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Vietnam and the U.S.-China trade war**

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Trade diversion and labor market adjustment: Vietnam and the U.S.-China trade war*

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Abstract

This paper investigates the effects of the U.S.-China trade war on trade diversion and the labor market in a third country, Vietnam. We exploit variation in Vietnamese exports to the U.S. across industries and districts based on the extent of the U.S. tariff hikes on Chinese imports and provide evidence of a positive effect on labor market outcomes in Vietnam. Vietnamese workers and districts that are more exposed to the trade war display higher employment, working hours, and wages as a result. Our findings reveal that bilateral trade policy can have substantial offsetting effects on trade flows and labor markets in third countries.

JEL codes: F14, F16, R23

Keywords: trade diversion, trade war

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1 Introduction

Trade wars can cause large economic disruptions, increase policy uncertainty, affect global supply chains, and reduce world income.¹ The U.S.-China trade war in 2018 marked an unprecedented return to protectionism after a decades-long trend of shrinking global trade barriers. Between July 2018 and September 2019, the U.S. rolled out tariffs between 10 percent and 25 percent on 66.4% of the value of total imports from China to the U.S., or 14.5% of the value of total U.S. imports overall (see Table 1).² Average U.S. tariffs on China were more than five times higher than before the trade war³ and affected a broad range of sectors covering two thirds of all Harmonized System (HS) 8-digit products.⁴⁵

Given the magnitude and multi-sectoral breadth of the tariff increases and the size of the trade flows affected, this trade shock has the potential to generate large economic effects. Importantly, it can be expected to impact not only the two countries directly involved, but potentially third countries as well. As imports from China become relatively more expensive, U.S. demand may be diverted either to goods produced domestically or, alternatively, to goods produced in foreign countries other than China. While the former kind of trade diversion would benefit domestic U.S. industries and thus serve the alleged purpose of the tariff increases, the latter may serve to counteract this purpose.⁶ At the same time, it may have unintended beneficial effects on third countries, which may experience an increase in import demand diverted from China.

This paper investigates the impact of the U.S.-China trade war on the labor market of a third country, Vietnam.⁷ While the existing literature has analyzed the trade war consequences in the U.S. and China⁸, we study the effects of this bilateral trade war on a third country. We conduct our analysis at three different levels (individual, district, and gender-education cell) to explore the effect of trade war exposure on wages, employment, and working hours in Vietnam. We measure

¹See, e.g., Handley and Limao (2017), Antras and de Gortari (2020), and Crowley (2019), Ossa (2014, 2015).

²In terms of 2017 import levels.

³Average U.S. tariffs on imports from China increased from 3.8% in June 2018 to 19.3% in February 2020.

⁴See, for example, Bown (2021) and Chor and Li (2021).

⁵Tariffs leveled off in February 2020 after implementation of the Phase One agreement between the U.S. and China to end the trade war conditional on China increasing its imports from the U.S.

⁶However, it may also benefit consumers in the U.S., if it helps to mitigate consumer price increases.

⁷The U.S. is the biggest export market for both China and Vietnam. See Table 2 for the value of trade of Vietnam and China, respectively, with the U.S. during 2016-2019, compared with other main trading partners.

⁸We review this literature in the next section.

district-level trade war exposure as the sum of Vietnam’s export growth to the U.S. across industries, weighted by the pre-trade war industry composition of employment at the district level. Intuitively, we expect Vietnamese districts with greater employment in industries that subsequently experienced greater export growth to be more exposed to a potential increase in U.S. import demand. Of course, Vietnam’s export growth to the U.S. could be driven partly by domestic or foreign shocks unrelated to the U.S.-China trade war. To correctly identify trade war exposure as the change in exports that is due to tariff increases by the U.S. on China, we use detailed micro-level information on U.S. tariffs at the product level. More specifically, we instrument for export growth across industries using the industry-specific shares of 8-digit products with tariff increases within each 4-digit industry. The identifying assumption of the exogeneity of initial industry employment across districts is plausibly fulfilled in our case, since changes in U.S. tariffs on China are unlikely to be related to pre-existing employment patterns in Vietnam.

The impact of the U.S.-China trade war on Vietnam is interesting for several reasons. First, while many countries experienced sharp increases in their exports to the U.S. between 2018 and 2019, as exports from China decreased, Vietnam was the largest gainer in relative terms. Figure 1 shows that, between 2018 and 2019, it experienced an increase in exports of manufacturing goods to the U.S. of almost 40 percent.⁹ Figure 2 shows that Chinese and Vietnamese export shares to the U.S. diverted sharply in 2019. While the share of exports from China to the U.S. dropped from around 20 percent to about 17.5 percent (by 12%) between 2018 and 2019, the share of Vietnamese exports to the U.S. rose from about 21.5 to about 26 percent (by 20%) over the same period. This mirror-like pattern appears even more distinctively in monthly year-to-year movements of U.S. goods imports from Vietnam and China. Figure 3 shows that, from January 2019, U.S. imports from Vietnam increased remarkably by up to 50%, while imports from China simultaneously dropped by up to -30%. This is in sharp contrast to the period before, where trade flow changes were smaller and without any clear correlation between U.S. imports from Vietnam and China. This evidence suggests that the U.S.-China trade war was likely an important determinant of the surge in trade flows between the U.S. and Vietnam. It is consistent with the fact that Vietnamese imports increased in the U.S. but remained unchanged in the rest of the world, as shown in Figure 4.

⁹At the G20 summit in June 2019, President Trump called Vietnam ‘almost the single worst abuser of everybody’ (Guardian, 2019).

Second, Vietnam is similar to China in terms of its comparative advantage in labor-intensive industries, governmental stability, and favorable geographic location. Figure 5 plots the revealed comparative advantage index for Vietnam against the one for China by product groups in 2016. The two countries share similar comparative advantages in specific industries, such as textiles and clothing, hides and skins, and machinery and electronics. This suggests that Vietnam is a good candidate for a second-best source country for U.S. imports, as tariff hikes increase the cost of importing from China.¹⁰

Finally, domestic migration within Vietnam is limited due to the *ho kau* system, which prevents unregistered migrants from access to health care and schooling for their children (IOM (2020)). As a consequence, workers are less likely to move in response to trade-induced changes in wages or employment opportunities, and changes in labor market outcomes are more likely to be concentrated in trade-exposed industries or districts, rather than get diffused over skill groups nationally, as predicted by standard (Heckscher-Ohlin) trade theory.

Our analysis proceeds in three steps. First, we estimate the effect of the U.S.-China trade war on labor market outcomes at the individual level. This analysis allows exploring the differential impact of the trade war by gender and education. However, since our individual-level data are not longitudinal, we cannot condition on individual outcomes before the trade war, and thus cannot rule out the possibility that estimated effects are at least partly due to pre-existing differences across individuals (e.g. productivity) that are potentially correlated with export growth. To address this, in our second approach, we estimate the effects of the trade war at the district level, where we can condition on labor market outcomes before 2018, i.e. before the start of the trade war. By doing so, we net out any remaining (time-invariant) average individual or industry unobservable characteristics, which could potentially be correlated both with the share of products in the industry targeted by U.S. tariffs in China as well as industry-specific labor market outcomes in Vietnam. Furthermore, we provide evidence that shows that our results are not due to pre-existing relative trends in export growth in industries subsequently hit by tariff increases. In particular, we estimate

¹⁰See also Ha and Phuc (2019), Nicita (2019), and Reed and Romei (2019). Ha and Phuc (2019) note that, according to the U.S. International Trade Commission, 'mobile phone imports from Vietnam more than doubled in the first four months of 2019 compared to the same four-month period in 2018, and computer imports also increased by 79 percent across the same period. There was also an increase in the number of Vietnamese garments, textiles, furniture, and dried fish exported to the U.S. - goods which were previously processed in China before Trump's tariffs hikes.'

changes in labor market outcomes during 2016-2019 while controlling for changes during 2013-2016 (the period before the trade war) and find that our results remain robust.¹¹ Third, we further disaggregate the district-level observational units and estimate changes in average labor market outcomes for groups of a given gender and education in the district.¹²

We find consistent evidence that the impact on employment, working hours, and hourly wages is positive and larger for individuals that are more exposed to the U.S.-China trade war. Specifically, we find that among individuals in districts at the 75th percentile of trade war exposure compared to individuals in districts at the 25th percentile, the probability of employment is 1.3 percentage points higher. Conditional on being employed, they work 0.5 hours more per week, and real hourly wages are 0.07 percent greater. Furthermore, we find that in districts at the 75th percentile of trade war exposure compared to districts at the 25th percentile, employment growth is greater by 1.1 percentage points and wage growth, conditional on employment, is 0.02 percent greater. We also explore whether the trade war affects the form of employment in Vietnam and find that trade war exposure decreases the probability of employment in the informal sector and in micro-enterprises. This result, and the findings on overall employment, indicate that the trade-war-induced export growth contributed towards shifting workers out of informal contracts and small firms into formal contracts and larger firms.¹³ Our estimated effects are net of any potential migration responses of individuals across industries or districts, which could at least partially offset trade-induced differences in labor market outcomes.¹⁴

We also analyze the heterogeneity of labor market effects of trade war exposure by gender, education, and industry of employment. We find that the positive effects on employment and working hours can be attributed exclusively to women. Wage effects are positive for both women and men, although the effect is greater for the former. To some extent, the trade war thus served to narrow the gender gap in Vietnam, where women are less likely to be employed, work fewer hours, and earn lower wages compared to men. Moreover, we find positive effects of trade war exposure on employment, working hours, and wages only for non-college-educated individuals. Finally, we find

¹¹Since data for 2013 are not available at the district level, we perform this estimation at the province level instead.

