Online Appendix to "The Effect of U.S.-China Trade War on U.S. Investment" (For Online Publication)

Mary Amiti
Federal Reserve Bank of New York

Sang Hoon Kong
Columbia University

David E. Weinstein
Columbia University and NBER

April 29, 2021

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A.1 Introduction

This online appendix contains supplementary theoretical and empirical results. Section A.2 presents the proofs of the various propositions in the theory section. Section A.3 lists our set of economic surprise variables. Section A.4 describes how we estimate the U.S. employment of multinational firms and construct the share variables. Section A.5

presents sample statistics. We present the sources for each event in Section A.6. Section A.7 explains the details behind the construction of Figure 2. Section A.8 presents the correlations between each latent macro variable and measures of observable macro variables. Section A.9 discusses FactSet data qaulity issues and shows are results are robust even if we replace the FactSet measure of China Revenue Share used in the paper with the Compustat measure for 2017. Section A.10 shows the results of including a dummy that is one if the firm's output industry was protected on the coefficients estimate for each event. Section A.11 presents the results of using five-day event windows. Finally, Section A.12 provides details on how we used the stock-price data to calibrate the Perla et al. (2021) model.

A.2 Proofs of Propositions

In this section, we provide details on the derivations for each of our variables.

A.2.1 Proposition 1

Proposition. *1 If the elasticity of substitution between labor and capital for all firms is constant, the log change in wages equals the employment-share weighted average of firm stock returns, i.e.,*

$$\hat{w} = \sum_f \frac{L_f}{L} \hat{r}_f,$$

and the log change in employment in each firm equals $\hat{L}_f = \sigma \left(\hat{r}_f - \sum_{f'} \frac{L_{f'}}{L} \hat{r}_{f'} \right)$.

Proof. Totally differentiating equations (2) and (3) yields:

$$\hat{y}_f = -\hat{a}_{Vf}, \tag{A.1}$$

and

$$\sum_f \frac{L_f}{L} \left(\hat{a}_{Lf} - \hat{a}_{Vf} \right) = \hat{L}, \tag{A.2}$$

Substituting equation (4) into equation (A.2) yields-

$$-\sum_f \frac{L_f}{L} \sigma \left(\hat{w} - \hat{r}_f \right) = \hat{L}, \tag{A.3}$$

or

$$\hat{w} = \sum_f \frac{L_f}{L} \hat{r}_f - \frac{\hat{L}}{\sigma} \tag{A.4}$$

Substituting equation (A.1) into equation (4) yields

$$-\hat{y}_f - \hat{a}_{Lf} = \sigma \left(\hat{w} - \hat{r}_f \right) \tag{A.5}$$

or

$$\hat{L}_f = \sigma\left(\hat{r}_f - \hat{w}\right) = \sigma\left(\hat{r}_f - \sum_{f'} \frac{L_{f'}}{L}\hat{r}_{f'} + \frac{\hat{L}}{\sigma}\right), \tag{A.6}$$

where we use f' as an alternative index of firms. Since the change aggregate employment can be written as

$$\hat{L} = \sum_f \hat{L}_f L_f, \tag{A.7}$$

we have

$$\hat{L} = \sigma \sum_f \left(\hat{r}_f - \sum_{f'} \frac{L_{f'}}{L}\hat{r}_{f'} + \frac{\hat{L}}{\sigma}\right) L_f, \tag{A.8}$$

$$\hat{L} = \sigma \sum_f \left(\hat{r}_f L_f - L_f \sum_{f'} \frac{L_{f'}}{L}\hat{r}_{f'}\right) + \hat{L}\sum_f L_f, \tag{A.9}$$

$$\hat{L} = \sigma L \sum_{f'} \frac{L_{f'}}{L}\hat{r}_{f'} - \sigma L \sum_{f'} \frac{L_{f'}}{L}\hat{r}_{f'} + \hat{L}L, \tag{A.10}$$

$$\hat{L} = \hat{L}L \Longrightarrow \hat{L} = 0. \tag{A.11}$$

which establishes that

$$\hat{L}_f = \sigma\left(\hat{r}_f - \hat{w}\right) = \sigma\left(\hat{r}_f - \sum_{f'} \frac{L_{f'}}{L}\hat{r}_{f'}\right) \tag{A.12}$$

□

A.2.2 Proposition 2

Proposition. *2 If the expenditures on intermediate inputs are a constant fraction of sales, the impact of a trade policy change on firm output is given by*

$$\hat{y}_f = \frac{\omega_{Lf}\sigma}{\omega_{Lf} + \omega_{Vf}}\left(\hat{r}_f - \sum_{f'} \frac{L_{f'}}{L}\hat{r}_{f'}\right)$$

where ω_{Lf} and ω_{Vf} denote the payments to labor and specific factors as a share of revenue.

