Online Appendix to "Trade Protection, Stock-Market Returns, and Welfare" (For Online Publication)

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Introduction

This online appendix contains supplementary theoretical and empirical results. Section A presents the proofs of the propositions in the theory section.

Turning to data and measurement issues, B.1 provides a list of all the variables and the data sources used. Section B.2 presents sample statistics. We present the sources for each event in Section B.3. Section B.4 explains the details behind the construction of Figure 2. Section B.5 discusses data quality issues regarding the China revenue shares from FactSet and compares them to China revenue shares from Compustat. Section B.6 describes how we estimate the U.S. employment of multinational firms and construct the input share variables.

Section C.1 summarizes the estimation of our factor model in equation (21) and that of the event study regression in equation (22). Section C.2 describes how we adapt the methodology of Campbell and Vuolteenaho (2004) to separate the expected cash flow effect from the policy's macro effect on stock returns. Section C.3 presents the correlations between each latent macro variable and measures of observable macro variables. Section C.4 shows how we measure the policy impact on inflation expectations. In Section C.5, we describe how to estimate pre- and post-policy variances in consumption.

We also perform a number of additional robustness tests. Section D.1 shows the event study regression results from further including a dummy that is one if the firm's output industry was protected on the coefficient estimate for each event. Section D.2 presents the event study regression results from using five-day event windows. Section D.3 presents the event study regression results from using Compustat China revenue shares instead. Section D.4 presents the event study regression results as the event study regression results from using five-day event windows.

Finally, we turn to additional details for the welfare calculations. Section E.1 describes how we reweight our sample of publicly listed firms using the size distribution of U.S. firms. Section E.2 provides details on how we used the stock-price data to calibrate the Perla et al. (2021) model.

A **Proofs of Propositions**

In this section, we provide details on the derivations for the proofs of each proposition.

A.1 Proof of Proposition 1

Proposition. 1 If the elasticity of substitution between labor and the specific factor for all firms is constant, the log change in wages equals the employment-share weighted average of the log changes in cash flow, 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 (1) and (2) yields:

$$\hat{y}_f = -\hat{a}_{Vf},\tag{A1}$$

and

$$\sum_{f} \frac{L_f}{L} \left(\hat{a}_{Lf} - \hat{a}_{Vf} \right) = \hat{L},\tag{A2}$$

Substituting equation (3) into equation (A2) yields

$$-\sum_{f} \frac{L_f}{L} \sigma \left(\hat{w} - \hat{r}_f \right) = \hat{L},\tag{A3}$$

or

$$\hat{w} = \sum_{f} \frac{L_f}{L} \hat{r}_f - \frac{\hat{L}}{\sigma}.$$
(A4)

Substituting equation (A1) into equation (3) yields

$$-\hat{y}_f - \hat{a}_{Lf} = \sigma \left(\hat{w} - \hat{r}_f \right) \tag{A5}$$

or

$$\hat{L}_f = \sigma \left(\hat{r}_f - \hat{w} \right) = \sigma \left(\hat{r}_f - \sum_{f'} \frac{L_{f'}}{L} \hat{r}_{f'} + \frac{\hat{L}}{\sigma} \right).$$
(A6)

Since the change in aggregate employment can be written as

$$\hat{L} = \sum_{f} \hat{L}_{f} L_{f},$$

we have

$$\hat{L} = \sigma \sum_{f} \left(\hat{r}_{f} - \sum_{f'} \frac{L_{f'}}{L} \hat{r}_{f'} + \frac{\hat{L}}{\sigma} \right) L_{f},$$
$$\hat{L} = \sigma \sum_{f} \left(\hat{r}_{f} L_{f} - L_{f} \sum_{f'} \frac{L_{f'}}{L} \hat{r}_{f'} \right) + \hat{L} \sum_{f} L_{f},$$
$$\hat{L} = \sigma L \sum_{f'} \frac{L_{f'}}{L} \hat{r}_{f'} - \sigma L \sum_{f'} \frac{L_{f'}}{L} \hat{r}_{f'} + \hat{L}L,$$

$$\hat{L} = \hat{L}L \Longrightarrow \hat{L} = 0$$

which establishes that

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

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A.1.1 Extension of Proposition 1 to Model Endogenous Aggregate Employment Rates

Starting with equation (A4) and defining \hat{P} to be the change in the consumer price level, we now can add an upward sloping labor supply curve by defining the log change in employment relative to some base level *L* as

$$\hat{L}^s = \rho \left(\hat{w} - \hat{P} \right),$$

where $\rho > 0$ denotes the slope of the labor supply curve. Substituting the expression for \hat{L}^s into equation (A4) gives us

$$\hat{w} = \left(\frac{\sigma}{\sigma + \rho}\right) \sum_{f} \frac{L_f}{L} \hat{r}_f + \left(\frac{\rho}{\sigma + \rho}\right) \hat{P},$$

which shows that the log change in wages now also depends on the log change in the price level. Substituting this expression into equation (A6) gives us

$$\hat{L}_f = \sigma \left(\hat{r}_f - \hat{w} \right) = \sigma \left(\hat{r}_f - \left(\frac{\sigma}{\sigma + \rho} \right) \sum_f \frac{L_f}{L} \hat{r}_f - \left(\frac{\rho}{\sigma + \rho} \right) \hat{P} \right).$$

This expression continues to show that the relative employment of a firm increases when it sees relatively higher returns to its specific factor. Thus, the relationship between log change in firm employment and returns to its specific factor in Proposition 1 is robust to allowing for an upward sloping labor supply curve.

A.2 Proof of Proposition 2

Proposition. 2 *If the expenditures on intermediate inputs are a constant fraction of sales, the log change in output is a linear combination of the log changes in returns to the specific factors:*

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

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

$$\omega_{Lf}\hat{a}_{Lf} + \omega_{Vf}\hat{a}_{Vf} + \sum_{i}\omega_{if}\hat{a}_{if} = 0.$$

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

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

Substituting this into equation (A5) yields

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

Substituting into equation (A1) gives us

$$-\hat{y}_{f} - \frac{\omega_{Vf}}{\omega_{Lf}}\hat{y}_{f} = \sigma\left(\hat{w} - \hat{r}_{f}\right)$$
$$\hat{y}_{f} + \frac{\omega_{Vf}}{\omega_{Lf}}\hat{y}_{f} = \sigma\left(\hat{r}_{f} - \hat{w}\right)$$
$$\hat{y}_{f}\left(1 + \frac{\omega_{Vf}}{\omega_{Lf}}\right) = \sigma\left(\hat{r}_{f} - \hat{w}\right)$$
$$\hat{y}_{f}\left(\frac{\omega_{Lf} + \omega_{Vf}}{\omega_{Lf}}\right) = \sigma\left(\hat{r}_{f} - \hat{w}\right)$$
$$\hat{y}_{f} = \frac{\omega_{Lf}\sigma}{\omega_{Lf} + \omega_{Vf}}\left(\hat{r}_{f} - \hat{w}\right)$$

Making use of our wage result from Proposition 1 gives us

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

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A.3 **Proof of Proposition 3**

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

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

The vectors of log changes in firm output prices and markups are given by $\hat{p} = A_1 \hat{r}$ and $\hat{\mu} = A_2 \hat{r}$, where the elements of the matrices A_i are combinations of the factor and input shares. If the share of total expenditures on intermediate inputs is constant, then

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

where \widehat{TFPR}_f is the log change in the firm's revenue total factor productivity. Finally, the vector of changes in quantity TFP (\widehat{TFP}) is given by $\widehat{TFP} = \mathbf{A}_3 \hat{\mathbf{r}}$.