¹²This estimation corresponds to the skill-cell approach of Altonji and Card (1991) for estimating the effects of immigration on domestic wages.

¹³This relates to findings in McCaig and Pavenik (2018) according to which labor in Vietnam reallocated from the informal to the formal sector in response to the U.S.-Vietnam Bilateral Trade Agreement.

¹⁴We find little evidence for trade-war-induced migration during the observed period.

wage effects to be positive in the industries where Vietnam has a comparative advantage (apparel, furniture, leather, textile) as well as in other industries (chemical, mineral).

The rest of the paper is organized as follows. Section 2 discussed the related literature. In Section 3, we set out the context for our study and describe our measure of trade war exposure and our instrumental variable. Section 4 discusses the data, while Section 5 presents our estimation strategy and empirical findings. Section 6 discusses our robustness checks, and Section 7 concludes.

2 Related literature

Our paper contributes to the highly influential recent literature analyzing the economic effects of the U.S.-China trade war. Most of this literature focuses on effects in the U.S., documenting detrimental effects in the form of increasing prices (Amiti et al. (2019), Fajgelbaum et al. (2019), Flaaen et al. (2020), Cavallo et al. (2021))¹⁵ and decreasing investment (Amiti et al. (2020)), employment (Flaaen and Pierce (2019)), exports (Handley et al. (2020)), and consumption (Waugh (2019)). Due to the limited availability of micro-level data, there is only a small number of studies investigating effects on China, mainly using data on subsets of firms (Huang et al. (2020), Benguria et al. (2020), He et al. (2021)) or locations (Jiao et al. (2020)). Chor and Li (2021) provide large-scale evidence of a local decrease in night lights and inferred decrease in income per capita. On a global level, Fajgelbaum et al. (2023) show a large cross-country variation in the export growth of products targeted by the U.S. tariffs on China. Our paper adds to this literature and documents positive effects on employment, working hours, and wages in Vietnam. In light of the existing evidence regarding detrimental effects in the U.S., our results suggest that trade diversion towards Vietnam might have acted as a buffer, without which U.S. welfare losses might have been even larger than estimated.

We also contribute to the literature on the impact of trade shocks on labor markets more generally. A prominent branch of this literature is concerned with the impact of import competition from China on the U.S. labor market, documenting negative effects on wages, employment, and labor

¹⁵Amiti et al. (2019) estimate that the pass-through of tariffs on U.S. domestic import prices had translated into a USD 1.4 bn monthly income loss by the end of 2018. Fajgelbaum et al. (2019) estimate a loss of USD 51 bn (0.27% of GDP), which is reduced to USD 7.2 bn (0.04% of GDP) when gains generated by the new tariffs are considered. Similarly, Cavallo et al. (2021) disentangle the effect of tariffs and find that U.S. firms bore a large incidence of the tariffs. Flaaen et al. (2020) analyze the effect of the global 2018 safeguards tariffs and find a price pass-through to consumer prices above 100 percent.

force participation rates at the firm (Bernard et al. (2006)), industry (Acemoglu et al. (2016), Pierce and Schott (2016)), region (Autor et al. (2013)), and worker (Autor et al. (2014)) level over the period 1977 until 2011. There is also evidence of negative effects of Chinese import competition on plants in Mexico (Utar and Ruiz (2013)) between 1990 to 2006, on regions in Norway (Balsvik et al. (2015)) and Spain (Donoso et al. (2014)) from the late 1990s to 2007, Germany (Dauth et al. (2014)) between 1988 and 2008, and Brazil (Costa et al. (2016)) between 2000 and 2010, and on firms and workers in Denmark (Ashournia et al. (2014)) during 1997 and 2008 and the U.K. (Lyon and Pessoa (2021)) during 2000 and 2007.¹⁶ The general methodological challenge in these studies is to find a plausibly exogenous source of variation in exposure to import competition to identify the impact of trade with China. Changes in U.S. imports, for example, may be correlated with unobserved shocks to U.S. demand that might also affect labor market outcomes. To identify the effects of a supply shock from China, Autor et al. (2013) and Autor et al. (2014) instrument for U.S. imports using imports from China to high-income countries other than the U.S. Branstetter et al. (2019) and Cabral et al. (2020) identify negative effects in Portugal via variation in not only direct import competition from China but also indirect import competition in Portuguese export markets in Europe. Other studies use changes in imports that result from changes in trade policies such as tariff reductions (see, e.g., Topalova (2010), Kovak (2013), and Hakobyan and McLaren (2016) for negative income or employment effects in India, Brazil, and North America, respectively) or the removal of quotas (see Utar (2014) and Utar (2018) for negative earnings and employment effects of the removal of Multi-Fiber Agreement quotas on products from China in Denmark). Several studies investigate the effects of changes in U.S. tariffs on imports from Vietnam. Brambilla et al. (2012) find negative income effects in response to the imposition of U.S. anti-dumping duties on catfish in Vietnam. McCaig (2011), Fukase (2013), McCaig and Pavcnik (2018), and McCaig et al. (2022) find evidence for faster declines in poverty, greater wage growth, labor reallocation from the informal to the formal sector, and an increase in firm entry and industry employment in Vietnam, respectively, in response to a reduction of U.S. tariffs on Vietnamese imports due to the U.S.-Vietnam Bilateral Trade Agreement.

Our paper differs from this literature in several important aspects. First, we evaluate the effects of changes in bilateral trade policy on labor market outcomes in a third country, where the

¹⁶Dauth et al. (2014) find positive effects in German regions specialized in export-oriented industries.

assumption of the exogeneity of changes in trade flows with respect to labor market outcomes is more likely to be fulfilled.¹⁷ More specifically, we use changes in U.S. tariffs on Chinese imports during the U.S.-China trade war to predict individual- and district-level employment, working hours, and wages in Vietnam. Similar to Autor et al. (2013) and Autor et al. (2014), we estimate differences in outcomes resulting from variation in the distribution of workers with similar observable characteristics across industries with different levels of exposure to the shock. However, while Autor et al. (2013) and Autor et al. (2014) investigate labor markets effects of a foreign supply shock (from the perspective of U.S. producers), we identify labor market effects of a foreign *demand* shock (from the perspective of Vietnamese producers). Second, compared to most existing studies, our data provide a rare opportunity for studying the impact of a large trade shock in a developing country, where labor market adjustment patterns may differ significantly from those in developed countries. Third, we evaluate short-term changes in labor market outcomes between 2016 and 2019, a period during which other explanatory factors, such as technology, will most likely have remained unchanged. Fourth, unlike most previous studies, we analyze the effects of tariff increases rather than decreases.¹⁸

We also contribute to the literature that estimates trade-diversion effects of trade policy. Magee (2008) estimates the impact of regional trade agreements (RTAs) on trade flows between 1980 and 1998 and finds weak evidence for trade diversion from countries outside the RTA. Eicher et al. (2012) find strong evidence of trade diversion of preferential trade agreements (PTAs) during 1960–2000. Waseda and Wakayama (2014) analyze the impact of RTAs in 67 countries from 1980 to 2006 and find evidence for trade diversion at the product level, particularly among developing countries. Cheong et al. (2015) find that the trade diversion effect of PTAs is comparable in size to the trade creation effect in a sample of 216 countries from 1980 to 2010. Russ and Swenson (2019) find that the Korea-U.S. Free Trade Agreement diverted imports from other U.S. trading partners at about the same magnitude as (net) imports from South Korea increased. The common challenge for identification in this literature is due to the fact that trade agreements and trade flows are likely to be jointly determined. In comparison, we exploit the unexpected nature of the U.S.-China trade

¹⁷In analyzing the effects of indirect import competition, Branstetter et al. (2019) also use bilateral trade flows (from China to Portuguese export markets in Europe) to estimate labor market outcomes in a third country (Portugal).

¹⁸Brambilla et al. (2012) also look at the effects of tariff increases in a developing country in the short run. They focus on the effects of a tariff increase on a single product (catfish) in the country targeted by the tariff rather than in a third country.

war, which allows us to identify the extent of trade diversion caused by this trade policy.¹⁹ In addition, while U.S. tariff increases on imports from China may be endogenous to trade between these two countries, they are unlikely to be related to U.S. imports from Vietnam.

3 Trade war exposure

As discussed in the Introduction, Vietnam is the largest gainer in relative terms at the onset of the trade war: the sharp increase in U.S. tariffs on Chinese products in 2018-2019 is accompanied by a large increase in Vietnamese exports to the U.S. We would expect that the boost in import demand for Vietnamese products might have led in turn to an increase in producer prices in trade-war-exposed industries in Vietnam. A rise in prices in a given industry may increase employment, working hours, and wages in that industry, if workers cannot costlessly switch industries in response to the demand shock, for example, due to search costs. Kim and Vogel (2021) develop an assignment model with search frictions to analyze how changes in industry prices affect labor market outcomes for workers with common observable characteristics in different industries. They show that, in response to trade-induced producer price hikes in certain industries, employment probabilities, average hours, and wages increase for worker groups disproportionately employed in those industries compared to other groups. Their results extend Stolper and Samuelson-like effects to arbitrarily many worker groups and a broader range of adjustment margins and are consistent with empirical specifications based on a monopolistic competition model as in, e.g., Autor et al. (2013).²⁰

Accordingly, we estimate the labor market effects of the trade war using variation in trade war exposure across districts based on differences in their industry composition of employment. More specifically, we measure trade war exposure at the district level as a weighted sum of industry-specific export changes, where weights are given by the employment shares of workers in the district

¹⁹The start of the trade war was unanticipated, as illustrated by the sudden drop in the S&P 500 index following the announcement by the U.S. government in March 2018 (see Huang et al. (2019)).

