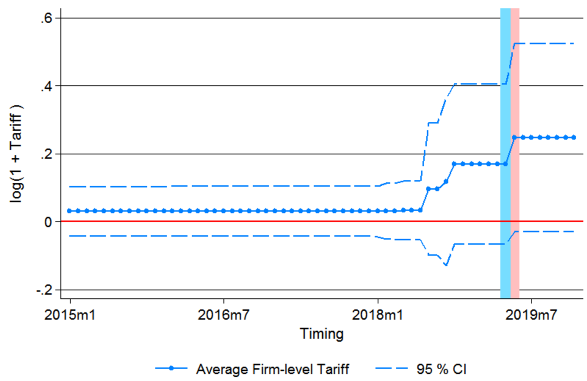


Notes: Each axis presents the city rank of density of job vacancies from a data set. To facilitate comparison across datasets, we standardize the level of vacancies to be a city rank within [0, 288], where a larger number stands for a higher level of density of job vacancies. In Figure A.2(a), we compare our data (*51job.com* 2019) to the 2018 urban employment from *China City Statistics Year Book*. In Figure A.2(b), we compare our data to *zhaopin.com* 2018. Points below rank 50 are not shown for neatness as the points in *zhaopin* data are too close to each other.

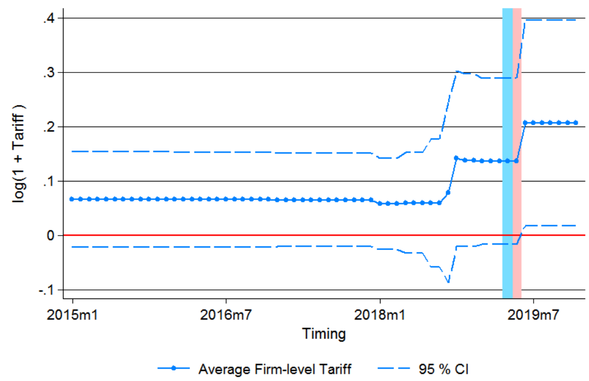
B.1 Firm-specific Tariff Exposure Measures

Figure A.3: Average U.S. and Chinese Tariffs (Firm Level)

(a) US Tariff on Chinese Goods



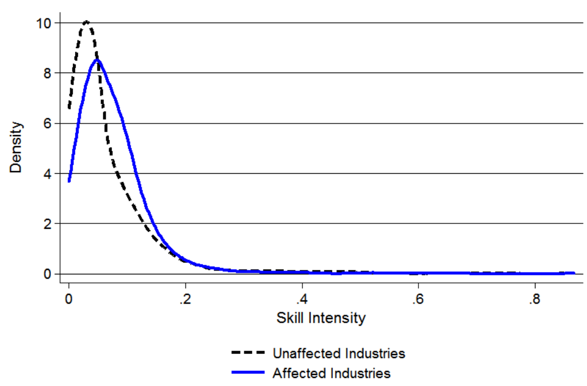
(b) Chinese Tariff on the US Goods



B.2 Tariff Shocks and Product Skill Intensity

Figure A.4: Skill Intensity: Industries Affected by US Tariffs on Chinese Products