Proof. In order to prove the first sentence in the proposition, we note that the sum of the input shares must equal one: $\omega_{Lf} + \omega_{Vf} + \sum_i \omega_{if} = 1$. Totally differentiating equation (4) and dividing both sides by p_f , we obtain

$$\omega_{Lf}\hat{w} + \omega_{Vf}\hat{r}_f + \sum_i \omega_{if}\hat{q}_i = \hat{p}_f.$$
(A7)

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

$$\hat{p}_{f}^{e} \equiv \frac{\hat{p}_{f} - \sum_{i} \omega_{if} \hat{q}_{i}}{1 - \sum_{i} \omega_{if}} = \theta_{Lf} \hat{w} + \theta_{Vf} \hat{r}_{f}, \tag{A8}$$

Using Proposition 1, we can rewrite equation (A8) as

$$\theta_{Lf} \sum_{f'} \frac{L_{f'}}{L} \hat{r}_{f'} + \theta_{Vf} \hat{r}_f = \frac{\hat{p}_f - \sum_i \omega_{if} \hat{q}_i}{1 - \sum_i \omega_{if}} \equiv \hat{p}_f^e.$$
(A9)

We prove the relationship between output prices and returns to the specific factor given in the second sentence of the proposition by noting that one firm's input price is another firm's output price, so $\hat{q}_i = \hat{p}_i$. Since cash flow equals payments to the specific factor, we have $\omega_{Lf}\hat{w} + \omega_{Vf}\hat{r}_f + \sum_i \omega_{if}\hat{p}_i = \hat{p}_f$ or $\omega_{Lf}\sum_f \frac{L_f}{L}\hat{r}_f + \omega_{Vf}\hat{r}_f = \hat{p}_f - \sum_i \omega_{if}\hat{p}_i$. We can write this more compactly in matrix form as $\Theta_1\hat{r} = \Theta_2\hat{p}$, where \hat{r} and \hat{p} are vectors of changes in returns to specific factors and prices; Θ_1 is a matrix defined as

$$\boldsymbol{\Theta}_{1} \equiv \begin{bmatrix} \omega_{V1} + \frac{\omega_{L1}L_{1}}{L} & \frac{\omega_{L1}L_{2}}{L} & \cdots & \frac{\omega_{L1}L_{F}}{L} \\ \frac{\omega_{L2}L_{1}}{L} & \omega_{V2} + \frac{\omega_{L2}L_{2}}{L} & \vdots \\ \vdots & & \ddots & \vdots \\ \frac{\omega_{LF}L_{1}}{L} & \cdots & \cdots & \omega_{VF} + \frac{\omega_{LF}L_{F}}{L} \end{bmatrix}$$

and Θ_2 is defined as

$$\boldsymbol{\Theta_2} \equiv \begin{bmatrix} 1 - \omega_{11} & -\omega_{12} & \cdots & -\omega_{1F} \\ -\omega_{21} & 1 - \omega_{22} & \vdots \\ \vdots & & \ddots & \vdots \\ -\omega_{F1} & \cdots & \cdots & 1 - \omega_{FF} \end{bmatrix}$$

Thus, we have $\hat{p} = A_1 \hat{r}$, where $A_1 \equiv \Theta_2^{-1} \Theta_1$

In order to derive how markups move with returns to the specific factor as stated in the second sentence, note that we can write the log of the firm's markup over marginal costs as

$$\ln \mu_f = \ln \frac{\left(p_f - c_f\left(w, 0, q_1, \dots, q_n\right)\right) y_f}{c_f\left(w, 0, q_{1f}, \dots, q_{nf}\right) y_f} = \ln \left(r_f V_f\right) - \ln \left[c_f\left(w, 0, q_1, \dots, q_n\right)\right] - \ln y_f.$$

Using the fact that the log change in $c_f(w, 0, q_1, ..., q_n)$ is the share of labor in variable costs (i.e., labor and materials) multiplied by the change in wages plus the share of each input *i*

in variable costs multiplied by the change in its price, we can write the log change in firm markups $(\hat{\mu}_f)$ as

$$\hat{\mu}_{f} = \hat{r}_{f} - \frac{\omega_{Lf}}{1 - \omega_{Vf}} \hat{w} - \frac{\sum_{i} \omega_{if} \hat{q}_{i}}{1 - \omega_{Vf}} - \hat{y}_{f}$$

$$= \hat{r}_{f} - \frac{\omega_{Lf}}{1 - \omega_{Vf}} \sum_{f'} \frac{L_{f'}}{L} \hat{r}_{f'} - \frac{\sum_{i} \omega_{if} \hat{q}_{i}}{1 - \omega_{Vf}} - \frac{\omega_{Lf} \sigma}{\omega_{Lf} + \omega_{Vf}} \left(\hat{r}_{f} - \sum_{f'} \frac{L_{f'}}{L} \hat{r}_{f'} \right),$$
(A10)

where we move to the second line by using Propositions 1 and 2 to express changes in wages (\hat{w}) and changes in firm output (\hat{y}_f) in terms of movements in the returns to specific factors. Similarly, if we define Ω to be a matrix whose elements are input requirements, so

then the third term in equation (A10) can be written in matrix form as $\Omega A_1 \hat{r}$. We can now express equation (A10) in matrix form as

$$\hat{\boldsymbol{\mu}} = \left(\boldsymbol{\Theta}_{\mathbf{3}} - \boldsymbol{\Omega} \mathbf{A}_{\mathbf{1}}\right) \hat{\boldsymbol{r}} = \mathbf{A}_{\mathbf{2}} \hat{\boldsymbol{r}},$$

where $\mathbf{A_2} \equiv (\mathbf{\Theta_3} - \mathbf{\Omega}\mathbf{A_1})$ and

$$\Theta_{3} \equiv \begin{bmatrix} 1 - \frac{\omega_{L1}L_{1}}{(1 - \omega_{V1})L} & -\frac{\omega_{L1}L_{2}}{(1 - \omega_{V1})L} & \cdots & -\frac{\omega_{L1}L_{F}}{(1 - \omega_{V1})L} \\ -\frac{\omega_{L2}L_{1}}{(1 - \omega_{V2})L} & 1 - \frac{\omega_{L2}L_{2}}{(1 - \omega_{V2})L} & \vdots \\ \vdots & & \ddots & \vdots \\ -\frac{\omega_{LF}L_{1}}{(1 - \omega_{VF})L} & \cdots & \cdots & 1 - \frac{\omega_{LF}L_{F}}{(1 - \omega_{VF})L} \end{bmatrix} \\ - \begin{bmatrix} \frac{\omega_{L1}\sigma}{\omega_{L1} + \omega_{V1}} & 0 & \cdots & 0 \\ 0 & \frac{\omega_{L2}\sigma}{\omega_{L2} + \omega_{V2}} & \vdots \\ \vdots & & \ddots & \vdots \\ 0 & \cdots & \cdots & \frac{\omega_{LF}\sigma}{\omega_{LF} + \omega_{VF}} \end{bmatrix} \begin{bmatrix} 1 - \frac{L_{1}}{L} & -\frac{L_{2}}{L} & \cdots & -\frac{L_{F}}{L} \\ -\frac{L_{1}}{L} & 1 - \frac{L_{2}}{L} & \vdots \\ \vdots & & \ddots & \vdots \\ -\frac{L_{1}}{L} & \cdots & \cdots & 1 - \frac{L_{F}}{L} \end{bmatrix}$$

In order to prove that the ERP equals productivity (the third sentence of the proposition), we multiply both sides of equation (4) by firm output (y_f) to obtain

$$p_f y_f - \sum_i m_{if} q_i = L_f w + V_f r_f,$$

where m_{fi} is the amount of intermediates of type *i* used in production. If we assume that the share of *total* expenditures on intermediate inputs in sales is constant (i.e., $\sum_i \omega_{if}$ is constant for each firm *f*), we can rewrite this as

$$p_f y_f - p_f y_f \sum_i \omega_{if} = L_f w + V_f r_f,$$

or

$$p_f y_f \left(1 - \sum_i \omega_{if} \right) = L_f w + V_f r_f,$$

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

$$(dp_f y_f + p_f dy_f) \left(1 - \sum_i \omega_{if}\right) = L_f dw + V_f dr_f + w dL_f + r_f dV_f.$$

Dividing through by $p_f y_f$ produces

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

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

$$\widehat{\text{TFPR}}_f \equiv \hat{p}_f + \hat{y}_f - \theta_{Lf}\hat{L}_f - \theta_{Vf}\hat{V}_f = \theta_{Lf}\hat{w} + \theta_{Vf}\hat{r}_f = \hat{p}_f^e,$$

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 TFPR.