²⁰More specifically, a change in labor market outcome $K \in \{E, H, W\}$ for workers of group g is given by $d \ln K_g = \rho_g^K \left[\sum_{j=1}^J \pi_{gj}^{J(j)} d \ln p_j - d \ln P_g \right]$, where $E(H, W)$ is employment (work hours, wages), π_{gj} is the share of employment of group g in industry j , and $d \ln p_j$ is the change in the producer price in industry j . See their equation (26) and the corresponding text for more details.

across industries in the pre-trade war period. Our trade war exposure measure is as follows:

$$TW_d = \sum_j \frac{L_{dj}}{L_d} \frac{\Delta X_j}{L_j}, \quad (1)$$

where L_{dj}/L_d is the employment share in industry j in district d in 2016, ΔX_j is the change in Vietnamese exports to the U.S. for industry j during 2016–2019, and L_j is aggregate Vietnamese employment in industry j in 2016; $\Delta X_j/L_j$ is a proxy for the change in the producer price in industry j . Our measure of exposure to the U.S.-China trade war corresponds closely to the measure of import competition from China in Autor et al. (2013).

Unobserved differences across industries unrelated to the U.S.-China trade war may affect both changes in labor market outcomes and export growth to the U.S.²¹ To identify the causal effect of the U.S.-China trade war on labor market outcomes in Vietnam, we use an instrumental-variable estimation, exploiting the nature of this trade shock, which entailed large unexpected and product-specific tariff increases. This allows us to use the products effectively subject to a tariff hike as a price-based instrument to proxy for price changes in an industry. Given the availability of tariff data at a highly disaggregate level, we can construct an instrumental variable based on the specific (8-digit) products targeted by U.S. tariff hikes within any given (4-digit) industry.²² Thus, our instrumental variable for trade war exposure at the district level is given by

$$TW_{d,IV} = \sum_j \frac{L_{dj}}{L_d} \frac{P_j^t/P_j}{L_j}, \quad (2)$$

where P_j^t/P_j is the share of (8-digit) products targeted by U.S. tariff hikes within any given (4-digit) industry j .²³ The first stage of our instrumental-variable estimation thus delivers a measure of the extent of trade diversion from China to Vietnam during the period of the U.S. tariff changes. In the second stage, we use this variation in Vietnamese exports to identify the impact of (diverted) exports to the U.S. on labor market outcomes in Vietnam. In particular, such variation can be

²¹For example, there may be differences in the productivity growth of firms across industries.

²²This instrument is finer and, possibly, more exogenous than the Bartik (1991) instrument based on industry growth rates, which is commonly used in the literature.

²³As an alternative to the share of targeted products in an industry, we also tried using a measure of the average tariff-induced price increase in industry j given by $\sum_k (P_{jk}^t/P_j) \Delta T_k$. This corresponds to a weighted sum of tariff increases where the weights are given by the share of products subject to a specific tariff shock, ΔT_k , in an industry's total number of products. Results hardly changed, which is not surprising given that the size of the tariff increases does not vary a lot.

expected to be unrelated to industry-specific supply shocks (e.g., due to technological change) in Vietnam and industry-specific demand shocks unrelated to the U.S.-China trade war in countries other than the U.S. and China.

4 Data

We construct our dataset using three main sources of data. The first one is the Vietnam Labor Force Survey (LFS) data from the Vietnamese General Statistics office. The LFS is conducted quarterly, with the technical support from the International Labor Organization (ILO). Our main analysis is based on the LFS conducted in 2016 and 2019.²⁴ We use the 2016 data to construct employment shares at the district level by 4-digit industry, which we employ to construct the trade war exposure measure and its instrument.²⁵ We also use data from the LFS in 2013 to control for trends in labor market outcomes before the trade war in one of our robustness checks discussed in Section 6.

The second data source is COMTRADE, from which we extract the data on exports from Vietnam to the U.S. at the 4-digit level.²⁶ The export data are employed to construct our trade war exposure measure, described in Equation (1) above.

Finally, the third source of data is the U.S. International Trade Commission, which provides detailed information about the specific 8-digit products (Harmonized Tariff Schedule classification) that were subject to tariff hikes over the period 2018-2019. We use these disaggregated data to measure the share of products subject to a tariff hike within each 4-digit ISIC Rev. 4 category. This provides an exogenous proxy for the trade shock, which we use in constructing our instrument for trade war exposure, described in Equation (2) above.

5 Estimation strategy and empirical findings

This section investigates the effects of the U.S.-China trade war on the labor market in Vietnam. We examine three main outcomes: employment rates, number of working hours, and real hourly wages. As discussed in Section 3, we expect that greater exposure to a relative price increase due to

²⁴The 2020 LFS is not employed in the analysis due to the potential confounding effect of COVID-19.

²⁵The Vietnam Labor Force Survey employs the Vietnam Standard Industry Classification, which we convert into ISIC Rev. 4.

²⁶We convert the trade data reported according to the SITC Rev. 4 into ISIC Rev. 4 classification.

the higher import demand results in a relative increase in employment, working hours, and wages. We empirically test this hypothesis in two ways: at the individual level and at the district level.

Table 3 describes the variables in our dataset. The sample at the individual level (panel A) comprises quarterly observations during 2019. Women are just over half of the sample and about 70 percent of individuals are employed. The average number of working hours for those employed is 41, with an average hourly wage of about 1.45 USD. The majority is married (73%), and about 1.2% are classified as migrants.²⁷ Finally, about 10% of the sample have attained college (or higher) education. The sample at the district level (Table 3, panel B) comprises 686 districts observed quarterly in 2016 and 2019. The trade war exposure variable (see Equation (1)) and the instrumental variable (see Equation (2)) are measured at the district level, as discussed in Section 3. Figure 6 presents a scatter plot of the trade war exposure measure, plotted against its instrument. The graph offers two main takeaways. First, there is considerable variation in average industry-specific export growth across Vietnamese districts during 2016-2019.²⁸ Second, the plot illustrates the substantial power of our instrument, based on the industry-specific shares of products targeted by tariff hikes, to predict export growth from Vietnam to the U.S. across districts. We further discuss the validity of our instrument in the sections below.

5.1 Individual-level analysis

We first estimate the effects of trade war exposure using the data set at the individual level. The econometric specification is as follows:

$$Y_{id} = \alpha + \beta_1 TW_d + X'_i \beta_2 + Z'_d \beta_3 + \phi_q + \epsilon_{id}, \quad (3)$$

where Y_{id} is the labor market outcome (employment status, working hours, log hourly real wage) of individual i in district d in 2019; TW_d is trade war exposure in district d over the period 2016-2019 measured as a weighted sum of export changes across industries, where the weight of any given industry j is the employment share of that industry in district d according to Equation (1); X'_i is a vector of control variables at the individual level in 2019 (including age, gender, marital

²⁷A migrant is defined as an individual who has moved into the place of residence for less than one year.

²⁸Much of the variation in our instrument for trade war exposure comes from variation in the industry composition across districts, rather than variation in the share of targeted products across industries. Therefore, we measure trade war exposure at the district level rather than at the industry level.

status, education); Z'_d is a vector of district variables in 2016 (including employment rate, share of migrants, rural location, $(\log)(\text{total population})$); ϕ_q represents quarterly time dummies, and ϵ_{id} is the error term. Standard errors are clustered at the district level.

Our analysis compares individuals in districts subject to greater trade war exposure to otherwise observationally similar individuals in less-exposed districts. Given the cross-sectional dimension of the dataset, we estimate post-trade war outcomes rather than their respective growth rates. Of course, differences in labor market outcomes across individuals in different districts may be due to unobserved pre-existing differences across districts unrelated to the trade war. We account for such differences in our district-level specification in Section 5.2 below.

Table 4 presents the effects of trade war exposure at the district level on the probability of employment in 2019. Columns (1) and (2) report the results of the OLS estimation: individuals in districts more exposed to the trade war have a higher probability of being employed. The effect is positive and statistically significant at the 1% level in the basic specification (column 1) and in the specification with controls at the district level (column 2). As discussed in Section 2, the OLS estimates of the effects of the trade war could be biased, if export growth (used to calculate TW_d) is driven partly by domestic shocks or other foreign shocks unrelated to the U.S.-China trade war. To correctly identify the change in Vietnamese exports to the U.S. induced by the U.S.-China trade war, we instrument trade war exposure using the share of products subject to U.S. tariff hikes within industry j during the U.S.-China trade war, according to Equation (2). Columns (3) and (4) report the results of this IV estimation.²⁹ Both the OLS and IV estimations show a positive and statistically significant effect of trade war exposure on the probability of employment. The estimated coefficient in our preferred regression (column 4) indicates that the probability of employment of an individual in a district at the 75th percentile of trade war exposure is 1.3 percentage points greater than that of an individual in a district at the 25th percentile.

We further investigate the form of employment by estimating Equation (3), where Y_{id} is a dummy for being employed without a (written) contract or for working in a micro-enterprise, defined as an enterprise with fewer than 10 employees. Results in Table 5 show that, interestingly, individuals in districts with greater trade war exposure are less likely to be employed without a contract (columns

²⁹The bottom panel of Table 4 reports the F-statistic of the excluded instrument, which is above 15 in the specification with all controls included. Table A1 in the Online Appendix presents the first stage of the IV estimation and shows a strong correlation between the trade war exposure variable and its instrument.