(a) Distribution of Industry Skill Intensity



(b) Industry Skill Intensity and Tariff Change

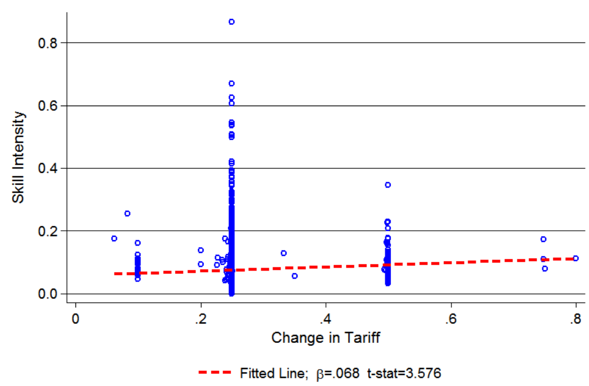
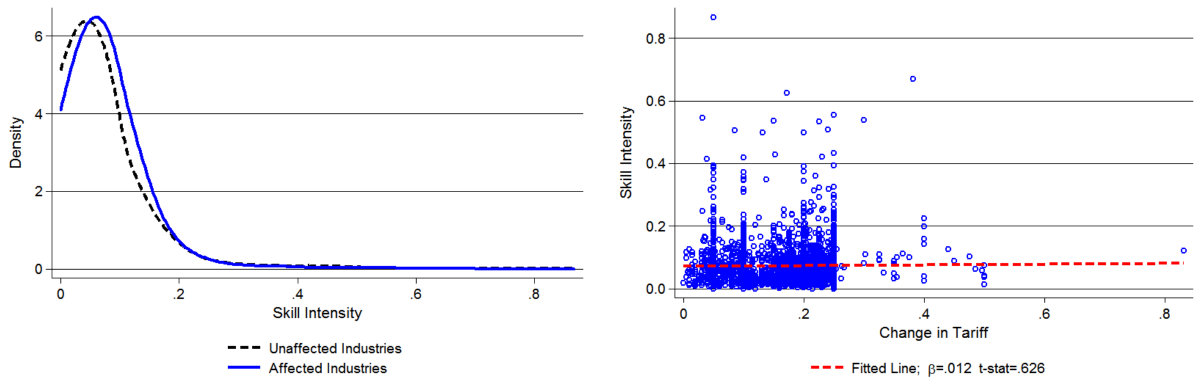


Figure A.5: Skill Intensity: Industries Affected by Chinese Tariffs on US Products

(a) Distribution of Industry Skill Intensity (b) Industry Skill Intensity and Tariff Change