Proof. We can totally differentiate the unit-cost equation to obtain

$$\omega_{Lf}\hat{a}_{Lf} + \omega_{Vf}\hat{a}_{Vf} + \sum_i \omega_{if}\hat{a}_{if} = 0. \tag{A.13}$$

If we assume that the share of expenditures in intermediate inputs is unchanged as a result of a policy change, i.e., $\sum_i \omega_{if}\hat{a}_{if} = 0$, we then can write

$$\hat{a}_{Lf} = -\frac{\omega_{Vf}}{\omega_{Lf}}\hat{a}_{Vf} \tag{A.14}$$

Substituting this into equation (A.5) yields

$$-\hat{y}_f + \frac{\omega_{Vf}}{\omega_{Lf}}\hat{a}_{Vf} = \sigma\left(\hat{w} - \hat{r}_f\right). \tag{A.15}$$

Substituting into equation (A.1) gives us

$$-\hat{y}_f - \frac{\omega_{Vf}}{\omega_{Lf}}\hat{y}_f = \sigma\left(\hat{w} - \hat{r}_f\right) \tag{A.16}$$

$$\hat{y}_f + \frac{\omega_{Vf}}{\omega_{Lf}}\hat{y}_f = \sigma\left(\hat{r}_f - \hat{w}\right) \tag{A.17}$$

$$\hat{y}_f\left(1 + \frac{\omega_{Vf}}{\omega_{Lf}}\right) = \sigma\left(\hat{r}_f - \hat{w}\right) \tag{A.18}$$

$$\hat{y}_f\left(\frac{\omega_{Lf} + \omega_{Vf}}{\omega_{Lf}}\right) = \sigma\left(\hat{r}_f - \hat{w}\right) \tag{A.19}$$

$$\hat{y}_f = \frac{\omega_{Lf}\sigma}{\omega_{Lf} + \omega_{Vf}}\left(\hat{r}_f - \hat{w}\right) \tag{A.20}$$

Making use of our wage result from Proposition 1 gives us

$$\hat{y}_f = \frac{\omega_{Lf}\sigma}{\omega_{Lf} + \omega_{Vf}}\left(\hat{r}_f - \sum_{f'}\frac{L_{f'}}{L}\hat{r}_{f'}\right) \tag{A.21}$$

□

A.2.3 Proof of Proposition 3

Proposition. 3 *The log change in the ERP for a firm ($\hat{p}^e_f$) in a specific factors model is given by*

$$\hat{p}^e_f = \theta_{Vf}\hat{r}_f + \theta_{Lf}\sum_{f'}\frac{L_{f'}}{L}\hat{r}_{f'}$$

and if the share of total expenditures on intermediate inputs is constant, then

$$\widehat{TFPR}_f \equiv \hat{p}_f + \widehat{TFP}_f = \hat{p}^e_f,$$

where $\widehat{TFPR}_f$ is the log change in the firm's revenue total factor productivity.

Proof. By the definition of shares, we have $\omega_{Lf} + \omega_{Vf} + \sum_i \omega_{if} = 1$. Totally differentiating equation (5) and dividing both sides by p_f, we obtain

$$\omega^L_f\hat{w} + \omega^V_f\hat{r}_f + \sum_i \omega_{if}\hat{q}_i = \hat{p}_f. \tag{A.22}$$

If we divide both sides by $(1 - \sum_i \omega_{if})$ and rearrange, we obtain:

$$\hat{p}^e_f \equiv \frac{\hat{p}_f - \sum_i \omega_{if}\hat{q}_i}{1 - \sum_i \omega_{if}} = \theta_{Lf}\hat{w} + \theta_{Vf}\hat{r}_f, \tag{A.23}$$

Using Proposition 1, we can rewrite equation (A.23) as

$$\theta_{Lf}\sum_{f'}\frac{L_{f'}}{L}\hat{r}_{f'}+\theta_{Vf}\hat{r}_f=\frac{\hat{p}_f-\sum_i\omega_{if}\hat{q}_i}{1-\sum_i\omega_{if}}\equiv\hat{p}^e_f. \tag{A.24}$$