1-2) and less likely to be employed in a micro-enterprise (columns 3-4), according to both OLS and IV estimations. Trade war exposure, therefore, seems to shift individuals out of informal employment and small enterprises into more formal employment and larger firms.³⁰

In Table 6, we examine the effect of trade war exposure on working hours, conditional on employment. Similar to our results for employment, we find a positive and statistically significant relationship between trade war exposure and the number of working hours: workers in districts more exposed to the trade war work longer hours per week. This result holds true in the OLS analysis (columns 1 and 2) and the IV analysis (columns 3 and 4). According to the estimated coefficient in our preferred regression (4), a worker in a district at the 75th percentile of the change in trade war exposure works 0.5 hours more per week than a worker in a district at the 25th percentile.

Finally, Table 7 shows the impact of trade war exposure on individual wages, conditional on employment. Again, we find a positive and statistically significant effect in both the OLS and the IV estimations: wages are higher in districts with greater trade war exposure. The coefficient of trade war exposure decreases, as we add district controls, suggesting that district controls may partially account for higher wages in districts with greater trade war exposure. The fact that the IV estimates are greater than the OLS estimates indicates that confounding factors account for smaller wages in districts with greater trade war exposure.³¹ According to the estimated coefficient in our preferred specification (4), a worker in a district at the 75th percentile of trade war exposure earns a wage that is 0.07 percent greater than that of a worker in a district at the 25th percentile.

5.1.1 Heterogeneity

As described above, we find that the U.S.-China trade war had a positive impact on labor market outcomes in Vietnam. Are these positive effects evenly distributed across the labor force? Tables 8 and 9 examine whether the labor market effects of trade war exposure vary by gender and education. Interestingly, we find that average effects on employment and working hours are solely due to the impact on women and the non-college educated. Wages increase for both women and men, but more so for the former. Thus, while women in Vietnam are less likely to be employed, work fewer hours, and earn lower wages on average, their labor market outcomes improve with greater exposure to

³⁰This is consistent with findings in McCaig and Pavcnik (2018).

³¹This could be because exporters are more competitive, if wages are lower.

the U.S.-China trade war, which diminishes the gap. Wages increase for the non-college-educated, while there is no statistically significant impact on wages for the college-educated. The non-college educated, who are on average less likely to be employed, work fewer hours and earn lower wages, experience an increase in their relative employment, working hours, and wages compared to the college-educated.

The U.S.-China trade war may affect Vietnamese workers differently, depending on the industry in which they work. In particular, we expect wages to respond in manufacturing industries where Vietnam’s comparative advantage is large. Table 10 presents the estimates of the wage effects of trade war exposure by manufacturing industries.³² Overall, we find positive wage effects in industries where Vietnam’s comparative advantage is greatest (textile, leather, furniture, apparel) but also in other industries (minerals and chemical).

5.2 District-level analysis

Our results at the individual level may, in part, be due to pre-existing (time-invariant) differences across individuals, industries, or districts before the trade war. Therefore, as a next step, we analyze the impact of the trade war on labor market outcomes measured at the district level. This allows us to condition on pre-existing labor market characteristics in the pre-trade war period, hence controlling for potential time-invariant differences across individuals, industries, or districts.

To this end, we estimate the following specification:

$$Y_{dq2019} = \alpha + \beta_1 TW_d + \beta_2 Y_{dq2016} + X'_d \beta_3 + \phi_q + \epsilon_{dq}, \quad (4)$$

where Y_{dq2019} (Y_{dq2016}) is the average employment rate (share of no-contract employment, working hours, real hourly wage) of individuals in district d in quarter q in 2019 (2016), $TW_d = \sum_j (L_{jd}/L_d)(\Delta X_j/L_j)$ is the trade war exposure in district d over the period 2016-2019 modeled as the weighted sum of export growth in different industries j (see Equation (1)); X'_d is a vector of control variables related to the labor force and demographic characteristics in district d as of 2016 (population (in logs), the share of migrants, the employment share, the share of women, the percentage of married individuals, average age, the share of college-educated workers, and an

³²Table 10 does not show industries where the estimated coefficients for trade war exposure are not statistically significant or the number of observations is too small.

indicator variable for rural location), ϕ_q represents quarterly time dummies, and ϵ_{dq} is the error term. Again, we instrument trade war exposure at the district level using our instrumental variable $TW_{d,IV} = \sum_j (L_{jd}/L_d)((P_j^t/P_j)/L_j)$ (Equation (2)).

Table 11 presents the effects of trade war exposure at the district level according to Equation (4) based on the initial (pre-war) employment structure across industries in each district. According to the OLS and IV estimations, employment growth is significantly greater in districts with greater trade war exposure (columns 1 and 2). Columns (3) and (4) show that the growth in the share of individuals employed without contracts or in micro-enterprises is smaller in districts with greater trade war exposure. This is consistent with our findings at the individual level, which suggest that trade war exposure may have contributed to greater formal employment in larger firms. In columns (5) and (6), we show that there is a positive correlation between trade war exposure and the growth of average hours worked in the district in the OLS estimation, although the coefficient is less precisely estimated in the IV estimation (column 6). Finally, our results in columns (7) and (8) show that wage growth is significantly greater in districts with greater trade war exposure according to both the OLS and IV estimations. The positive and statistically significant effects on employment and wage growth according to our IV estimations are greater than in our OLS estimations, indicating that there might be unobserved factors accounting for greater trade war exposure in districts with lower employment and wage growth. According to estimated coefficients in our preferred regressions (columns 2,4,8), we find that in districts at the 75th percentile of trade war exposure compared to districts at the 25th percentile, employment growth is greater by 1.1 percentage points, growth in the rate of no-contract employment is smaller by 3.41 percentage points, and wage growth, conditional on employment, is 0.02 percent greater. A remaining threat to our identification is given by potential unobserved differences in changes across industries over time that are correlated both with our measure of trade war exposure as well as with changes in labor market outcomes. We address this issue in our robustness check in Section 6.2 by controlling for pre-trade war growth rates in labor market outcomes and find that our results remain robust.

In sum, our estimation results show that employment growth and wage growth are greater in Vietnamese districts that are more exposed to the U.S.-China trade war, given their initial industry composition of employment, compared to less exposed districts, consistent with our results at the

individual level. This indicates that industry shocks translated into localized labor market shocks, in line with imperfect mobility of workers across districts.

5.3 Discussion

Overall, individuals in Vietnamese districts that are more exposed to the U.S.-China trade war, given their pre-trade war industry composition, have higher employment and wage growth, and smaller growth in informal employment, over 2016-2019 compared to individuals with similar observable characteristics in less-exposed districts.

Our analysis investigates the effects of trade war exposure using i) variation in the extent to which industries were targeted by U.S. tariffs and ii) variation in industry composition across districts. However, workers may move in response to trade-war-induced differences in employment opportunities and wages across industries or districts. Our estimates are net of any effects due to endogenous migration, which could bias the estimated trade-war-induced employment and wage gains toward zero. Migrants' self-selection might also affect our estimation results, if migrants' unobserved characteristics are correlated with labor market outcomes. If individuals indeed moved in response to trade-war-induced differences in labor market opportunities, we would expect greater migration into districts with higher trade war exposure. We can test for this using information in the labor force data about individuals' migrant status. To do so, we estimate equation (3), where Y_{id} is a dummy for a recent move in 2019. Table 12 presents the results of this estimation. Individuals who are resident in trade-war exposed districts are, indeed, more likely to classify as migrants according to the specifications in columns (1) and (3). However, the effect becomes statistically insignificant once we add district controls in columns (2) and (4). Thus, trade war exposure does not seem to contribute to the probability of migrating over and above what is captured by observable district characteristics. This suggests that our results are not likely to suffer from significant biases due to an endogenous migration of individuals across districts.

Note that our measure of trade war exposure may also be correlated with other economic shocks at the industry level. For example, if increases in tariffs on U.S. imports from China are correlated with increases in Vietnamese exports to third countries, or increases in Vietnamese exports to the U.S. diverted from countries other than China, our estimates of how changes in U.S. tariffs on China affect Vietnamese workers may overstate the true impact of the U.S.-China trade war. However, we

do not observe any other changes in industry-specific tariff policies towards Vietnam or Vietnamese competitors during the sample period.³³ We therefore interpret any such potentially correlated changes in Vietnamese exports to be causally related to the U.S.-China trade war.

6 Robustness

6.1 Gender-education-cell analysis

The district-level analysis aggregates the main outcome variables at the district level to control for pre-war (average district) outcomes. However, in doing so, we cannot account for individual characteristics, such as gender and education, that could affect labor market outcomes (beyond controlling for the share of women and the college-educated in the district). In this section, we follow the estimation strategy originally proposed by Altonji and Card (1991) and analyze labor market effects at the district level by group cells, distinguishing groups of individuals by gender and education.

We estimate the following specification:

$$Y_{fcdq19} = \alpha + \beta_1 TW_d + \beta_2 Y_{fcdq16} + \beta_3 D_f + \beta_4 D_c + \phi_q + \epsilon_{fcdq}, \quad (5)$$

where Y_{fcdq19} (Y_{fcdq16}) is the employment rate (rate of no-contract employment, working hours, real hourly wage) of individuals in gender group f and education group c in district d and quarter q in 2019 (2016), TW_d is the trade war exposure in district d during 2016-2019 (see Equation (1)), D_f is a nation-wide gender fixed effect, D_c is a nation-wide education fixed effect, ϕ_q represents the quarterly time dummies, and ϵ_{fcdq} is the error term. We instrument trade war exposure at the district level using our instrumental variable $TW_{d,IV}$ (Equation (2)).³⁴ The coefficient β_1 now identifies the average effect of trade war exposure on labor market outcomes of a particular gender-education group in a given district.