B.3 Heterogeneous Response to Tariff Shocks

Figure A.6: Heterogeneous Response in the Number of Job Vacancies

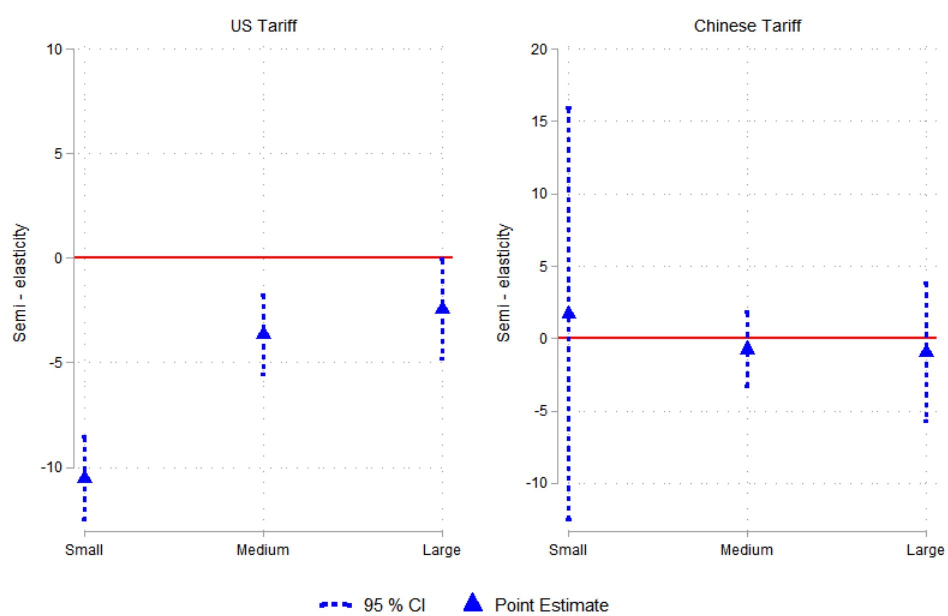


Figure A.7: Heterogeneous Response in Wage Schedule

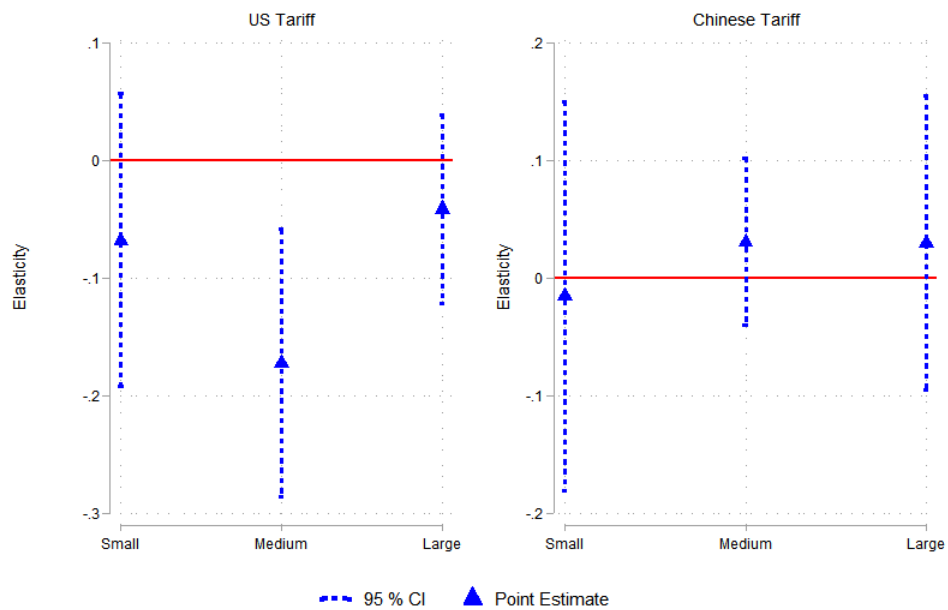
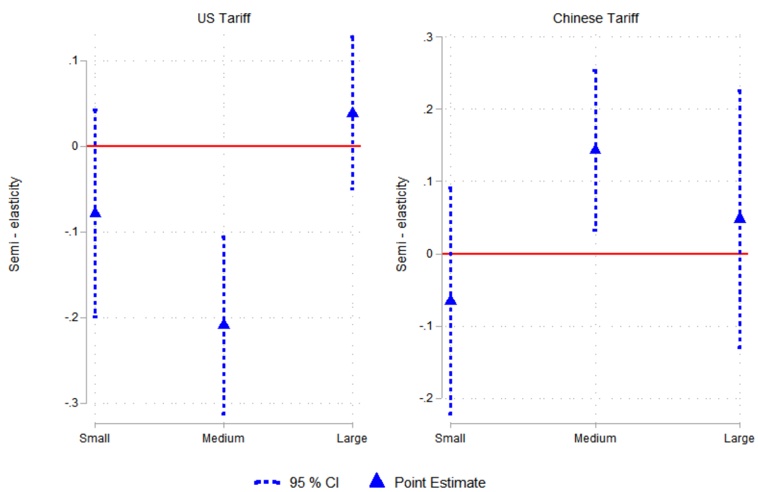


Figure A.8: Heterogeneous Response in Job Requirement

(a) College Degree (or above)



(b) Work experience (years)