In order to prove that the ERP equals productivity, we multiply both sides of the firm's zero-profit condition (5) by firm output (y_f) to obtain

$$p_fy_f-\sum_i m_{if}q_i=L_fw+V_fr_f, \tag{A.25}$$

where m_{fi} is the amount of intermediates of type i used in production. If we assume that the share of intermediate inputs in production is constant, we can rewrite this as

$$p_fy_f-p_fy_f\sum_i\omega_{if}=L_fw+V_fr_f, \tag{A.26}$$

or

$$p_fy_f\left(1-\sum_i\omega_{if}\right)=L_fw+V_fr_f, \tag{A.27}$$

where the left-hand side is value added. Totally differentiating this expression and remembering that $\sum_i\omega_{if}$ is fixed yields

$$(dp_fy_f+p_fdy_f)\left(1-\sum_i\omega_{if}\right)=L_fdw+V_fdr_f+wdL_f+r_fdV_f. \tag{A.28}$$

Dividing through by p_fy_f produces

$$(\hat{p}_f+\hat{y}_f)\left(1-\sum_i\omega_{if}\right)=\omega_{Lf}\hat{w}+\omega_{Lf}\hat{L}_f+\omega_{Vf}\hat{r}_f+\omega_{Vf}\hat{V}_f. \tag{A.29}$$

Dividing through by $(1-\sum_i\omega_{if})$ and rearranging produces

$$TFPR_f\equiv\hat{p}_f+\hat{y}_f-\theta_{Lf}\hat{L}_f-\theta_{Vf}\hat{V}_f=\theta_{Lf}\hat{w}+\theta_{Lf}\hat{r}_f=\hat{p}^e_f, \tag{A.30}$$

where θ_{Lf} and θ_{Vf} are the shares of labor and the specific factor in value added. Since the left-hand side of this equation is revenue TFP, we have proved that the ERP is the same as TFP. □

A.3 Economic Surprise Variables

The 65 series we use are ISM manufacturing, ISM non-manufacturing, ISM prices, construction spending, durable goods new orders, factory orders, initial jobless claims, ADP payroll employment, non-farm payrolls, unemployment rate, total job openings, consumer credit, non-farm productivity, unit labor costs, retail sales, retail sales less auto, federal budget balance, trade balance, import price index, building permits, housing starts, industrial production, capacity utilization, business inventories, Michigan consumer sentiment, PPI core, PPI, CPI core, CPI, Empire State manufacturing index, Philadelphia Fed BOS, GDP (advance estimate), GDP (second estimate), GDP price index, personal income, personal spending, PCE price index, core PCE price index, wholesale inventories, new home sales, CB consumer confidence, leading economic index, employment cost index, Wards total vehicle sales, continuing claims retail sales ex auto and gas, NAHB housing market index, change in manufacturing payrolls, MNI Chicago, PMI pending home sales, Richmond Fed manufacturing index, Dallas Fed manufacturing index, existing home sales, Chicago Fed national activity index, capital goods (non-defense ex air), NFIB small business optimal index, Cap goods ship. ex air, KC Fed manufacturing activity, Markit U.S. manufacturing purchasing managers index, Case-Shiller home price index, and Markit U.S. services purchasing managers index, federal funds shock, forward guidance shock, asset purchase shock, and the Federal Reserve information shock.

A.4 Estimates of U.S. Employment for Multinational Firms and Construction of Share Variables

We obtained employment data from a number of sources. The firm-level employment data for the listed firms in our sample are from Compustat. However, one potential issue with using these data is that the reported employment is for the consolidated firm, and thus for multinationals it covers employment in the U.S. and in foreign subsidiaries, whereas our interest is in U.S. employment. We address this issue by supplementing the Compustat data with employment data from the National Establishment Time Series (NETS) for 2014 (the most recent year available to us), which provides data on an establishment basis for U.S. firms. We merged the NETS data with the Compustat data by DUNS number to obtain the domestic firm employment.

This merge required us to adjust the data for the different years. To do this, we first use Compustat's geographic segments data to identify multinational firms, which we define as a firm that reported non-zero long-lived assets (atlls) abroad for 2017. For non-multinational firms, we assume that the Compustat employment numbers accurately reflect their U.S. employment. For the multinationals in our sample, we used NETS data for 2014 (the latest year available to us) to compute domestic U.S. employment. For these firms, we then regressed their logged NETS employment on their reported Compustat employment in 2014, foreign revenue share, and an indicator for exporting to China. The regression results are presented in Table A.1. Next, we calculated the ratio between the predicted 2014 NETS employment from this regression and the 2014 Compustat employment to compute an adjustment factor that tells us how much the Compustat data overstated domestic employment for that firm in 2014. We then multiplied this adjustment factor by the 2017 Compustat employment to arrive at our estimates of the multinationals' U.S. employment in 2017.