Table 13 presents our results at the gender-education-district level. We find that workers of a

³³The trade agreement of the Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP), which entered into force in Vietnam on 14 January 2019, is of a more general nature. The same is true for the EU-Vietnam trade agreement, which went into effect only on 1 August, 2020.

³⁴Table A2 in the Online Appendix presents the first stage of the IV estimation at the cell level. It confirms the strong correlation between our trade war exposure variable and its instrument.

particular gender and education experience greater wage growth in districts with greater trade war exposure. The effect of trade war exposure on employment growth is positive but not statistically significant in the OLS and IV estimations. Interestingly, however, effects become statistically significant when estimating growth in informal employment, suggesting that greater exposure to the trade war in a district reduces the probability that workers of a given gender and education work without a contract.

6.2 Pre-trade war growth

A remaining threat to our identification is due to potential unobserved pre-existing time-varying differences across industries over time, which might be correlated with trade war exposure and changes in labor market outcomes. To verify that our results are specific to exposure to the U.S.-China trade war, we estimate the effect of trade war exposure (during 2016-2019) on past growth rates in employment, no-contract employment, working hours, and wages (during 2013-2016). As our labor force data are not available at the district level in 2013, we perform this estimation at the province level, instead.³⁵

We estimate the following specification:

$$\Delta Y_{pq16-19} = \alpha + \beta_1 TW_p + \Delta Y_{pq13-16} + X_p' \beta_2 + \phi_q + \epsilon_{pq}, \quad (6)$$

where $\Delta Y_{pq16-19}$ ($\Delta Y_{pq13-16}$) is the growth rate of the outcome variable (employment rate, rate of no-contract employment, working hours, real hourly wage) during 2016-2019 (2013-2016), $TW_p = \sum_j (L_{jp}/L_p)(\Delta X_j/L_j)$ is trade war exposure in province p over the period 2016-2019 modeled as the weighted sum of export growth in different industries j , analogous to TW_d in Equation (1), X_p' is a vector that includes the population (in logs) and an indicator variable for rural area in province p in 2016, ϕ_q represents the quarterly time dummies, and ϵ_{pq} is the error term. We instrument the measure of trade war exposure using the shares of targeted products across industries within each province, $TW_{p,IV} = \sum_j (L_{jp}/L_p)((P_j^t/P_j)/L_j)$, analogously to $TW_{d,IV}$ in Equation (2).

Table 14 presents the results of this estimation. The results are in line with the findings in our

³⁵There are 63 provinces compared to 686 districts in our sample. We choose to perform our main analysis at the district level for greater precision of our estimates. However, all our results remain valid at the province level (results are available upon request).

specifications at the individual, district, and cell levels. Trade war exposure is positively related to average regional employment, working hours, and wages, and negatively associated with informal employment, even when we control for pre-trade war growth rates. This suggests that our main results are not due to differences in growth trends across industries before the trade war.

7 Conclusion

We show that the U.S. tariff hikes on Chinese products in the course of the U.S.-China trade war in 2018–2019 had significant effects on trade flows and labor market outcomes in Vietnam. As exports from China to the U.S. dropped, exports from Vietnam to the U.S. rose in mirror-like fashion in industries affected by the tariffs, in stark contrast to non-affected industries and the period before the start of the trade war. This plausibly exogenous trade shock to Vietnam provides us with a unique opportunity to study labor market adjustment in response to a change in trade flows. Moreover, we document that bilateral trade policy can, via trade diversion, have significant effects on labor markets in third countries.

Otherwise observationally similar Vietnamese individuals and regions that were more exposed to an increase in U.S. exports diverted from China experienced greater (growth in) employment, working hours, and wages over the 2016–2019 period. Specifically, we find that for individuals in districts at the 75th percentile of trade war exposure compared to individuals in districts at the 25th percentile, the employment growth rate was 1.1 percentage points greater, and hourly wage growth was 0.02 percent greater.

Our results provide valuable insights regarding the broader question of the potential global evolution of exporting patterns. For example, it is unclear whether (and which) other countries will take over labor-intensive manufacturing from China, as the latter moves into more technologically advanced production (see Hanson (2020)). We find that, in the short run, a tariff-induced drop in Chinese exports to the U.S. was partially substituted by a rise in exports from Vietnam, which is similar to China in terms of its comparative advantages in production. It would be interesting to see how the short-run effects that we estimate evolve over time, and whether their impetus could precipitate structural changes in Vietnam in the longer run, such as a change in production patterns towards different products, or a change in employment patterns towards a greater share of women

and formal employment. Vietnam might benefit from the U.S.-China trade war via a structural change in the composition of goods produced. Atkin et al. (2021), for example, find that countries that export more complex goods due to changes in trade policy start growing faster as a result of greater opportunities for knowledge accumulation and technological spillovers. This suggests that an exogenous shift in Vietnamese employment towards more complex industries (such as, e.g., the chemical industry) could increase economic growth in Vietnam in the long run. We leave these important questions for future research.

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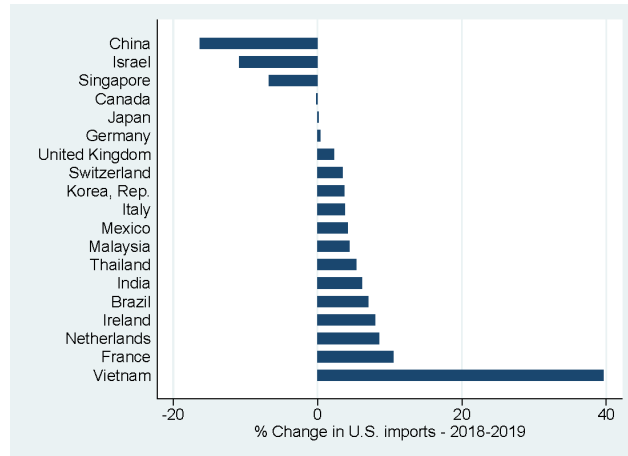
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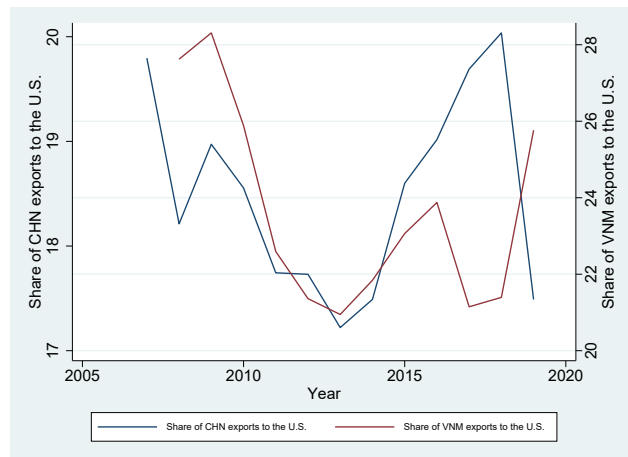
A Figures

Figure 1: Change in U.S. goods imports



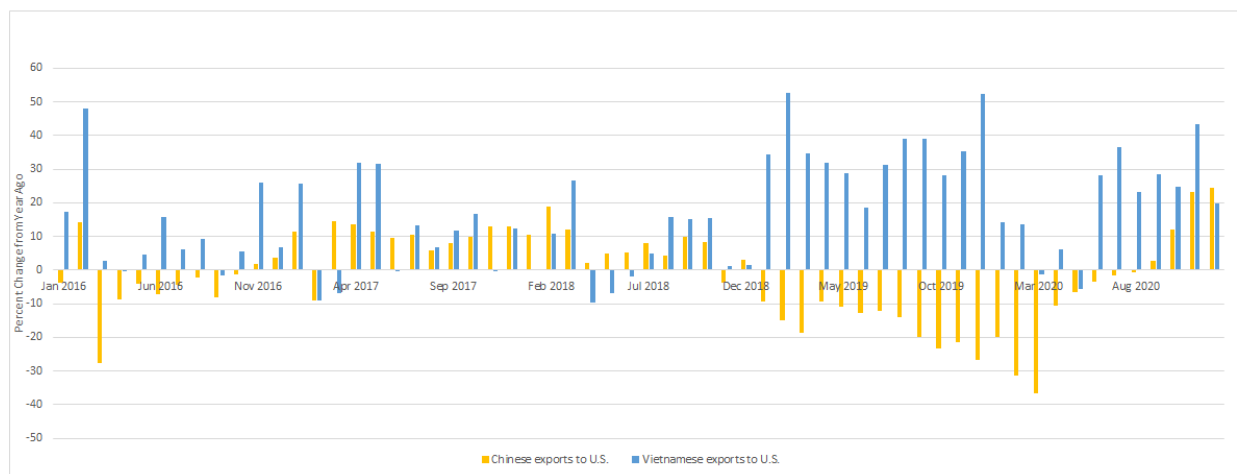
Source: COMTRADE

Figure 2: Vietnamese and Chinese manufacturing export shares to the U.S.