Finally, we prove the last sentence by noting that the first sentence gives us $\hat{p}^e = \Theta_4 \hat{r}$, where

$$\boldsymbol{\Theta}_{4} \equiv \begin{bmatrix} \theta_{V1} + \frac{\theta_{L1}L_{1}}{L} & \frac{\theta_{L1}L_{2}}{L} & \cdots & \frac{\theta_{L1}L_{F}}{L} \\ \frac{\theta_{L2}L_{1}}{L} & \theta_{V2} + \frac{\theta_{L2}L_{2}}{L} & \vdots \\ \vdots & & \ddots & \vdots \\ \frac{\theta_{LF}L_{1}}{L} & \cdots & \cdots & \theta_{VF} + \frac{\theta_{LF}L_{F}}{L} \end{bmatrix};$$

the second sentence gives us $\hat{p} = A_1 \hat{r}$; and the third sentence gives us $\hat{p} + \widehat{\text{TFP}} = \hat{p}^e$. Combining these expressions gives us $\widehat{\text{TFP}} = \hat{p}^e - \hat{p} = (\Theta_4 - A_1) \hat{r} = A_3 \hat{r}$, where $A_3 \equiv (\Theta_4 - A_1)$.

B Data and Measurement Issues

B.1 Summary of Data Sources

Data	Description
event dates	Source: Factiva and Google search. See Section B.3 for details.
stocks	Source: CRSP. Daily close price, dividends, and market capitalization of stocks.

Data	Description
firm balance sheet items	Source: Compustat. We first obtain quarterly measures of gross sales [saleq], operating income after depreciation [oiadpq], interest expenses [xintq], cost of tangible fixed property used in the production of revenue less accumulated depreciation [ppentq], and the net value of intangible assets [intanq]. Profits or accounting cash flows are calculated by subtracting interest expenses [xintq] from operating income after depreciation [oiadpq]. For all variables except for ppentq and intanq, we sum across quarters to arrive at their annual values. For ppentq and intanq, we take their values from the last quarter as their annual values.
expected inflation rates	Source: Richard Crump based on Abrahams et al. (2016). Calculated based on the differences in yields between nominal bonds and inflation indexed bonds after making appropriate adjustments for liquidity, inflation risk, and real interest rate risk. See Section C.4 for details.
exchange rate index	Source: FRED. Federal Reserve's Trade Weighted U.S. Dollar Index: Broad, Goods and Services.
VIX	Source: FRED. CBOE Volatility Index.
supply chain	Source: Capital IQ and Bloomberg. Identity of the subsidiaries and major suppliers of each firm.
China Im- porter/Exporter	Source: Datamyne. Combined with supply chain data to determine whether each firm imported from or exported to China (via sea) in 2017 either directly or through a subsidiary/supplier.
China revenue share	Source: FactSet and Compustat. The share of each firm's revenue in 2018 from sales in China used in our baseline specification is from FactSet. We obtain an alternative measure for 2017 from Compustat, which we use in our robustness test in Section D.3. See Section B.5 for details on related data quality issues.
domestic firm employment	Source: Compustat and NETS. We first obtain firm-level annual employment from Compustat, which includes employment abroad for multinational firms. We merge this data with employment figures from NETS to obtain the domestic firm employment. See Section B.6 for details.

Data	Description
import values and tariffs	Source: U.S. Census Bureau, U.S. Trade Representative (USTR), and U.S. International Trade Commission (USITC). We obtain 2017 U.S. import values for each good (HTS10) and exporting country from the U.S. Census Bureau. We also obtain the pre- and post-policy tariffs at the same level from USTR and USITC. These are used to estimate the policy effect on expected tariff revenues in Section 4.1.
Fama-French factors	Source: Kenneth French's website. Fama-French 3 and 5 Factors [Daily].
US firm-size distribution (goods/services)	Source: U.S. Census Bureau. We obatin the U.S. employment shares of firms for each firm-size bin for goods (2-digit NAICS: 11, 21-23, and 22-33) and services (remaining 2-digit NAICS) sectors in 2017. The list of firm-size bins we use are listed in Figure 4. These employment shares are also used to reweight our sample of firms (see Section E.1 for details).
US firm-size distribution (NAICS4)	Source: U.S. Census Bureau. We obtain the U.S. employment shares of firms for each firm-size bin for 4-digit NAICS sectors in 2017. The list of firm-size bins we use are less than 100, 100-499, and more than 500 employees. These employment shares are also used to reweight our sample of firms to calculate the industry expected TFPR effect in Table 7.
industry labor productivity	Source: BLS. Annual real output per worker for each 4-digit NAICS industry.
VAR state variables	Source: FRED, Robert Shiller's website, and Kenneth French's website. We obtain the yield difference between 10-year and 3-month maturity treasury bills from FRED. The log price-earnings ratio (PE) is calculated by dividing the monthly average S&P 500 Index by the 12-month trailing average S&P 500 earnings obtained from Robert Shiller's website. The difference in book-to-market ratios of value and growth stocks (BMS) is constructed using data from Kenneth French's website (see Section C.2 for details).

Data	Description
labor and specific-factor shares	Source: Compustat and BEA Input-Output table. Firm cash flow as a share of revenue is calculated by dividing accounting cash flows with gross sales (see third row of this table for definitions) in 2017, obtained from Compustat. We use the BEA's 450-by-450 industry (6-digit NAICS) IO table in 2012 to construct labor and materials shares of revenue. In Section B.6, we describe how we combine all of these shares to construct the labor and specific-factor shares of value added (θ_{Lf} and θ_{Vf}).
economic surprise variables	Source: Daniel Lewis based on Lewis et al. (2019). The difference between a macroeconomic data release value and the Bloomberg median of economists' forecast on the previous day. The 65 series we use to construct our economic surprise variables 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 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.

B.2 Sample Statistics

	Ν	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

Table B.2: Descriptive Statistics

Note: $\hat{\epsilon}_{ft}$ is the abnormal return estimated from equation (21). 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 (from Factset). 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 equal to when a firm's 6-digit NAICS code is affected by the U.S. tariff announcement.

B.3 Event Dates

The following table presents the event dates (i.e., the date of the first news report of each increase in tariffs), the date that new tariffs would be implemented, event group, and the news link of each event. The earliest event date was identified via Factiva and Google Search.

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

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

B.4 Construction of Figure 2

In order to construct Figure 2, we consider four outcome variables $X_t \in \{\hat{R}_t, E_t [\hat{P}^{10}], XR_t, VIX_t\}$. $\hat{R}_t \equiv \sum_f S_{f,t-1} \hat{R}_{ft}$ is the average log change in stock prices of firms in our sample on day t, weighted by their market capitalization on the previous day $S_{f,t-1}$. $E_t [\hat{P}^{10}] \equiv 10 \times (\hat{\pi}_t^{10} - \hat{\pi}_{t-1}^{10})$ is the expected price change on day t based on the 10-year inflation expectation discussed in Section C.4. XR_t is the exchange-rate index (Federal Reserve's Trade Weighted U.S. Dollar Index: Broad, Goods, and Services) on day t. The exchange-rate index is measured in foreign currency per dollar, so higher values correspond to dollar appreciation. VIX_t is an index that measures the expected volatility of the U.S. stock market on day t.