We also created an indicator for whether the firm was a multinational using information from Compustat's geographic segments data. We assume that the Compustat employment numbers accurately reflect U.S. domestic employment for firms that did not have direct investments abroad. For the sample of multinationals, we regressed the log domestic employment in the NETS data in 2014 on the log employment in Compustat for the same year, a dummy that equaled 1 if the firm was an exporter to China, and the share of foreign revenues for the firm from FactSet. We then used the estimated coefficients to predict each multinational firm's domestic employment and used these estimates in lieu of the employment numbers in Compustat.

Table A.1: Estimating U.S. Employment for Multinational Firms

	(1) log NETS employment (2014)
log Compustat employment (2014)	0.938***
	(0.037)
Foreign Revenue Share	-1.438***
	(0.247)
China Exporter	0.345
	(0.222)
Constant	-0.053
	(0.325)
R^2	0.56
N	612

In order to construct the labor and capital share variables (θ_{Lf} and θ_{Vf}), we set $r_f V_f / (p_f y_f)$ equal to the firm's ordinary income after depreciation less interest expenses, divided by sales as reported in Compustat in 2017 and kept firms for which this value was positive.[1] Because Compustat does not separately report the compensation of employees and materials cost by firm, we need to use industry-level data in order to infer $wL_f / (p_f y_f)$ and $\sum_i \omega_{if}$. To do this, we set LSHARE_f and MSHARE_f equal to the compensation of employees divided by output and intermediate-input expenses divided by output in the NAICS 6-digit industry containing the firm, as reported in the 2012

[1]Ordinary income after depreciation equals firm revenue less cost of goods sold, and expenses related to marketing, administration, depreciation. Labor costs appear in the cost of goods sold and the market and administration expenses lines. We also tried an alternative measure of $r_f V_f$ in which we did not subtract interest expenses, but it only had small effects on the results.

450×450 Bureau of Economic Analysis Input-Output table (the most recently available disaggregated IO table). Since we are using data from two different sources to compute the shares, they may not sum to 1. Therefore, in order to preserve this property, we set $wL_f/(p_f y_f) = \Theta_f \text{LSHARE}_f$ and $\sum_i \omega_{if} = \Theta_f \text{MSHARE}_f$, where

$$\Theta_f = \frac{\left(1 - \frac{r_f V_f}{p_f y_f}\right)}{\text{LSHARE}_f + \text{MSHARE}_f}.$$

Once we constructed these variables we used equation (10) to construct θ_{Lf} and θ_{Vf}. In order to compute $\overline{RV}_b$ in equation (46), we first computed the median value of $r_f V_f$ for all of the firms in a bin to minimize the effect of outliers; however, some of the smaller bins still had negative values of $\overline{RV}_b$. We therefore ran the following regression $\overline{RV}_b = \alpha_i + \beta EMP_b$, where α_i is an industry dummy and β is a parameter, and EMP_b is the average employment of a firm in the bin. The R^2 from this regression is 0.95. We used the fitted values from this regression as our estimates of $\overline{RV}_b$ as these were always positive.

A.5 Sample Statistics

Table A.2: Descriptive Statistics

	N	Mean	Standard Deviation	25th Percentile	Median	75th Percentile
$\hat{\epsilon}_{ft}$	80,674	0.02	2.81	-0.93	-0.00	0.93
China Importer Dummy	80,674	0.29	0.45	0.00	0.00	1.00
Large Company Dummy	80,674	0.55	0.50	0.00	1.00	1.00
China Exporter Dummy	80,674	0.04	0.20	0.00	0.00	0.00
China Revenue Share	80,674	0.04	0.13	0.00	0.00	0.03
Industry Protected Dummy	80,674	0.03	0.17	0.00	0.00	0.00

Note: ϵ_{ft} is estimated from equation (28). The China Importer and China Exporter dummies equal 1 for firms that import or export to China as recorded in Datamyne. China Revenue Share is the share of a firm's revenues that come from China. The Large Company Dummy is 1 when a firm has at least 1,000 employees, sourced from Compustat. The Industry Protected Dummy is defined as when a firm's 6-digit NAICS code is affected by U.S. tariff events.