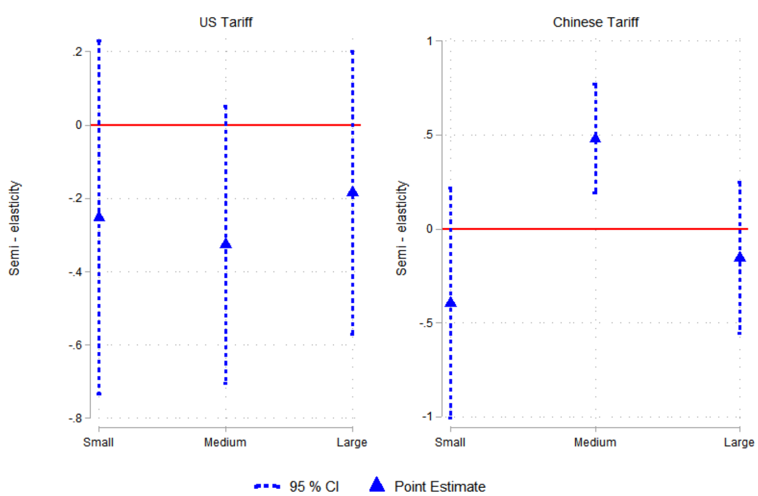
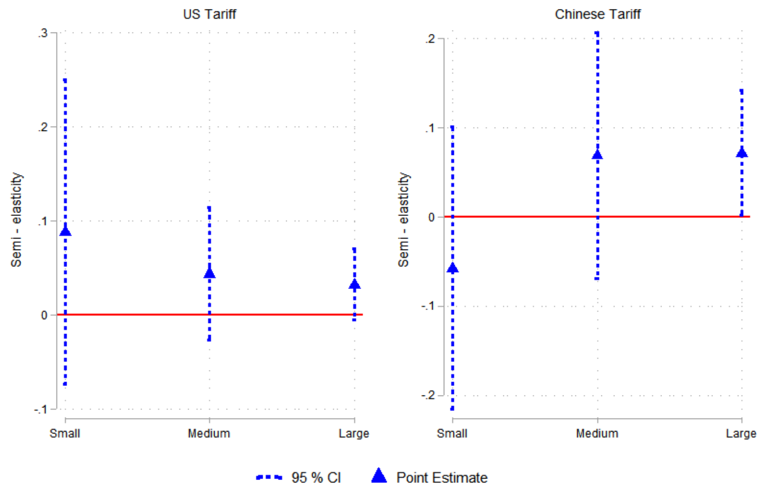
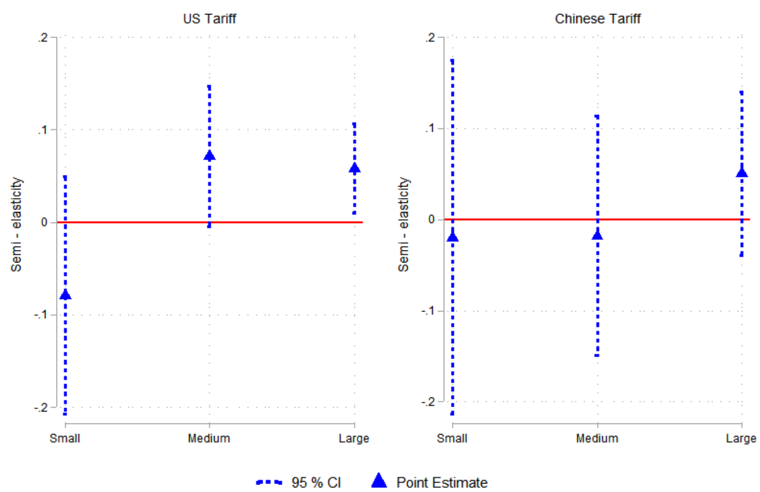


Figure A.9: Heterogeneous Response in Non-Wage Compensation

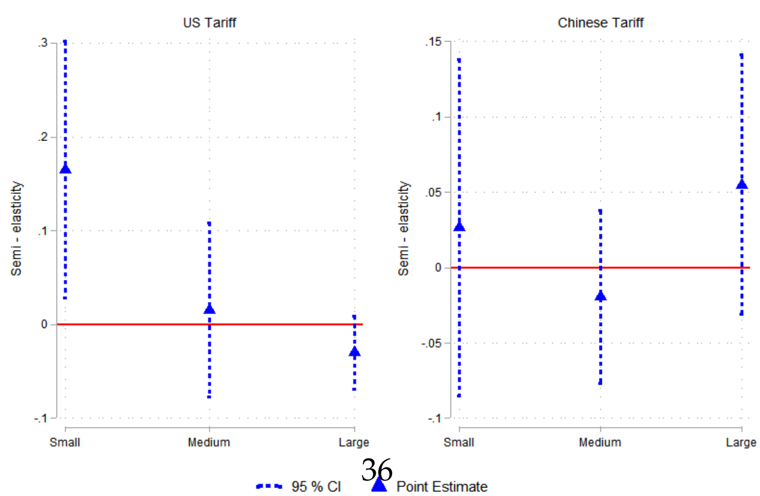
(a) Share of Jobs Offering Bonus



(b) Share of Jobs Offering Subsidy



(c) Share of Jobs Offering Insurance



C Table Appendix

Table A.1: Cross-validation: sample means across data sources

	Sample mean		
	51job (2019)	Zhaopin (2008-10)	Census (2005)
Wage distribution			
1500 or lower	0.956	0.145	0.778
1501-3000	0.00	0.164	0.176
3001-4000	0.00	0.214	0.021
4001-8000	0.025	0.244	0.022
8001 or higher	0.008	0.126	0.003
Education			
High school or below	0.228	0.114	0.766
Some College	0.772	0.886	0.235
Firm **ownership**			
Private sector	0.742	0.930	0.589
SOE and collectives	0.059	0.070	0.271
Industry			
Primary, manufacturing and utility	0.432	0.267	0.453
Construction and transportation	0.068	0.135	0.118
IT and communication	0.299	0.185	0.016
Finance, insurance and real estate	0.013	0.052	0.063
Health, education and welfare	0.163	0.033	0.102
Trade, hospitality and entertainment	0.130	0.175	0.165
Public sector	0.034	0.000	0.060