We construct the point estimates used in the figure as follows. 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 using observations between January 1, 2016 and December 31, 2019 for $X_t \in \{\hat{R}_t, E_t [\hat{P}^{10}], XR_t, VIX_t\}$:

$$X_t = \alpha^X + \sum_{s=-5}^{5} \beta_s^X D_{jts} + \epsilon_t^X.$$

 $\hat{\beta}_s^X$ is our estimate of the movement in X_t , s days from an event. Since we have 11 events, the cumulative movement of X_t , from their average level, s days from the event is given by

$$\psi_s^X \equiv 11 \sum_{k=-5}^{s} \hat{\beta}_k^X. \tag{B1}$$

Figure 2 then plots ψ_s^X for $s \in [-5, 5]$ and for each $X_t \in \{\hat{R}_t, E_t \left[\hat{P}^{10} \right], XR_t, VIX_t \}$.

B.5 FactSet Data Quality Issues

There are two potential issues with the FactSet data. First, 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). 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.

Second, we were unable to access the 2017 FactSet data. Instead, about 90 percent of the observations correspond to 2018, and the rest 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. For this robustness, we construct our China revenue-share variable using firms' direct disclosures of foreign sales in 2017 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, we show the robustness to using these data in Section D.3.

B.6 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. To do this, we first used 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. domestic employment. 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 equals 1 if the firm was an exporter to China, and the share of foreign revenues for the firm from FactSet. The regression results are presented in Table B.4. We then multiplied the ratio between the multinational firm's predicted domestic employment and its Compustat employment in 2014 by its Compustat employment in 2017 to estimate its domestic employment in 2017. These are the employment numbers we use to assign firms to different firm-size bins in Section E.1.

In order to construct the labor and specific-factor share variables (θ_{Lf} and θ_{Vf}), we set $r_f V_f / (p_f y_f)$ equal to the firm's operating 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 450×450 Bureau of Economic Analysis Input-Output table (the most recently available disaggregated IO

¹Operating income after depreciation equals firm revenue less cost of goods sold, sales, general and administrative expenses and 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.

	(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
Ν	612

Table B.4: Estimating U.S. Employment for Multinational Firms

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 (7) to construct θ_{Lf} and θ_{Vf} . In order to compute \overline{RV}_b , which is used in equation (E4), 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.

C Estimation

C.1 Summary of Estimating Equations, Observables, and Unobservables

The following tables summarize our main estimating equations of the factor model and the treatment effects, describing each variable and indicating whether it is observed or estimated.

Equation Estimation Ng (2002)	(21): $\hat{R}_{ft} = \alpha_f + \sum_{k=1}^{K} \beta_{kf} \delta_{kt} + \epsilon_{ft}$ n Method: principal components method following Bai and
Variable	Description
\hat{R}_{ft}	Observed log change in asset prices of firm f on day t ; asset prices on
	day t include dividend payments issued on the same day
$lpha_f$	Estimated parameter that captures firm f 's average return over the
	sample period
δ_{kt}	Estimated parameter that captures the level of the k^{th} latent macro
100	variable on day t
β_{kf}	Estimated parameter that captures the sensitivity of firm f 's returns to
,,	the k^{th} latent macro variable δ_{kt}
ϵ_{ft}	Error term; firm f 's abnormal return on day t
\ddot{K}	Estimated total number of latent macro variables; obtained from
	minimizing equation (24) following Bai and Ng (2002)

Equation (22): $\epsilon_{ft} = \sum_{j \in \Omega^{UC}} \sum_{i=1}^{N} \gamma_{ij} Z_{fi} D_{jt}^{\mathcal{L}} + \xi_t D_{jt}^{\mathcal{L}} + \tilde{\nu}_{ft}$ Estimation Method: OLS regression

Variable	Description
ϵ_{ft}	Error term from equation (21); firm f 's abnormal return on day t
γ_{ij}	Estimated parameter that captures how exposure variable <i>i</i> affects the
	average daily abnormal returns of exposed firms within an event
	window of length \mathcal{L} for event j
Z_{fi}	Observed firm f 's exposure to trade with China through channel i . We
	use three different exposure variables in our main specification: a
	dummy equal to one if it imports from China; a dummy equal to one if
	it exports to China; and the share of revenue it derives from China
$D_{it}^{\mathcal{L}}$	Dummy variable that equals one if day <i>t</i> falls within the event window
5	of length \mathcal{L} around event j
ξ_t	Estimated parameter that captures the average idiosyncratic market
	movement on day <i>t</i> that cannot be explained by either the factor model
	given in equation (21) or the exposure of the firm to China given in
	equation (22)
$ ilde{ u}_{ft}$	Error term for firm f on day t

C.2 Return Decomposition

Campbell and Shiller (1988) develop a log-linear approximate present-value decomposition that allows for time-varying cash flows and discount rates that we follow. Let x_t and d_t denote the price and dividend of an asset in period t, respectively. A first-order Taylor expansion of a return in period t + 1, \hat{R}_{t+1} , around its mean log dividend-price ratio

 $(\overline{\log d_t} - \log x_t)$ is given by:

$$\hat{R}_{t+1} \equiv \log(x_{t+1} + d_{t+1}) - \log(x_t) \approx k + \rho \log(x_{t+1}) + (1 - \rho) \log(d_{t+1}) - \log(x_t),$$

where $\rho \equiv 1/(1 + \exp(\log d_t - \log x_t))$ and $k \equiv -\log(\rho) - (1-\rho)\log(1/\rho-1)$ are parameters of linearization. Campbell (1991) extends this approach to decompose the returns of an asset as follows:

$$\hat{R}_{t+1} = \underbrace{(E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta \log d_{t+1+j}}_{\equiv \hat{R}_{t+1}^{CF}} - \underbrace{(E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \hat{R}_{t+1+j}}_{\equiv \hat{R}_{t+1}^{DR}} + \underbrace{E_t \hat{R}_{t+1}}_{\equiv \hat{R}_{t+1}^{E}}.$$
(C1)

The first term \hat{R}_{t+1}^{CF} captures news about future cash flows while the second term \hat{R}_{t+1}^{DR} captures news about future discount rates. \hat{R}_{t+1}^{E} is simply the expected return at t + 1 based on information available at time t. The decomposition makes clear that an increase in expected future cash flows leads to higher unexpected returns whereas an increase in expected future discount rates leads to lower unexpected returns. Only in a special case in which discount rates are constant over time, can movements in unexpected returns be fully attributed to changes in expected cash flows.