A.6 Event Dates

The following table presents the event date (earliest news date), tariffs effective date, event group, and the news link of each event.

Table A.3: Event Dates

Earliest News Dates	Date Effective	Event Group	News Link
2018/1/22	2018/2/7	US	washington post
2018/2/28	2018/3/23	US	reuters
2018/3/22	2018/4/2	China	nytimes
2018/5/29	2018/7/6	US	npr
2018/6/15	2018/7/6	China	npr
2018/6/19	2018/9/24	US	wsj
2018/8/2	2018/9/24	China	reuters
2019/5/5	2019/5/10	US	dw
2019/5/13	2019/6/1	China	cnbc
2019/8/1	2019/9/1	US	cnbc
2019/8/23	2019/9/1	China	cnbc

Note: 2019/5/5 was not a trading date. We therefore considered the next trading date, 2019/5/6 for the analysis in the paper.

A.7 Construction of Figure 2

A.7.1 Stock-Price Plot

We constructed the stock price plot as follows. Let $R_t \equiv \sum_f S_{f,t-1} r_{ft}$. For $s \in [-5, 5]$, define $D_{jts} = 1$ if day t is s days after event j (note that if $s = 0$, day t is on the same day as event j); $D_{jts} = 0$ otherwise. We then estimate the following regression for the set of days t between January 1, 2016 and December 31, 2019:

$$R_t = \alpha + \sum_{s=-5}^{5} \beta_s D_{jts} + \epsilon_t. \tag{A.31}$$

In this case $\hat{\beta}_s$ is our estimate of the stock price movement s days after an event. Since we have 11 events, the cumulative movement of stock prices from their average level six days before the event is given by

$$\psi_s \equiv 11 \sum_{k=-5}^{s} \hat{\beta}_k. \tag{A.32}$$

The plot then shows ψ_s for $s \in [-5, 5]$.

A.7.2 Price Change Plot

We define the expected price change on day t based on the 10-year inflation expectation as $E_t\left[\hat{P}^{10}\right] \equiv 10 \times \left(\hat{\pi}_t^{10} - \hat{\pi}_{t-1}^{10}\right)$. We then estimate the following regression for the set of days t between January 1, 2016 and December 31, 2019

$$E_t\left[\hat{P}^{10}\right] = \alpha + \sum_{s=-5}^{5} \beta_s D_{jts} + \epsilon_t \tag{A.33}$$

where α and β_s are parameters to be estimated, and ϵ_t is an error term. We compute ψ_s as in equation (A.32) using these new estimates of β_s for $s \in [-5, 5]$. The exchange rate and VIX plots are constructed analogously using changes in the VIX or the trade weighted exchange rate instead of the expected price change.

Table A.4: Regression of Exchange Rate and VIX on the Sum of Event Window Dummies

	(1) Exchange-Rate	(2) Exchange-Rate	(3) VIX	(4) VIX
Event Dummy	0.099*	0.098	3.471***	5.479***
	(0.051)	(0.070)	(1.344)	(1.913)
Event Dummy × China Event Dummy		0.003		-3.898
		(0.100)		(2.645)
N	972	972	1004	1004

A.8 Correlation Between Macro Variables and Latent Factors

In this section, we present correlations between the four latent macro variables that we estimate (labeled factor1-factor4), and the macro variables that we discuss in Figure 2.

Table A.5: Correlation Matrix

	factor1	factor2	factor3	factor4	market return	inflation	exchange rate
factor2	0.00						
factor3	0.01	0.01					
factor4	0.00	−0.01	0.00				
market return	0.84***	0.07*	−0.19***	0.26***			
inflation	0.51***	−0.24***	0.02	−0.10**	0.43***		
exchange rate	−0.24***	0.15***	−0.03	−0.22***	−0.24***	−0.15***	
vix	−0.69***	−0.10***	0.17***	−0.22***	−0.76***	−0.37***	0.20***

A.9 FactSet Data Quality Issues

In FactSet data, firms sometimes report geographic revenue shares for units that are more aggregate than countries (e.g., Asia/Pacific). In these cases, FactSet imputes the undisclosed revenue share for a country using that country's GDP weight within a more aggregate geographic unit for which the data are disclosed (e.g., China's GDP share within Asia/Pacific region). To summarize the extent of this imputation, FactSet provides a confidence factor that ranges from 0.5 to 1, with 1 indicating no imputation. Fortunately, within our sample of firms, the mean confidence factor for the China revenue share is 0.996 with a range of 0.98 to 1, and our China revenue share variable comes mostly from direct disclosures. A problem with the FactSet data that we could access is that while about 90 percent of the observations correspond to 2018, some of them are for 2019. In order to make sure that an endogeneity problem was not driving our results, we reran our event studies using 2017 Compustat data on China revenue shares, which do not contain imputations when firm reporting is unclear. The results were very similar to using the FactSet data. See the Appendix.