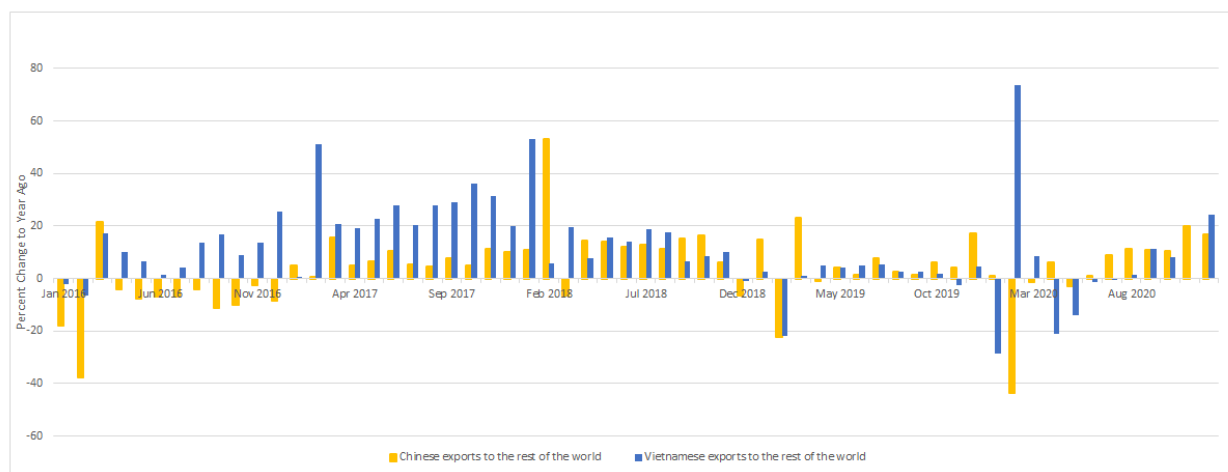
Source: COMTRADE

Figure 3: Change in Vietnamese and Chinese goods exports to the U.S.



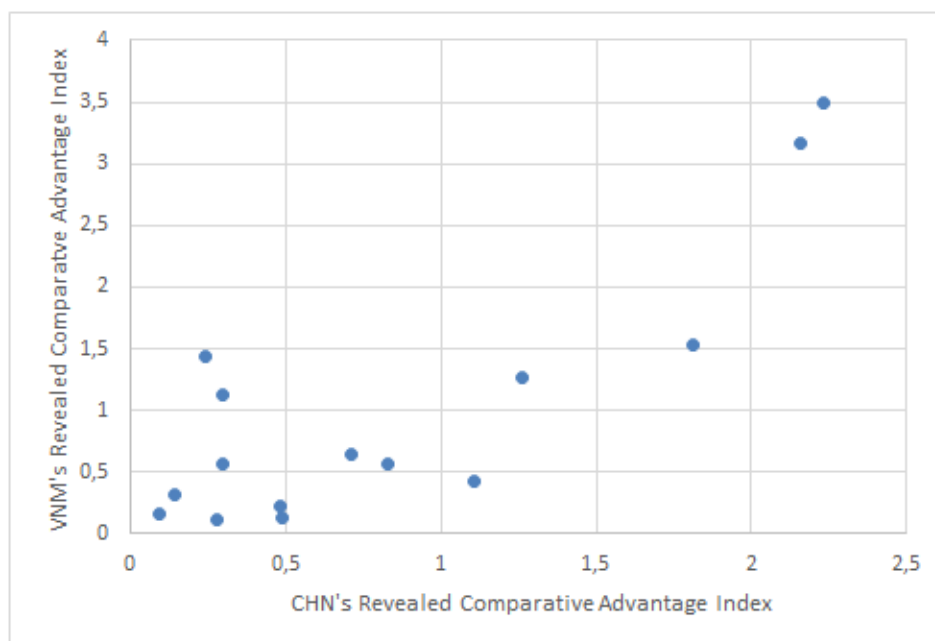
Source: U.S. International Trade Commission.

Figure 4: Change in Vietnamese and Chinese goods exports to the rest of the world



Source: International Monetary Fund.

Figure 5: Revealed comparative advantage by product groups in Vietnam and China (2016)

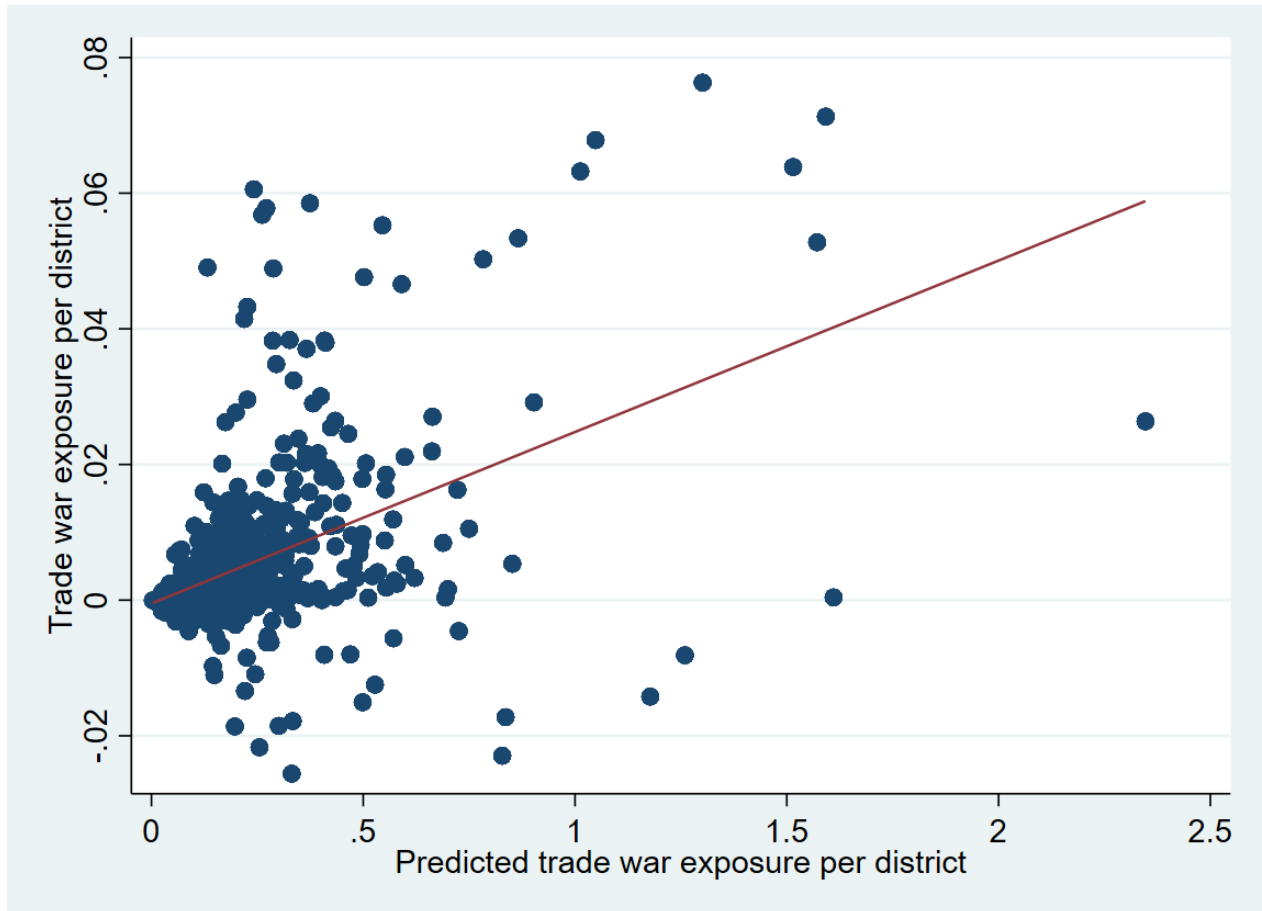


Source: WITS (2022) and own calculations.

Note: The figure displays the Revealed Comparative Advantage (RCA) indexes in Vietnam and China by products groups in 2016. The RCA index of country i for product j is measured as the product's share in the country's exports in relation to its share in world trade:

$RCA_{ij} = (x_{ij}/x_{it})/(x_{wj}/x_{wt})$, where x_{ij} and x_{wj} are the values of country i 's exports of product j and world exports of product j , and x_{it} and x_{wt} are the country's total exports and world total exports. Products groups are as defined by WITS (World Integrated Trade Solution) based on HS 1988/92 classifications. The correlation between the RCA indexes of Vietnam and China is 0.81.

Figure 6: Trade War Exposure measure versus its instrument based on the share of products targeted by U.S. tariffs on China



Note: $N = 686$ (686 districts). Coefficient = 0.04, SE = 0.007, $t = 5.63$. Trade war exposure per district is a weighted sum of industry-specific export growth in a district during 2016-2109 (see Equation (1)). The instrument for trade war exposure is a weighted sum of industry-specific shares of products in a district targeted by U.S. tariffs on China (see Equation (2)).

B Tables

Table 1: U.S. Tariff Waves on Imports from China, July 6, 2018 - September 1, 2019

| Tariff wave | Date enacted | # Products (HTS-8) | Share of HTS-8 products | 2017 U.S. imports bil. US\$ | % | Tariff (%) rate |
|-------------|--------------|--------------------|-------------------------|-----------------------------|-----|-----------------|
| 1 | Jul 6, 2018 | 818 | 5.6 | 34 | 1.4 | 25 |
| 2 | Aug 23, 2018 | 279 | 1.9 | 16 | 0.6 | 25 |
| 3 | Sep 24, 2018 | 5,759 | 39.4 | 200 | 8.3 | 10 |
| 4 | Jun 1, 2019 | 5,759 | 39.4 | 200 | 8.3 | 25 |
| 5 | Sep 1, 2019 | 3,229 | 22.0 | 101 | 4.2 | 15 |

Source: U.S. International Trade Commission and Bown (2021).