Campbell and Vuolteenaho (2004) apply this decomposition to market returns, $\hat{R}_{M,t+1}$, and use a vector-autoregression (VAR) model to obtain estimates of $\hat{R}_{M,t+1}^{CF}$, $\hat{R}_{M,t+1}^{DR}$, and $\hat{R}_{M,t+1}^{E}$. Specifically, consider the following VAR model

$$z_{t+1} = a + \Gamma z_t + u_{t+1},$$
 (C2)

where z_{t+1} is an *m*-by-1 state vector; *a* and Γ are an *m*-by-1 vector and an *m*-by-*m* matrix of parameters respectively; and u_{t+1} is an i.i.d. *m*-by-1 vector of shocks. They include the market returns as the first state variable along with other known predictors of market returns to estimate the VAR model. Then, they form estimates of the discount rate news, cash flow news, and expected components as

$$\hat{R}_{M,t+1}^{DR} = -e'_1 \lambda u_{t+1} = -e'_1 \sum_{j=1}^{\infty} \rho^j \Gamma^j u_{t+1}$$
$$\hat{R}_{M,t+1}^{CF} = (e'_1 + e'_1 \lambda) u_{t+1}$$
$$\hat{R}_{M,t+1}^E = e'_1 (a + \Gamma z_t).$$

Here, e_k denotes a vector whose k^{th} element is 1 and the remaining elements are zero and $\lambda \equiv \rho \Gamma (I - \rho \Gamma)^{-1}$. Since the market return is included as the first state variable, $e'_1 \lambda$ captures the long-run significance of each VAR shock to discount-rate expectations.

We adapt the approach of Campbell and Vuolteenaho (2004) to our setting and rely on a VAR model to form estimates for the components of our latent macro factors δ_{kt} that are associated with expected cash flows δ_{kt}^{CF} , expected discount rates δ_{kt}^{DR} , and expected factor movements δ_{kt}^{E} , where

$$\delta_{kt} = \delta_{kt}^{CF} + \delta_{kt}^{DR} + \delta_{kt}^{E} \tag{C3}$$

for k = 1, ..., K. For the VAR model, we first include our four latent macro factors (after orthogonalizing them on the surprise variables²) in the state vector z_{t+1} along with a number of known predictors of market returns that we specify later. Once we have performed the decomposition in equation (C3), we calculate the share of each latent macro variable's effect on stock returns (i.e., $\beta_{kf}\delta_{kt}$) that is associated with changes to expected cash flows as $\eta_{kt}^{CF} = \delta_{kt}^{CF} / \delta_{kt}$ for each day *t*.

An added complication in our setting is the fact that we analyze daily movements in our latent macro factors, which requires the other state variables to be observed at the daily frequency. Unfortunately, many of the predictors of market returns used in previous studies are only available at the monthly frequency at best. To work around this issue, we first estimate the VAR model in equation (C2) at the monthly frequency as in Campbell and Vuolteenaho (2004) and form estimates for the three components as

$$\tilde{\delta}_{k,t+1}^{DR} = e'_k \lambda u_{t+1} = e'_k \sum_{j=1}^{\infty} \rho^j \Gamma^j u_{t+1}$$
$$\tilde{\delta}_{k,t+1}^{CF} = (e'_k + e'_k \lambda) u_{t+1}$$
$$\tilde{\delta}_{k,t+1}^E = e'_k (a + \Gamma z_t)$$

for k = 1, ..., K.³ The tildes denote that the variables are observed at the monthly frequency. We then regress the cash-flow component $(\tilde{\delta}_{kt}^{CF})$ on the overall factor movement $(\tilde{\delta}_{kt})$ to estimate how they covary with one another. The resulting OLS coefficient is given by $\eta_k^{CF} = cov(\tilde{\delta}_{kt}^{CF}, \tilde{\delta}_{kt})/var(\tilde{\delta}_{kt})$. We then use this OLS coefficient to predict the cash-flow component at the daily frequency:

$$\hat{\delta}_{kt}^{CF} = \eta_k^{CF} \delta_{kt},$$

and note that $\eta_k^{CF} = \hat{\delta}_{kt}^{CF} / \delta_{kt}$ can be interpreted as an estimate of the average share of each latent macro variable's effect on stock returns that is associated with changes to expected cash flows.

We can similarly estimate $\eta_k^{DR} = cov(\tilde{\delta}_{kt}^{DR}, \tilde{\delta}_{kt})/var(\tilde{\delta}_{kt})$ and predict the discount-rate component at the daily frequency:

$$\hat{\delta}_{kt}^{DR} = \eta_k^{DR} \delta_{kt},\tag{C4}$$

and note that $\eta_k^{DR} = \hat{\delta}_{kt}^{DR} / \delta_{kt}$ can be interpreted as an estimate of the average share of each latent macro variable's effect on stock returns that is associated with changes to expected discount rates.

$$\hat{r}_{ft}^{CF} \equiv \sum_{t} \sum_{k} \eta_k^{CF} \beta_{kf} \delta_{kt} + \hat{r}_{ft}^T, \quad \text{where } \hat{r}_{ft}^T \equiv \sum_{j \in \Omega^{UC}} \sum_{i=1}^N \gamma_{ij} Z_{fi} D_{jt}^{\mathcal{L}},$$

²Since movements in the δ_{kt} can occur due to macro data releases unrelated to the event, we exclude the impact of this type of information on the δ_{kt} . We regress the latent macro variables, δ_{kt} , on the 65 economic surprise variables listed in Section B.1 and use the residuals as our measure of δ_{kt} in the VARs.

³We follow Campbell and Vuolteenaho (2004) and set $\rho = 0.95^{1/12}$ to reflect a per annum discount factor of 0.95.

In our baseline specification, we include three additional variables in the state vector. The first is the yield difference between 10-year and 3-month maturity treasury bills (TY) obtained from the Federal Reserve Economic Data (FRED). The second is the log priceearnings ratio (PE) calculated by dividing the monthly average S&P 500 Index by the 12-month trailing average S&P 500 earnings obtained from Robert Shiller's website.⁴ The third is the difference in book-to-market ratios of value and growth stocks (BMS). This variable is constructed using data from Kenneth French's website. He forms portfolios of value (high book-to-market, top 30%) and growth (low book-to-market, bottom 30%) stocks at the end of June of each year *t* based on book values for the last fiscal year ending in t - 1 and market values (price times shares outstanding) at the end of December in year t - 1. These values are used to calculate the value-weighted average book-to-market ratios for the last day of July each year. Then, for the days between the first day of July in year *t* to the last day of June in year t + 1, the market values are updated using daily value-weighted returns.⁵

Table C.1: Estimated V	'AK Model
------------------------	-----------

	factor1	factor2	factor3	factor4	ΤY	PE	BMS
L.factor1	-0.251*	0.051	0.335**	0.172	16.710**	3.871**	6.618**
	(0.147)	(0.130)	(0.137)	(0.117)	(7.858)	(1.505)	(2.925)
T () O	0.107	0.070*	0.00	0.004	6 400	0.000	0.007
L.factor2	-0.107	-0.270*	0.026	0.204	-6.498	0.282	-3.287
	(0.167)	(0.148)	(0.156)	(0.133)	(8.948)	(1.713)	(3.331)
I factor?	0 162	0.081	0.012	0.004	2 767	1 216	Q 1Q1***
L.Iactor5	(0.102)	-0.001	0.013	0.004	(7,707	1.210	-0.404
	(0.145)	(0.129)	(0.136)	(0.116)	(7.783)	(1.490)	(2.897)
L.factor4	-0.046	0.315*	0.244	-0.165	-16.395	0.903	10.706***
	(0.195)	(0.173)	(0.182)	(0.155)	(10.434)	(1.998)	(3.884)
	((()	()	((()
L.TY	0.001	-0.001	-0.000	0.001	0.959***	0.016**	-0.037***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.034)	(0.007)	(0.013)
	. ,	. ,	. ,	. ,	. ,	. ,	
L.PE	-0.005	0.008	0.003	-0.013**	0.577	0.838***	0.041
	(0.007)	(0.006)	(0.006)	(0.005)	(0.353)	(0.068)	(0.132)
L D) (0	a aa a		0.001	0.000	0.400		0.040
L.BMS	0.003	-0.000	0.001	-0.009***	0.433^{**}	0.055	0.860***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.183)	(0.035)	(0.068)
R2	.154	.139	.139	.273	.964	.902	.884
Ν	47						

Standard errors in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

The estimated VAR model reported in Table C.1 has comparable explanatory power as that of Campbell and Vuolteenaho (2004), with the R^{2} 's for the first four factors being

⁴Campbell and Vuolteenaho (2004) use 10-year trailing average earnings to construct the price-earnings ratio. We follow the discussion in Chen and Zhao (2009) and instead use the 12-month trailing average earnings, which is more commonly used.