Ideally, we would have wanted to use the 2017 China revenue share from FactSet. Unfortunately, we had to resort to using numbers from later years due to our limited access to FactSet's database. In this section, we test the robustness of our event-study results to this shortcoming by constructing our China revenue-share variable using firms' direct disclosures of foreign sales in 2017, which we obtained from Compustat's geographic segments data. More specifically, we identified firms' sales in China by searching for geographic segments whose description included the word "China," "PRC" (People's Republic of China), "Hong Kong," "Macao," and other similar variations. For this search, we excluded segments with references to Taiwan and screened for exclusionary phrases such as "except China" or "excluding China." For firms that did not report any segments for China, we assumed that they made no sales there.

We find that the China revenue shares constructed this way substantially undercount the number of firms in our sample that have sales in China from 0.43 in Table 1 to 0.09. Despite this large difference, Tables A.6 and A.7 show that our event study results remain very similar when we use the Compustat China revenue shares instead. When we looked more closely at the data, we found that the Compustat data do well in capturing the foreign sales of larger firms but miss the sales of smaller firms that FactSet identifies through its proprietary algorithm. Therefore, the similarity of the results despite the substantial undercounting suggests that most of the differential effects from the trade-war announcements were driven by larger firms with more visible sales in China.

Table A.6: Impact of U.S. Tariff Announcements on Stock Returns (2017 Compustat China Revenue Share)

	(1) Cumulative	(2) 22Jan18	(3) 28Feb18	(4) 29May18	(5) 19Jun18	(6) 06May19	(7) 01Aug19
China Importer	-1.87***	-0.02	-0.18***	-0.03	-0.11	-0.14**	-0.15*
	(0.56)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.09)
China Exporter	-2.58**	0.01	0.03	-0.23***	-0.54***	-0.12	-0.01
	(1.06)	(0.10)	(0.10)	(0.09)	(0.11)	(0.12)	(0.18)
China Revenue Share	-11.43***	-1.18***	-0.29	-0.31	-0.33	-1.15***	-0.55**
	(1.68)	(0.22)	(0.24)	(0.26)	(0.23)	(0.24)	(0.26)

Table A.7: Impact of Chinese Tariff Announcements on Stock Returns (2017 Compustat China Revenue Share)

	(1) Cumulative	(2) 22Mar18	(3) 15Jun18	(4) 02Aug18	(5) 13May19	(6) 23Aug19
China Importer	-0.68	0.08	-0.00	-0.01	-0.18***	-0.11*
	(0.44)	(0.05)	(0.06)	(0.08)	(0.07)	(0.06)
China Exporter	-1.71**	0.01	-0.09	-0.24*	-0.10	-0.15*
	(0.71)	(0.09)	(0.07)	(0.13)	(0.09)	(0.08)
China Revenue Share	-9.89***	-0.53**	-0.45*	-1.08***	-0.88***	-0.36
	(1.68)	(0.25)	(0.23)	(0.29)	(0.20)	(0.31)

A.10 Disaggregated Industry Protected Specification

Table A.8: Robustness Tests (Industry Protected)

	(1) Cumulative	(2) 22Jan18	(3) 28Feb18	(4) 29May18	(5) 19Jun18	(6) 06May19	(7) 01Aug19
China Importer	-1.42**	0.02	-0.19***	0.02	-0.07	-0.15**	-0.09
	(0.57)	(0.07)	(0.07)	(0.06)	(0.07)	(0.08)	(0.10)
China Exporter	-2.50**	-0.00	0.02	-0.23***	-0.52***	-0.12	0.02
	(1.06)	(0.09)	(0.10)	(0.09)	(0.11)	(0.12)	(0.18)
China Revenue Share	-10.07***	-0.83***	-0.19	-0.12	-0.65***	-1.17***	-0.40
	(1.91)	(0.22)	(0.22)	(0.28)	(0.25)	(0.24)	(0.26)
Industry Protected	-0.36	-0.81***	1.08***	-0.17***	-0.08	0.11	-0.24*
	(1.28)	(0.20)	(0.33)	(0.06)	(0.08)	(0.08)	(0.13)