Notes: Our 51job sample consists of job vacancies collected from 51job.com from May to November 2019. Sample Zhaopin is used in Kuhn and Shen (2013), who collected job ads posted on Zhaopin.com for several months during 2008 to 2010. 2005 Census data of urban employment comes from 2005 1% National Population Sample Survey conducted by China's National Bureau of Statistics. Kuhn and Shen (2013) pick the urban employment from eight highest-income provinces to compare the sample characteristics with their data from Zhaopin.com in 2008-2010 for the similarity of job locations.

Table A.2: Descriptive Statistics by Month

	(1) 2019 May		(2) 2019 June		(3) 2019 July		(4) 2020 August		(5) 2020 September		(6) 2019 October		(7) 2019 November	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Wage														
Wage per vacancy - lower bound (1000 USD/year)	10.50	14.69	10.51	11.22	10.56	11.66	10.55	14.04	10.54	11.71	10.55	12.06	11.63	30.61
Wage per vacancy - upper bound (1000 USD/year)	15.95	17.07	16.01	14.48	16.05	14.98	16.02	17.05	15.96	14.68	16.00	15.33	17.90	51.67
Wage per vacancy - mean (1000 USD/year)	13.22	15.64	13.26	12.61	13.30	13.05	13.29	15.30	13.25	12.95	13.27	13.43	14.76	40.98
Non-wage compensations														
Share of vacancies providing subsidies to employee	0.53	0.50	0.53	0.50	0.53	0.50	0.52	0.50	0.53	0.50	0.53	0.50	0.57	0.50
Share of vacancies providing bonus to employee	0.44	0.50	0.43	0.50	0.44	0.50	0.43	0.50	0.44	0.50	0.44	0.50	0.51	0.50
Share of vacancies providing insurances to employee	0.66	0.47	0.67	0.47	0.67	0.47	0.66	0.47	0.67	0.47	0.67	0.47	0.72	0.45
Job requirement														
Working experience required by the job - lower bound (year)	1.54	1.62	1.55	1.63	1.57	1.64	1.55	1.63	1.56	1.65	1.54	1.63	1.58	1.71
Working experience required by the job - upper bound (year)	1.88	2.17	1.89	2.19	1.92	2.20	1.89	2.18	1.90	2.20	1.88	2.18	1.96	2.28
Working experience required by the job - mean (year)	1.71	1.89	1.72	1.90	1.74	1.92	1.72	1.90	1.73	1.92	1.71	1.90	1.77	1.99
Education level required by the job: college or higher	0.72	0.45	0.72	0.45	0.73	0.44	0.73	0.45	0.72	0.45	0.73	0.45	0.78	0.41
Firm characteristics														
Share of vacancies posted by mega firms (employement greater than 10000)	0.02	0.12	0.02	0.12	0.02	0.12	0.02	0.12	0.02	0.13	0.02	0.12	0.08	0.27
Share of vacancies posted by small firms (employement less than 50)	0.19	0.39	0.19	0.39	0.19	0.39	0.19	0.39	0.19	0.39	0.19	0.39	0.05	0.22
No. of vacancies per firm per month	7.55	21.69	8.39	26.02	6.50	22.44	6.45	17.74	4.78	22.08	5.02	22.04	4.63	18.81
No. of firms	18275		18703		17045		17643		13654		14349		13845	
No. of job vacancies	204140		226796		175737		174323		129171		135637		125218	

Notes: In this table, we only count firms and job vacancies by unique firm and job IDs, respectively. Cases when firms posting same job across months and job ID posted by multiple firms are not counted. Because of this, the total number of number of firms and job vacancies slightly differ from the total numbers in Table 1. The mean and SD of share of vacancies posted by small firms are similar during May to October because we only keep two decimal digits.