⁵Campbell and Vuolteenaho (2004) use the spread in book-to-market ratios of small value and growth stocks. We follow the recommendation of Chen and Zhao (2009) and instead use the spread between value and growth stocks of all sizes, which is more commonly used.

0.15, 0.14, 0.14, and 0.27, respectively. For the first and second factors, their respective lagged values have some predictive power although they are only statistically significant at the 10% level. The lag of the fourth factor also has predictive power over the second factor that is only statistically significant at the 10% level. For the third factor, the lag of the first factor has statistically significant predictive power. For the fourth factor, the lagged values of PE and BMS are both statistically significant predictors.

C.3 Correlation Between Latent and Observed Macro Variables

Table C.2 presents the correlations between the four latent macro variables that we estimate (labeled factor1-factor4), and the macro variables that we discuss in Figure 2.

	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***

Table C.2: Correlation Matrix

C.4 Measuring the Policy Impact on Expected Inflation

The estimation procedures described thus far enable us to measure all of the nominal variables in the equilibrium, but we still need to address how to identify movements in consumer prices and therefore real wages and welfare. We start with estimates of the 5- and 10-year expected inflation rates from Abrahams et al. (2016), which are calculated based on the differences in yields between nominal bonds and inflation indexed bonds after making appropriate adjustments for liquidity, inflation risk, and real interest rate risk. We denote their *Y*-year estimate of annual expected inflation on day *t* as $\hat{\pi}_t^Y$. The implied change in the *price level* over *Y* years is therefore *Y* times the change in average annual inflation rates, or $Y \hat{\pi}_t^Y$. Similarly, $(\hat{\pi}_t^Y - \hat{\pi}_{t-1}^Y)$ is the change in expected annual inflation on day *t* based on the prices of *Y*-year bonds, and $Y (\hat{\pi}_t^Y - \hat{\pi}_{t-1}^Y)$ is the associated expected change in the price level over *Y* years. Therefore, the expected impact of a set of policy announcements indexed by *j* on the price level (relative to its expectation the previous day) is

$$E\left[\hat{P}|\boldsymbol{\tau}\right] = \sum_{j} \sum_{t} \left[Y\left(\hat{\pi}_{t}^{Y} - \hat{\pi}_{t-1}^{Y}\right) \right] D_{jt}^{\mathcal{L}}.$$
(C5)

The overall expected change in the price level due to the tariff announcements is then the cumulative change revealed in the data as we sum across all days contained in any event window.

As with our estimates of $\hat{\delta}_{kt}$, we filter out the impact of economic surprises that are unrelated to policy by first estimating

$$Y\left(\hat{\pi}_{t}^{Y} - \hat{\pi}_{t-1}^{Y}\right) = \alpha^{Y} + \sum_{i=1}^{\overline{N}} \beta_{i}^{Y} E S_{it} + \epsilon_{t}^{\pi}, \tag{C6}$$

and then run the following regression:

$$\hat{\epsilon}_t^{\pi} = \alpha^{\pi} + \gamma^{\pi} \sum_{j \in \Omega^{UC}} D_{jt}^{\mathcal{L}} + \epsilon_t', \tag{C7}$$

where α^{π} and γ_{j}^{π} are parameters to be estimated. In this specification, γ^{π} tells us the average change in the expected price level *Y* years in the future during a day in one of the event windows. Our estimate of the impact of the tariff announcement on all the trade-war events on expected inflation is therefore

$$\hat{P}(\boldsymbol{\tau}) = N^w J \gamma^\pi, \tag{C8}$$

where N^w is the number of days in the window; and J is the number of events.

C.5 Measuring Consumption Variance

In order to compute the change in the variance of consumption before and after the announcements, we start with equation (28) and express it on a daily basis:

$$\hat{r}_{ft} = \hat{r}_{ft}^M + \hat{r}_{ft}^T$$

The macro effect on expected cash-flows on any day *t* is given by $\hat{r}_{ft}^M = \sum_k \beta_{kf} \delta_{kt}^{CF}$. We also estimate the treatment effect on *any* day by running the following regression:

$$\epsilon_{ft} \equiv \sum_{i=1}^{N} \gamma_{it} Z_{fi} D_t + \xi_t D_t + \nu_{ft},$$

where D_t is a dummy variable that is 1 on day t. Following equation (27), we can write the treatment effect on any day t as

$$\hat{r}_{ft}^T \equiv \sum_{i=1}^N \gamma_{it} Z_{fi} D_t.$$
(C9)

Note that on non-event days, we should expect γ_{it} to be non-zero only if expectations about tariff policy changed on those days.

In order to compute the change in expected consumption determined by these expected cash-flow movements, we start with equation (15) and express it on a daily basis:

$$\hat{C}_t = \frac{wL}{I} \sum_f \frac{L_f}{L} \hat{r}_{ft} + \sum_f \frac{r_f V_f}{I} \hat{r}_{ft} + \frac{TR}{I} \widehat{TR}_t - \hat{P}_t.$$
(C10)

We assume that changes in expected tariff revenues only happen on U.S. event days and that they move evenly on these days, so

$$\widehat{TR}_{t} = \begin{cases} \widehat{TR}(\boldsymbol{\tau}) / 18 & \forall t \text{ such that } \max_{j \in \Omega^{U}} D_{jt}^{\mathcal{L}} = 1 \\ 0 & \text{otherwise} \end{cases}$$

where $\widehat{TR}(\tau)$ is the estimate of expected change in tariff revenues we compute in Section 4. We then set $\hat{P}_t = \epsilon_t^{\pi}$, where ϵ_t^{π} is estimated in equation (C6).

We compute the consumption variance by first assuming that the average change in consumption on each day within a particular type of event (i.e., an increase in U.S. or Chinese tariffs) has its own mean. We can compute these means by running the following regression using the data for all days t and s such that $D_{jt}^{\mathcal{L}} = 1$ for some j:

$$\hat{C}_t = \sum_{s=-1}^{\mathcal{L}-2} \sum_{j \in \Omega^U} \alpha_s^U I_{jts} + \sum_{s=-1}^{\mathcal{L}-2} \sum_{j \in \Omega^C} \alpha_s^C I_{jts} + \epsilon_t^C,$$

where I_{jts} is an indicator variable that is 1 if day t = j + s; $\mathcal{L} \ge 1$ denotes the length of the event window in days; and α_s^U and α_s^C tell us the mean movement of consumption on day s in U.S. and Chinese event, respectively. The number of observations in this regression will equal $\mathcal{L} |\Omega^{UC}| - \mathcal{N}$, where \mathcal{N} denotes the number of days that fall in two event days. We then compute our estimate of the variance of consumption during event windows as

$$\hat{\sigma}_{\tau}^{2} = \left(\mathcal{L}\left|\Omega^{UC}\right| - \mathcal{N} - 1\right)^{-1} \sum_{t} \left(\hat{\epsilon}_{t}^{C} - \frac{1}{\mathcal{L}\left|\Omega^{UC}\right| - \mathcal{N}} \sum_{s} \hat{\epsilon}_{s}\right)^{2}.$$