A.11 Robustness to Using Five-Day Window

Table A.9: Impact of U.S. Tariffs Announcements on Stock Returns (Five-Day Window)

	(1) Cumulative	(2) 22Jan18	(3) 28Feb18	(4) 29May18	(5) 19Jun18	(6) 06May19	(7) 01Aug19
China Importer	-2.75***	-0.00	-0.18***	-0.03	-0.12**	-0.21***	-0.02
	(0.75)	(0.06)	(0.05)	(0.05)	(0.06)	(0.08)	(0.07)
China Exporter	-0.95	0.12	-0.06	-0.17**	-0.02	-0.11	0.04
	(1.30)	(0.08)	(0.08)	(0.08)	(0.09)	(0.11)	(0.13)
China Revenue Share	-11.97***	-0.65***	-0.28*	0.10	-0.22	-0.91***	-0.44*
	(2.47)	(0.16)	(0.16)	(0.22)	(0.20)	(0.20)	(0.26)

Note: This table presents the estimated coefficients on the U.S. events obtained from estimating equation (29); the estimated coefficients for the Chinese events are presented in Table A.10. The dependent variable ($\hat{\epsilon}_{ft} \times 100$) is the abnormal return obtained from estimating equation (28) with four factors multiplied by 100. China Importer is a dummy that equals 1 if the firm or any of its subsidiaries or suppliers import from China. China Exporter is a dummy that equals 1 if the firm or its subsidiaries export to China. China Revenue Share is the share of the firm's revenue that comes from sales in China reported in percentage points. Column 1 presents the cumulative of the coefficients on each of the U.S. event days. Standard errors are in parentheses. Asterisks correspond to the following levels of significance: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. The number of observations is 122,002.

Table A.10: Impact of Chinese Tariff Announcements on Stock Returns

	(1) Cumulative	(2) 22Mar18	(3) 15Jun18	(4) 02Aug18	(5) 13May19	(6) 23Aug19
China Importer	0.39	0.12***	0.02	0.06	-0.11*	-0.02
	(0.62)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)
China Exporter	-3.49***	-0.07	-0.38***	-0.17*	-0.02	-0.07
	(1.11)	(0.08)	(0.10)	(0.10)	(0.09)	(0.08)
China Revenue Share	-19.33***	-0.74***	-0.81***	-0.76**	-1.38***	-0.17
	(2.43)	(0.16)	(0.20)	(0.35)	(0.26)	(0.24)

Note: This table presents the estimated coefficients on the Chinese events obtained from estimating equation (29); the estimated coefficients for the U.S. events are presented in Table A.9. The number of observations is therefore the same as in Table A.9. The dependent variable ($\hat{\epsilon}_{ft} \times 100$) is the abnormal return obtained from estimating equation (28) with four factors multiplied by 100. China Importer is a dummy that equals 1 if the firm or any of its subsidiaries or suppliers import from China. China Exporter is a dummy that equals 1 if the firm or its subsidiaries export to China. China Revenue Share is the share of the firm's revenue that comes from sales in China reported in percentage points. Column 1 presents the cumulative effect of the coefficients on each of the China announcement event days. Standard errors are in parentheses. Asterisks correspond to the following levels of significance: *** $p < 0.01$, **$p < 0.05$, and * $p < 0.1$.

A.12 Welfare Calculation Based on Perla et al. (2021)

In this section, we detail how our results can be used to calculate the welfare effects of our trade-war events based on the model of Perla et al. (2021). For comparability, we retain the notation in their paper whenever possible for this section. We show that in their setup, if one knows how a policy affects the ratio between the average and the minimum firm profits ($\bar{\pi}_{rat} = \pi_{ave}/\pi_{min}$), one can calculate the resulting welfare effects.

Equation (46) in Perla et al. (2021) shows that welfare on a balanced growth path can be written as

$$\overline{U} = \frac{\rho \ln c + g}{\rho^2}, \tag{A.34}$$

where ρ is the discount rate, g is the economic growth rate, and

$$c = \left(1 - \tilde{L}\right) \Omega^{\frac{1}{\sigma-1}} \lambda_{ii}^{\frac{1}{1-\sigma}} \left(E\left[z^{\sigma-1}\right]\right)^{\frac{1}{\sigma-1}} \tag{A.35}$$