Table 2: Value of trade in Vietnam and China with U.S. and most important trade partners, 2016–2019

| | Trade with U.S. (in billions current US\$) | | Exports to other main trading partners (in billions current US\$) | | |
|-------------------------|---|-----------------|--|------------------|-------------|
| | Imports from U.S. | Exports to U.S. | China | Exports to Japan | South Korea |
| <i>Panel A. Vietnam</i> | | | | | |
| 2016 | 10.758 | 44.838 | 21.950 | 14.671 | 11.406 |
| 2019 | 10.821 | 66.461 | 41.434 | 20.426 | 19.729 |
| Growth 2016–2019 | 0.5% | 48.22% | 88.76% | 39.22% | 72.97% |
| | | | Hong Kong | Exports to Japan | Vietnam |
| <i>Panel B. China</i> | | | | | |
| 2016 | 115.594 | 481.310 | 287.251 | 129.268 | 50.037 |
| 2019 | 106.626 | 472.464 | 279.616 | 143.223 | 75.586 |
| Growth 2016–2019 | -13.56% | -8.5% | -2.65% | 10.79% | 51.06% |

Source: COMTRADE.

Table 3: Descriptive statistics

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|--|---------|---------|-----------|--------|-----------|
| Panel A: Individual characteristics (2019) | | | | | |
| Employed | 522681 | 0.711 | .453 | 0 | 1 |
| Employed - no contract | 189,614 | 0.38 | 0.484 | 0 | 1 |
| Employed - micro-enterprise | 419,395 | 0.592 | 0.491 | 0 | 1 |
| Hourly wage (in thous. 2010 VND) | 409794 | 33.4 | 53.9 | 0 | 11250 |
| Hours worked | 409930 | 41.4 | 13.2 | 0 | 64 |
| Migrant | 522681 | 0.011 | 0.106 | 0 | 1 |
| Age | 522681 | 39 | 13.7 | 15 | 65 |
| Female | 522681 | 0.51 | 0.5 | 0 | 1 |
| Married | 522681 | 0.732 | 0.443 | 0 | 1 |
| College education | 522681 | 0.138 | 0.345 | 0 | 1 |
| Panel B: District characteristics (2016 unless stated otherwise) | | | | | |
| Δ Trade war exposure | 2744 | 0.199 | 0.369 | -0.073 | 2.977 |
| Δ Trade war exposure - U.S. tariff | 2744 | 0.220 | 0.243 | .003 | 2.346 |
| Share of employed | 2744 | 0.587 | 0.061 | 0.406 | 0.799 |
| Hours worked | 2728 | 40.03 | 5.92 | 15.86 | 63.451 |
| Log hourly wage (in thous. 2010 VND) | 2724 | 4.865 | 0.405 | 3.09 | 6.171 |
| Share of employed in 2019 | 2744 | .714 | 0.107 | 0.302 | 1 |
| Hours worked in 2019 | 2744 | 40.91 | 5.63 | 11 | 61.37 |
| Log hourly wage (in thous. 2010 VND) in 2019 | 2744 | 4.865 | 0.405 | 3.096 | 6.171 |
| Share of employed without contract in 2019 | 2736 | 0.006 | 0.0088 | 0 | 0.082 |
| Share of female | 2744 | 0.508 | 0.028 | 0.391 | 0.611 |
| Share of married | 2744 | 0.739 | 0.065 | 0.433 | 0.924 |
| Share of migrant population | 2744 | 0.010 | 0.016 | 0 | 0.197 |
| Population | 2744 | 132,609 | 96,239 | 8,001 | 1,022,890 |
| Age | 2744 | 38.97 | 2.473 | 29 | 46.15 |
| Share of college-educated | 2744 | 0.117 | 0.091 | 0 | 0.568 |
| Rural | 2744 | 0.653 | 0.323 | 0 | 1 |

Note: Authors' calculations on the basis of the Labor Force Surveys (GSO, 2016, 2019), COMTRADE and U.S. International Trade Commission, as detailed in Section 4.

Table 4: Employment

| | Employment status | | | |
|---------------------|---------------------|---------------------|--------------------|---------------------|
| | (1) | (2) | (3) | (4) |
| Trade War Exposure | 0.043*** (0.008) | 0.044*** (0.007) | 0.038** (0.015) | 0.054*** (0.020) |
| Observations | 522,681 | 522,681 | 522,681 | 522,681 |
| F-statistics | | | 22.64 | 15.62 |
| R-squared | 0.107 | 0.110 | 0.107 | 0.110 |
| Individual Controls | Yes | Yes | Yes | Yes |
| District controls | No | Yes | No | Yes |
| Estimation method | OLS | OLS | IV | IV |

Note: Robust standard errors (in parentheses) clustered at the district level. Individual controls include gender, age, marital status, college education, and rural location. District controls include log (population), the share of employed, and the share of migrants in 2016. Columns 3-4: Instrumental variable for Trade War Exposure is the share of products subject to a tariff increase within each 4-digit industry category, weighted by the share of employment in the industry, measured at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Employment form

| | No contract | | Micro-enterprise | |
|---------------------|----------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) |
| Trade War Exposure | -0.132*** (0.019) | -0.325*** (0.078) | -0.110*** (0.019) | -0.270*** (0.058) |
| Observations | 189,614 | 189,614 | 419,395 | 419,395 |
| F-statistics | | 15.05 | | 15.84 |
| R-squared | 0.322 | 0.292 | 0.260 | 0.246 |
| Individual Controls | Yes | Yes | Yes | Yes |
| District controls | Yes | Yes | Yes | Yes |
| Estimation method | OLS | IV | OLS | IV |

Note: Robust standard errors (in parentheses) clustered at the district level. Individual controls include gender, age, marital status, college education, and rural location. District controls include log (population), the employment rate, and the share of migrants in 2016. Columns 3-4: Instrumental variable for Trade War Exposure is the share of products subject to a tariff increase within each 4-digit industry category, weighted by the share of employment in the industry, measured at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Working hours

| | Working hours | | | |
|---------------------|---------------------|---------------------|---------------------|-------------------|
| | (1) | (2) | (3) | (4) |
| Trade War Exposure | 2.498*** (0.342) | 1.722*** (0.328) | 3.498*** (0.934) | 2.113* (1.095) |
| Observations | 409,930 | 409,930 | 409,930 | 409,930 |
| F-statistics | | | 23.29 | 16.12 |
| R-squared | 0.062 | 0.066 | 0.061 | 0.066 |
| Individual Controls | Yes | Yes | Yes | Yes |
| District controls | No | Yes | No | Yes |
| Estimation method | OLS | OLS | IV | IV |

Note: Robust standard errors (in parentheses) clustered at the district level. Individual controls include gender, age, marital status, college education, and rural location. District controls include log (population), the share of employed, and the share of migrants in 2016. Columns 3-5: Instrumental variable for Trade War Exposure is the share of products subject to a tariff increase within each 4-digit industry category, weighted by the share of employment in the industry, measured at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Wages

| | Log hourly wage | | | |
|---------------------|---------------------|--------------------|---------------------|---------------------|
| | (1) | (2) | (3) | (4) |
| Trade War Exposure | 0.186*** (0.037) | 0.058** (0.029) | 0.499*** (0.094) | 0.266*** (0.085) |
| Observations | 355,673 | 355,673 | 355,673 | 355,673 |
| F-statistics | | | 23.69 | 16.39 |
| R-squared | 0.166 | 0.205 | 0.138 | 0.195 |
| Individual Controls | Yes | Yes | Yes | Yes |
| District controls | No | Yes | No | Yes |
| Estimation method | OLS | OLS | IV | IV |

Note: Robust standard errors (in parentheses) clustered at the district level. Individual controls include gender, age, marital status, college education, and rural location. District controls include log (population), the share of employed, and the share of migrants in 2016. Columns 3-5: Instrumental variable for Trade War Exposure is the share of products subject to a tariff increase within each 4-digit industry category, weighted by the share of employment in the industry, measured at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Heterogeneity: gender

| | Employment | | Working hours | | Log hourly wage | |
|-------------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Trade War Exposure | 0.005 (0.006) | -0.002 (0.016) | 1.291*** (0.328) | 1.058 (1.060) | 0.042 (0.029) | 0.215*** (0.082) |
| Trade War Exposure *Female | 0.075*** (0.008) | 0.110*** (0.024) | 0.843*** (0.221) | 2.105*** (0.612) | 0.033*** (0.012) | 0.108*** (0.041) |
| Female | -0.167*** (0.005) | -0.175*** (0.007) | -2.854*** (0.110) | -3.145*** (0.167) | -0.284*** (0.008) | -0.306*** (0.014) |
| Observations | 522,681 | 522,681 | 409,930 | 409,930 | 355,673 | 355,673 |
| R-squared | 0.112 | 0.111 | 0.066 | 0.066 | 0.205 | 0.194 |
| Individual Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| District controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Estimation method | OLS | IV | OLS | IV | OLS | IV |