We use an analogous procedure to estimate the variances in consumption before the event window. We first drop any event j that is less than \mathcal{L} days after another event j'. We do this by dropping all events j in which $D_{jt-s}^{\mathcal{L}} = D_{j't}^{\mathcal{L}} \quad \forall j'$ and $s \in \{2, \mathcal{L} + 2\}$. We define the remaining set of events as Ω' . We now estimate the mean movements on days before events by running the following regression for all $j \in \Omega'$ and $t \in \{j - \mathcal{L} - 1, j - 2\}$

$$\hat{C}_t = \sum_{s=2}^{\mathcal{L}+2} \sum_{j \in \Omega'} \alpha_s^B I_{j-s,t}^B + \epsilon_t^B,$$

where $I_{j-s,t}^B$ is a dummy that is one if day t = j - s; α_s^B is our estimate of the mean movement in consumption *s* days before an event; and ϵ_t^B is the error term. Just as before, our estimate of the variance of consumption on any event day *t* is

$$\hat{\sigma}_{0}^{2} = \left(\mathcal{L}\left|\Omega'\right| - 1\right)^{-1} \sum_{t} \left(\hat{\epsilon}_{t}^{B} - \frac{1}{\mathcal{L}\left|\Omega'\right|} \sum_{s} \hat{\epsilon}_{s}^{B}\right)^{2}$$

Our estimate of consumption variance across all events, $\hat{\sigma}_{C\tau}^2$ is simply the sum of the variances on each day within the event windows, i.e., $\hat{\sigma}_{C\tau}^2 = \mathcal{L} \left| \Omega^{UC} \right| (\hat{\sigma}_{\tau}^2)$.⁶ Similarly, our estimate of the consumption variance before the events is $\hat{\sigma}_{C0}^2 = \mathcal{L} \left| \Omega^{UC} \right| (\hat{\sigma}_0^2)$. Therefore, the increase in variance across all these events is given by

$$\underline{\hat{\sigma}_{C\tau}^2 - \hat{\sigma}_{C0}^2} = \mathcal{L} \left| \Omega^{UC} \right| \left(\hat{\sigma}_{\tau}^2 - \hat{\sigma}_{0}^2 \right).$$

⁶We are implicitly making the assumption that $\text{Cov}(\epsilon_t, \epsilon_s) = 0$ when $t \neq s$. We checked the data for the most plausible violation of this covariance—autocorrelation of the errors within an event window—by regressing ϵ_t^C on ϵ_{t-1}^C if $D_{jt}^{\mathcal{L}} = D_{j,t-1}^{\mathcal{L}}$, i.e., both days t and t - 1 fall into the same event window. We would expect a positive coefficient if it takes the market time to absorb the information surrounding an event (e.g., past errors predict future errors) and a negative coefficient if market reactions to tariff announcements exhibit overshooting. We found that the coefficient on the lagged error is 0.064 with a t-statistic of 0.28. Thus, our assumption of zero covariance is borne out in the data.

D Robustness

D.1 Disaggregated Industry Protected Specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Cumulative	22Jan18	28Feb18	29May18	19Jun18	06May19	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)

Table D.1: Robustness Tests (Industry Protected)

Note: This table presents the estimated coefficients on the U.S. events obtained from estimating equation (22) as in Table 4, except we also include the dummy variable Industry Protected equal to 1 if the firm's main NAICS 6-digit industry is affected by the tariff announcement. Day fixed effects are not reported. The dependent variable ($\hat{\epsilon}_{ft} \times 100$) is the abnormal return obtained from estimating equation (21) 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 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 80,674.

D.2 Robustness to Using Five-Day Window

Table D.2: Impact of U.S. Tariffs Announcements on Stock Returns (Five-Day Window)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Cumulative	22Jan18	28Feb18	29May18	19Jun18	06May19	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 (22) using five-day windows; the estimated coefficients for the Chinese events are presented in Table D.3. The dependent variable ($\hat{\epsilon}_{ft} \times 100$) is the abnormal return obtained from estimating equation (21) 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 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.

	(1)	(2)	(3)	(4)	(5)	(6)
	Cumulative	22Mar18	15Jun18	02Aug18	13May19	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)

Table D.3: Impact of Chinese Tariff Announcements on Stock Returns (Five-Day Window)

Note: This table presents the estimated coefficients on the Chinese events obtained from estimating equation (22) using five-day windows; the estimated coefficients for the U.S. events are presented in Table D.2. The number of observations is therefore the same as in Table D.2. The dependent variable ($\hat{\epsilon}_{ft} \times 100$) is the abnormal return obtained from estimating equation (21) 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 Chinese 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.

D.3 Robustness to Using 2017 Compustat China Revenue Shares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Cumulative	22Jan18	28Feb18	29May18	19Jun18	06May19	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 D.4: Impact of U.S. Tariff Announcements on Stock Returns (2017 Compustat China Revenue Share)

Note: This table presents the estimated coefficients on the U.S. events obtained from estimating equation (22) using Compustat data for the China Revenue Share instead of FactSet; the estimated coefficients for the Chinese events are presented in Table D.5. Day fixed effects are not reported. The dependent variable $(\hat{e}_{ft} \times 100)$ is the abnormal return obtained from estimating equation (21) 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 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 80,674.

	(1)	(2)	(3)	(4)	(5)	(6)
	Cumulative	22Mar18	15Jun18	02Aug18	13May19	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)

Table D.5: Impact of Chinese Tariff Announcements on Stock Returns (2017 Compustat China Revenue Share)

Note: This table presents the estimated coefficients on the Chinese events obtained from estimating equation (22) using Compustat data for the China Revenue Share instead of FactSet; the estimated coefficients for the U.S. events are presented in Table D.4. Day fixed effects are not reported. See the notes to Table D.4 for variable definitions and the number of observations. Column 1 presents the cumulative effect of the coefficients on each of the Chinese 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.

Tables D.4 and D.5 show that our event study results remain very similar when we use the Compustat China revenue shares instead of the FactSet data. 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.

D.4 Estimating the Expected TFPR Effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Cumulative	22Jan18	28Feb18	29May18	19Jun18	06May19	01Aug19
China Importer	-0.84***	-0.05***	-0.06***	-0.00***	-0.04***	-0.07***	-0.05***
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
China Exporter	-0.88***	-0.03***	0.01	-0.08***	-0.16***	-0.04***	0.01
-	(0.05)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
China Revenue Share	-4.06***	-0.38***	-0.08***	-0.06***	-0.26***	-0.41***	-0.16***
	(0.13)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

Table D.6: Impact of U.S. Tariff Announcements on TFPR

Note: This table presents the estimated coefficients on the U.S. events obtained from estimating equation (22) using the daily firm-level expected TFPR effect calculated using equation (29) multiplied by 100 as the dependent variable. The estimated coefficients for the Chinese events are presented in Table D.7. Day fixed effects are not reported. 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 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 80,674.

	(1)	(2)	(3)	(4)	(5)	(6)
	Cumulative	22Mar18	15Jun18	02Aug18	13May19	23Aug19
China Importer	-0.40***	-0.07***	0.02***	0.02***	-0.06***	-0.05***
	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
China Exporter	-0.59***	-0.02	-0.03***	-0.07***	-0.02***	-0.06***
-	(0.05)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
China Revenue Share	-4.15***	-0.28***	-0.19***	-0.38***	-0.41***	-0.12***
	(0.14)	(0.03)	(0.01)	(0.02)	(0.01)	(0.01)

Table D.7: Impact of Chinese Tariff Announcements on TFPR

Note: This table presents the estimated coefficients on the Chinese events obtained from estimating equation (22) using the daily firm-level expected TFPR effect calculated using equation (29) multiplied by 100 as the dependent variable. The estimated coefficients for the U.S. events are presented in Table D.6. Day fixed effects are not reported. See the notes to Table D.6 for variable definitions and the number of observations. Column 1 presents the cumulative effect of the coefficients on each of the Chinese 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.