is the level of consumption. The level of consumption depends on the amount of labor devoted to goods production $\left(1 - \tilde{L}\right)$, the measure of varieties (Ω), the home trade share (λ_{ii}), and the $\sigma - 1$ moment of the firm productivity distribution: $E\left[z^{\sigma-1}\right] = \theta/(\theta - \sigma + 1)$, which is assumed to be distributed Pareto with shape parameter θ. The change in welfare can then be written as

$$d \ln \overline{U} = \frac{d\overline{U}}{\overline{U}} = \overline{U}^{-1} \left(\frac{d \ln c}{\rho} + \frac{dg}{\rho^2}\right), \tag{A.36}$$

where

$$d \ln c = d \ln \left(1 - \tilde{L}\right) + \frac{1}{\sigma - 1} d \ln \Omega + \frac{1}{1 - \sigma} d \ln \lambda_{ii}. \tag{A.37}$$

We can rewrite changes in consumption in the Perla et al. (2021) model as a function of policy-induced movements in profits. They define the profit ratio ($\bar{\pi}_{rat} \equiv \pi_{\text{ave}}/\bar{\pi}_{\text{min}}$) as the ratio of average firm operating profits to minimum firm operating profits (where operating profits are not inclusive of entry costs). Using equations (33), (48), and (50) from their paper, we can express each of the terms in this equation as a function of model parameters and the change in the profit ratio ($d\bar{\pi}_{rat}$):

$$d \ln \left(1 - \tilde{L}\right) = -\lambda_{ii} \left(\sigma - \frac{1 + \theta - \sigma}{\theta\left(1 - \chi\right)} \lambda_{ii}\right)^{-1} \frac{1 + \theta - \sigma}{\theta\left(1 - \chi\right)} \frac{d\bar{\pi}_{rat}}{\bar{\pi}_{rat} - 1} \tag{A.38}$$

$$d \ln \Omega = -\left(\frac{\left(1 - \chi\right) \theta\sigma}{1 + \theta - \sigma} \lambda_{ii}^{-1} - 1\right)^{-1} \frac{\left(1 - \chi\right) \theta\sigma}{1 + \theta - \sigma} \lambda_{ii}^{-1} \frac{d\bar{\pi}_{rat}}{\bar{\pi}_{rat} - 1} \tag{A.39}$$

$$d \ln \lambda_{ii} = \frac{-d\bar{\pi}_{rat}}{\bar{\pi}_{rat} - 1}. \tag{A.40}$$

Similarly, equation (31) of their paper can be used to derive that

$$dg = dg = \frac{\rho\left(1 - \chi\right)}{\chi\theta} d\bar{\pi}_{rat} \tag{A.41}$$

Thus, if we substitute equations (A.37)-(A.41) into equation (A.36), we can write the change in utility as a function of the policy induced change in the profit ratio ($d\bar{\pi}_{rat}$) and the model parameters.

We can integrate the two approaches by first writing the change in profits as

$$d\overline{\pi}_{rat} = \overline{\pi}_{rat}\left(d\ln\pi_{ave} - d\ln\pi_{min}\right), \tag{A.42}$$

where the initial profit ratio is calculated based on their model parameter values (Tables 1 and 2) and rewriting their equation (33) as

$$\overline{\pi}_{rat} = 1 + \frac{\sigma-1}{1+\theta-\sigma}\lambda_{ii}^{-1}. \tag{A.43}$$

We can compute $d\ln\pi_{ave}$ as follows:

$$d\ln\pi_{ave} = \sum_b w_b^F E\left[\hat{r}_b|\boldsymbol{\tau}\right], \tag{A.44}$$

where w_b^F is the share of all firms in the U.S. distribution in bin b and $E\left[\hat{r}_b|\boldsymbol{\tau}\right]$ is defined in equation (38) in our paper.[2] The minimum profit is determined by model parameters alone (see equation (G.19) of their Online Appendix), so $d\ln\pi_{min} = 0$. Equation (A.44) implies that the trade-war events affected average firm profits by $d\ln\pi_{ave} = -0.062$, which reduces the profit ratio by $d\overline{\pi}_{rat} = -0.115$. Substituting this into equation (A.41) reveals that markets are forecasting a decline in the economic growth rate of 0.3 percentage points ($dg = -0.003$), which yields a welfare loss of 9.0% ($d\ln\overline{U} = -0.090$).

[2]For this analysis, we do not use separate employment size bins for firms in goods or services sectors. We also further divide the narrowest bin of less than 100 employees that we used for our main analysis into the following three bins: <20 employees, 20-39 employees, and 40-99 employees.