Table A.3: Summary of Industry Tariff by Month

Time	$\bar{\tau}_t^{\text{US}}$		$\bar{\tau}_t^{\text{CHN}}$	
	Mean	Std. Dev.	Mean	Std. Dev.
2018m1	0.036	0.102	0.092	0.069
2018m2	0.036	0.103	0.092	0.069
2018m3	0.036	0.103	0.092	0.069
2018m4	0.045	0.110	0.095	0.075
2018m5	0.045	0.110	0.095	0.075
2018m6	0.045	0.110	0.095	0.075
2018m7	0.074	0.129	0.095	0.100
2018m8	0.074	0.129	0.095	0.100
2018m9	0.084	0.139	0.104	0.110
2018m10	0.144	0.130	0.172	0.100
2018m11	0.144	0.130	0.167	0.098
2018m12	0.144	0.130	0.167	0.098
2019m1	0.144	0.130	0.166	0.097
2019m2	0.144	0.130	0.166	0.097
2019m3	0.144	0.130	0.166	0.097
2019m4	0.144	0.130	0.166	0.097
2019m5	0.232	0.151	0.166	0.097
2019m6	0.232	0.151	0.251	0.114
2019m7	0.232	0.151	0.251	0.114
2019m8	0.232	0.151	0.251	0.114
2019m9	0.232	0.151	0.251	0.114
2019m10	0.232	0.151	0.251	0.114
2019m11	0.232	0.151	0.251	0.114
2019m12	0.232	0.151	0.251	0.114

Notes: The table summarizes tariff imposed by China and the US, respectively. For each country, the mean value of tariff is calculated as the simple average across sector-level tariff across HS 6-digit code.

Table A.4: Summary of Firm-level Tariff by Month

Time	$\text{Tariff}_{ft}^{\text{US}}$		$\text{Tariff}_{ft}^{\text{CHN}}$	
	Mean	Std. Dev.	Mean	Std. Dev.
2018m1	0.029	0.038	0.058	0.043
2018m2	0.031	0.042	0.058	0.043
2018m3	0.031	0.042	0.058	0.043
2018m4	0.032	0.044	0.060	0.047
2018m5	0.032	0.044	0.059	0.047
2018m6	0.032	0.044	0.059	0.047
2018m7	0.095	0.099	0.059	0.060
2018m8	0.095	0.099	0.059	0.060
2018m9	0.117	0.125	0.078	0.085
2018m10	0.169	0.120	0.141	0.083
2018m11	0.169	0.120	0.138	0.081
2018m12	0.169	0.120	0.138	0.081
2019m1	0.169	0.120	0.136	0.078
2019m2	0.169	0.120	0.136	0.078
2019m3	0.169	0.120	0.136	0.078
2019m4	0.169	0.120	0.136	0.078
2019m5	0.247	0.141	0.136	0.078
2019m6	0.247	0.141	0.206	0.096
2019m7	0.247	0.141	0.206	0.096
2019m8	0.247	0.141	0.206	0.096
2019m9	0.247	0.141	0.206	0.096
2019m10	0.247	0.141	0.206	0.096
2019m11	0.247	0.141	0.206	0.096
2019m12	0.247	0.141	0.206	0.096

Notes: The table summarizes firm-level tariff imposed by China and the US, respectively. For each country, the mean value of tariff is calculated as the simple average across firms.

Table A.5: Variable Description

Variable	Description
Wage	A numeric variable that captures the wage level (in 1000 US dollars) for each job vacancy. In each job ad, the wage information is listed in the format as a closed interval. We record two end points as the minimum wage and maximum wage, respectively, and take the midpoint of the interval as the mean wage.
Bonus	An indicator variable that equals if employers commit to provide a performance appraisal in addition to basic wage for a job.
Subsidy	An indicator variable that equals to one if employers commit to provide overtime subsidies, transportation, communication, and meal allowance for a job.
Insurance	An indicator variable that equals to one if employers commit to provide five insurances (unemployment, endowment, medial, work-related injury and maternity) for a job.
College Degree Requirement	An indicator variable that equals to one for jobs that require at least a college degree. Employers choose from the following standardized options the minimum level of education required for each job vacancy: middle school, high school, (3 or 4 years) college degree, master degree, and PhD degree.
Experience Requirement	A numeric variable that captures the years of working experience required for each job vacancy. Employers choose from the following standardized options the years of working experience required for each job vacancy: no experience needed, 1 year, 2 years, 3-4 years, 5-7 years, 8-9 years, and 10 years or above. For each interval, we record two end points and the midpoint as the minimum experience, maximum experience and mean experience, respectively. We record zero for the option "no experience needed", and 10 the option "10 years or above".