Note: Robust standard errors (in parentheses) clustered at the district level. Individual controls include gender, age, marital status, college education, and rural location. District controls include log (population), the share of employed, and the share of migrants in 2016. Columns 2,4,6: Instrumental variable for Trade War Exposure is the share of products subject to a tariff increase within each 4-digit industry category, weighted by the share of employment in the industry, measured at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Heterogeneity: education

| | Employment | | Working hours | | Log hourly wage | |
|---|----------------------|---------------------|----------------------|--------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Trade War Exposure | 0.048*** (0.008) | 0.051** (0.020) | 1.784*** (0.354) | 2.462** (1.146) | 0.090*** (0.030) | 0.316*** (0.089) |
| Trade War Exposure *College educated | -0.028*** (0.008) | 0.024 (0.029) | -0.360 (0.298) | -2.606 (1.925) | -0.171*** (0.034) | -0.350*** (0.080) |
| College educated | 0.196*** (0.005) | 0.182*** (0.008) | -1.055*** (0.215) | -0.466 (0.485) | 0.482*** (0.017) | 0.529*** (0.026) |
| Observations | 522,681 | 522,681 | 409,930 | 409,930 | 355,673 | 355,673 |
| R-squared | 0.110 | 0.110 | 0.066 | 0.065 | 0.207 | 0.196 |
| Individual Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| District controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Estimation method | OLS | IV | OLS | IV | OLS | IV |

Note: Robust standard errors (in parentheses) clustered at the district level. Individual controls include gender, age, marital status, college education, and rural location. District controls include log (population), the share of employed, and the share of migrants in 2016. Columns 2,4,6: Instrumental variable for Trade War Exposure is the share of products subject to a tariff increase within each 4-digit industry category, weighted by the share of employment in the industry, measured at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10: Wages by sector

| | Log hourly wage | | | | | | | |
|---------------------|--------------------|---------------------|--------------------|--------------------|---------------------|---------------------|---------------------|----------------------|
| | All Manu (1) | Apparel (2) | Chemical (3) | Furniture (4) | Leather (5) | Mineral (6) | Textile (7) | Other manu (8) |
| Trade War Exposure | 0.205** (0.085) | 0.265*** (0.055) | 0.414** (0.187) | 0.333** (0.149) | 0.348*** (0.067) | 0.468*** (0.180) | 0.436*** (0.118) | 0.281*** (0.106) |
| Observations | 11,837 | 15,268 | 839 | 4,794 | 8,397 | 3,062 | 1,558 | 1,330 |
| R-squared | 0.137 | 0.098 | 0.177 | 0.086 | 0.145 | 0.070 | 0.189 | 0.196 |
| Individual controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| District controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Estimation method | IV | IV | IV | IV | IV | IV | IV | IV |

Note: Robust standard errors (in parentheses) clustered at the district level. Individual controls include gender, age, marital status, college education, and rural location. District controls include log (population), the share of employed, and the share of migrants in 2016. Instrumental variable for Trade War Exposure (TW) is the change in the share of products subject to a tariff increase within each 4-digit industry category, weighted by the share of employment in the industry, measured at the district level. *** p<0.01, ** p<0.05, * p<0.1. Results are not shown for sectors where coefficients for TW are not statistically significant or the number of observations is lower than 800.

Table 11: District-level results

| | Employment | | No-contract employment | | Working hours | | Log hourly wage | |
|--------------------|---------------------|--------------------|---------------------------|----------------------|--------------------|------------------|---------------------|-------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Trade War Exposure | 0.042*** (0.007) | 0.054** (0.022) | -0.087*** (0.014) | -0.166*** (0.046) | 0.626** (0.291) | 0.344 (1.241) | 0.085*** (0.024) | 0.097* (0.057) |
| Observations | 2,744 | 2,744 | 2,718 | 2,718 | 2,744 | 2,744 | 2,744 | 2,744 |
| F-statistics | | 23.84 | | 21.27 | | 22.11 | | 24.03 |
| R-squared | 0.179 | 0.178 | 0.506 | 0.492 | 0.306 | 0.306 | 0.568 | 0.568 |
| District controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Estimation method | OLS | IV | OLS | IV | OLS | IV | OLS | IV |

Note: District controls include log (population), the share of migrants, the employment rate, the share of female workers, the share of married workers, the average age of workers, the share of workers by education (college), and an indicator variable for rural location at the district level in 2016. Columns 2,4,6,8: Instrumental variable for Trade War Exposure is the share of products subject to a tariff increase within each 4-digit industry category, weighted by the share of employment in the industry, measured at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Migration

| | Migrant status | | | |
|---------------------|---------------------|------------------|---------------------|------------------|
| | (1) | (2) | (3) | (4) |
| Trade War Exposure | 0.007*** (0.002) | 0.002 (0.002) | 0.015*** (0.004) | 0.005 (0.004) |
| Observations | 522,681 | 522,681 | 522,681 | 522,681 |
| F-statistics | | | 22.64 | 15.62 |
| R-squared | 0.011 | 0.013 | 0.010 | 0.013 |
| Individual controls | Yes | Yes | Yes | Yes |
| District controls | No | Yes | No | Yes |
| Estimation method | OLS | OLS | IV | IV |

Note: Robust standard errors (in parentheses) clustered at the district level. Individual controls include gender, age, marital status, college education, and rural location. District controls include log (population), the share of employed, and the share of migrants in 2016. Columns 3-4: Instrumental variable for Trade War Exposure is the share of products subject to a tariff increase within each 4-digit industry category, weighted by the share of employment in the industry, measured at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13: Gender-education-district-level results

| | Employment | | No-contract employment | | Working hours | | Log hourly wage | |
|--------------------|---------------------|------------------|------------------------|----------------------|---------------------|------------------|---------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Trade War Exposure | 0.017*** (0.005) | 0.005 (0.012) | -0.009*** (0.003) | -0.023*** (0.008) | 0.921*** (0.349) | 0.324 (0.810) | 0.099*** (0.025) | 0.209*** (0.047) |
| Observations | 2,681 | 2,681 | 2,681 | 2,681 | 2,681 | 2,681 | 2,672 | 2,672 |
| F-statistics | | 31.41 | | 32.10 | | 31.75 | | 31.59 |
| R-squared | 0.455 | 0.454 | 0.482 | 0.480 | 0.346 | 0.345 | 0.494 | 0.485 |
| Estimation method | OLS | IV | OLS | IV | OLS | IV | OLS | IV |

Note: Robust standard errors (in parentheses) clustered at the district level. Additional controls in columns 1-2 (3-4, 5-6, 7-8) are the employment rate (rate of no-contract employment, average hours worked, average log hourly wage) in the district in 2016. Columns 2,4,6,8: Instrumental variable for Trade War Exposure is the share of products subject to a tariff increase within each 4-digit industry category, weighted by the share of employment in the industry, measured at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 14: Province-level results conditional on pre-trade war growth

| | Δ Employment | | Δ No-contract employment | | Δ Working hours | | Δ Log hourly wage | |
|-------------------------------------|----------------------|----------------------|---------------------------------|----------------------|------------------------|--------------------|--------------------------|-------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Trade War Exposure (province level) | 0.168*** (0.060) | 0.285** (0.144) | -0.290*** (0.086) | -0.413*** (0.112) | 0.585 (2.747) | 7.145 (5.174) | 0.313 (0.221) | 0.769* (0.393) |
| $\Delta Y_{pq13-16}$ | -0.406*** (0.097) | -0.435*** (0.095) | -0.133*** (0.022) | -0.138*** (0.023) | -0.236 (0.144) | -0.292* (0.154) | -0.049 (0.074) | -0.035 (0.072) |
| Observations | 252 | 252 | 252 | 252 | 252 | 252 | 252 | 252 |
| F-statistics | | 5.89 | | 5.22 | | 6.06 | | 5.47 |
| R-squared | 0.395 | 0.375 | 0.432 | 0.419 | 0.350 | 0.333 | 0.333 | 0.303 |
| Province controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Estimation method | OLS | IV | OLS | IV | OLS | IV | OLS | IV |

Note: Province controls include log (population) and an indicator variable for rural location at the province level in 2016. Additional controls in columns 1-2 (3-4, 5-6, 7-8) are the growth in the employment rate (rate of no-contract employment, average hours worked, average log hourly wage) in the province during 2013-2016. Columns 2,4,6,8: Instrumental variable for Trade War Exposure is the share of products subject to a tariff increase within each 4-digit industry category, weighted by the share of employment in the industry, measured at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C Online Appendix

Table A1: First stage - individual level

| | Trade War Exposure | |
|----------------------------------|---------------------|---------------------|
| | (1) | (2) |
| Trade War Exposure - U.S. Tariff | 0.744*** (0.156) | 0.617*** (0.156) |
| Observations | 522,681 | 522,681 |
| R-squared | 0.206 | 0.257 |
| Individual controls | Yes | Yes |
| District controls | No | Yes |

Note: Robust standard errors (in parentheses) clustered at the district level. Individual controls include gender, age, marital status, college education, and rural location. District controls include log (population), the share of employed, and the share of migrants in 2016. The instrumental variable for Trade War Exposure is the share of products subject to a tariff increase within each 4-digit industry category, weighted by the share of employment in the industry, measured at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: First stage - cell level

| | Trade War Exposure | | | |
|----------------------------------|---------------------|---------------------|---------------------|--------------------|
| | (1) | (2) | (3) | (4) |
| Trade War Exposure - U.S. Tariff | 0.711*** (0.127) | 0.719*** (0.127) | 0.713*** (0.126) | 0.104** (0.043) |
| Observations | 2,681 | 2,681 | 2,681 | 2,672 |
| R-squared | 0.235 | 0.226 | 0.238 | 0.497 |

Note: Robust standard errors (in parentheses) clustered at the district level. The instrumental variable for Trade War Exposure is the share of products subject to a tariff increase within each 4-digit industry category, weighted by the share of employment in the industry, measured at the district level. Column 1 includes the employment rate at the cell level in 2016. Column 2 includes the share of no-contract employment at the cell level in 2016. Column 3 includes the average number of working hours at the cell level in 2016. Column 4 includes the average (log) real hourly wage at the cell level in 2016. *** p<0.01, ** p<0.05, * p<0.1.