C.1 Robustness Checks

Table A.6: Placebo - Number of Job Vacancies

Dept var: N^v_{ft}	Linear Models (1) FE	(2) FE	Poisson Regression (3) FE	(4) FE
(A) One-period lagged tariff				
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1})$	-4.247*	-3.753*	-0.386	-0.187
	(1.917)	(1.854)	(0.305)	(0.260)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1})$	-0.576	-0.511	-0.017	-0.133
	(1.059)	(0.996)	(0.200)	(0.221)
Observations	189,279	189,279	189,272	189,272
R-squared	0.761	0.763	-	-
City Control	-	Y	-	Y
Firm FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y

Notes: Details see Table 3.

Table A.7: Placebo - Wage (one-period lagged tariff)

Dept var:	Min Wage (1) FE	(2) FE	Mean Wage (3) FE	(4) FE	Max Wage (5) FE	(6) FE	Wage Dispersion (7) FE	(8) FE
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1})$	-0.005	-0.005	0.006	0.006	0.008	0.008	0.013	0.014
	(0.040)	(0.040)	(0.047)	(0.047)	(0.052)	(0.052)	(0.017)	(0.017)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1})$	-0.011	-0.011	-0.010	-0.010	-0.010	-0.010	0.001	0.001
	(0.026)	(0.026)	(0.033)	(0.033)	(0.037)	(0.037)	(0.018)	(0.018)
Observations	107,800	107,800	107,800	107,800	107,800	107,800	107,800	107,800
R-squared	0.738	0.738	0.734	0.734	0.732	0.732	0.736	0.736
City Control	-	Y	-	Y	-	Y	-	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Details see Table 4.

Table A.8: Placebo - None-wage Compensation (one-period lagged tariff)

Dept var:	*Bonus*		*Subsidy*		*Insurance*	
	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1})$	-0.003	-0.012	0.030	0.033	-0.006	-0.013
	(0.046)	(0.045)	(0.036)	(0.037)	(0.036)	(0.040)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1})$	0.018	0.019	-0.023	-0.025	-0.010	-0.020
	(0.032)	(0.036)	(0.017)	(0.017)	(0.021)	(0.019)
Observations	109,158	107,800	109,158	107,800	109,158	107,800
R-squared	0.854	0.855	0.863	0.863	0.863	0.864
City Control	-	Y	-	Y	-	Y
Firm FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y

Notes: Details see Table 5.

Table A.9: Placebo - Job Requirement (one-period lagged tariff)

Dept var:	College Degree		Min Experience		Mean Experience		Max Experience	
	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE	(8) FE
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1})$	-0.029	-0.040	-0.172	-0.161	-0.203	-0.191	-0.235	-0.220
	(0.052)	(0.048)	(0.168)	(0.143)	(0.198)	(0.168)	(0.229)	(0.193)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1})$	0.067*	0.068*	-0.035	-0.015	-0.053	-0.029	-0.072	-0.042
	(0.030)	(0.029)	(0.147)	(0.116)	(0.176)	(0.140)	(0.205)	(0.164)
Observations	109,158	107,800	108,877	107,544	108,877	107,544	108,877	107,544
R-squared	0.696	0.712	0.697	0.745	0.696	0.745	0.694	0.745
City Control	-	Y	-	Y	-	Y	-	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Details see Table 6.

Table A.10: Robustness: Pretrend Test

Dept var:	$d \ln emp_{f,2012-2013}$		$d \ln w_{f,2012-2013}$	
	(1) FE	(2) FE	(3) FE	(4) FE
$\Delta \text{Tariff}^{\text{CHN}}_{f,2018-2019}$	-0.034	-0.053	0.051	0.066
	(0.093)	(0.097)	(0.119)	(0.118)
$\Delta \text{Tariff}^{\text{US}}_{f,2018-2019}$	0.061	0.071	-0.086	-0.094
	(0.082)	(0.078)	(0.094)	(0.093)
Observations	4,669	4,669	4,669	4,669
R-squared	0.129	0.147	0.123	0.131
Firm Control	-	Y	-	Y
City FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y

Notes: Firm wage and employment use ASIP data in 2012 and 2013. Firm control is the logarithmic firm sales in 2012. Robust standard errors are clustered at the city level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. .