In Tables D.6 and D.7, we show that the effect of trade-war announcements are even larger on TFPR than abnormal returns. For example, while our import exposure variable was generally not a significant driver of abnormal returns following five out of six tariff announcements (see Table D.6), we see that these announcements led to significant declines in expected TFPR of exposed firms in all cases of U.S. protection. Similarly, Chinese retaliation announcements caused the expected TFPR of U.S. exporters to fall significantly in four out of five cases and always had a significant negative impact on the expected TFPR of firms selling in China. In order to give some sense of the economic magnitudes of these effects, we again consider the cumulative impact of these announcements on a firm that both imported from and exported to China and had revenue of 4 percent coming from China (equal to the average). Such a firm would have experienced a 3.0 percentage point drop in its expected TFPR.

E Welfare

E.1 Sampling

Since the sample of firms that report stock prices is not representative of the size distribution of U.S. firms, we need to re-weight the data before computing $\hat{w}(\tau)$ and $\sum_{f} \frac{r_f V_f}{I} \hat{r}_f(\tau)$ in equation (15). We know the share of U.S. workers employed in each firm-size bin *b* in the U.S. economy. In our baseline specification, we set the policy's impact on expected cash-flows for all U.S. firms in size bin *b* ($\hat{r}_b(\tau)$) as equal to the average effect for publicly listed firms in the same bin:

$$\hat{r}_{b}(\boldsymbol{\tau}) = E\left[\hat{r}_{f}(\boldsymbol{\tau}) | f \in \Omega_{b}\right],$$
(E1)

where Ω_b is the set of firms in our sample that belong to bin *b*. We explore alternative assumptions in Section 5.3. We use an identical procedure to compute the macro effects by bin $(\hat{r}_b^M(\boldsymbol{\tau}))$ and the treatment effects by bin $(\hat{r}_b^T(\boldsymbol{\tau}))$ on expected cash-flows. We then have

$$\hat{w}(\boldsymbol{\tau}) = \sum_{b} s_{b} \hat{r}_{b}(\boldsymbol{\tau}) = \sum_{b} s_{b} \hat{r}_{b}^{M}(\boldsymbol{\tau}) + \sum_{b} s_{b} \hat{r}_{b}^{T}(\boldsymbol{\tau}), \qquad (E2)$$

where s_b is the share of employees in bin b and $\sum_b s_b = 1$, $\hat{w}^M(\tau) \equiv \sum_b s_b \hat{r}_b^M(\tau)$ is the macro effect on expected wage, and $\hat{w}^T(\tau) \equiv \sum_b s_b \hat{r}_b^T(\tau)$ is the treatment effect on expected wage.

Similarly, we can use equation (29) to write the effect on expected TFPR for firms in bin *b*:

$$\begin{aligned} \bar{\mathrm{TFPR}}_{b}\left(\boldsymbol{\tau}\right) &= \theta_{Lb'}\hat{w}\left(\boldsymbol{\tau}\right) + \theta_{Vb'}\hat{r}_{b}\left(\boldsymbol{\tau}\right) \\ &= \theta_{Lb'}\left[\hat{w}^{M}\left(\boldsymbol{\tau}\right) + \hat{w}^{T}\left(\boldsymbol{\tau}\right)\right] + \theta_{Vb'}\left[\hat{r}_{b'}^{M}\left(\boldsymbol{\tau}\right) + \hat{r}_{b'}^{T}\left(\boldsymbol{\tau}\right)\right] \\ &= \left(\theta_{Vb'}\hat{r}_{b'}^{M}\left(\boldsymbol{\tau}\right) + \theta_{Lb'}\sum_{b}s_{b}\hat{r}_{b}^{M}\left(\boldsymbol{\tau}\right)\right) + \left(\theta_{Vb'}\hat{r}_{b'}^{T}\left(\boldsymbol{\tau}\right) + \theta_{Lb'}\sum_{b}s_{b}\hat{r}_{b}^{T}\left(\boldsymbol{\tau}\right)\right), \end{aligned} \tag{E3}$$

where the first term $\widehat{\text{TFPR}}_{b}^{M}(\boldsymbol{\tau}) \equiv \left(\theta_{Vb'}\hat{r}_{b'}^{M}(\boldsymbol{\tau}) + \theta_{Lb'}\sum_{b}s_{b}\hat{r}_{b}^{M}(\boldsymbol{\tau})\right)$ captures the policy's macro effect on expected TFPR for firms in bin *b*, and the second term $\widehat{\text{TFPR}}_{b}^{T}(\boldsymbol{\tau}) \equiv \left(\theta_{Vb'}\hat{r}_{b'}^{T}(\boldsymbol{\tau}) + \theta_{Lb'}\sum_{b}s_{b}\hat{r}_{b}^{T}(\boldsymbol{\tau})\right)$ captures its treatment effect.

In order to compute welfare, we need to also make a similar adjustment to the calculation of expected log change in consumption due to the policy in equation (15):

$$\hat{C}(\boldsymbol{\tau}) = \frac{wL}{I}\hat{w}(\boldsymbol{\tau}) + \sum_{f} \frac{r_{f}V_{f}}{I}\hat{r}_{f}(\boldsymbol{\tau}) + \frac{TR}{I}\widehat{TR}(\boldsymbol{\tau}) - \hat{P}(\boldsymbol{\tau}).$$

We transform this from a firm-level expression to one based on firm-size binned data:

$$\hat{C}(\boldsymbol{\tau}) = \frac{wL}{I}\hat{w}(\boldsymbol{\tau}) + \sum_{b} \frac{r_{b}V_{b}}{I}\hat{r}_{b}(\boldsymbol{\tau}) + \frac{TR}{I}\widehat{TR}(\boldsymbol{\tau}) - \hat{P}(\boldsymbol{\tau}).$$

In this expression, we need a means of measuring r_bV_b/I , which is not reported in BEA data. Fortunately, we do know the value of total returns to capital in the U.S. economy (RV^{US}) and can compute the median return in each bin from the Compustat data (\overline{RV}_b) .⁷ We then write the payments to the specific factor in the U.S. as

$$\overline{RV}_{b'}^{US} = \frac{L_{b'}^U RV_{b'}}{\sum_b L_b^U \overline{RV}_b} RV^{US},$$
(E4)

where L_b^U is the number of employees in bin *b* in the U.S. We then calculate the policy impact on expected log change in consumption as

⁷We use the median to reduce the influence of outliers in the data.

$$\hat{C}(\boldsymbol{\tau}) = \frac{wL}{I}\hat{w}(\boldsymbol{\tau}) + \sum_{b} \frac{\overline{RV}_{b}^{US}}{I}\hat{r}_{b}(\boldsymbol{\tau}) + \frac{TR}{I}\widehat{TR}(\boldsymbol{\tau}) - \hat{P}(\boldsymbol{\tau})$$
(E5)

$$= \left[\frac{wL}{I}\hat{w}^{M}(\boldsymbol{\tau}) + \sum_{b} \frac{\overline{RV}_{b}^{US}}{I}\hat{r}_{b}^{M}(\boldsymbol{\tau}) - \hat{P}(\boldsymbol{\tau})\right]$$

$$+ \left[\frac{wL}{I}\hat{w}^{T}(\boldsymbol{\tau}) + \sum_{b} \frac{\overline{RV}_{b}^{US}}{I}\hat{r}_{b}^{T}(\boldsymbol{\tau}) + \frac{TR}{I}\widehat{TR}(\boldsymbol{\tau})\right],$$
(E6)

where the first term $\hat{C}^{M}(\boldsymbol{\tau}) \equiv \left[\frac{wL}{I}\hat{w}^{M}(\boldsymbol{\tau}) + \sum_{b}\frac{\overline{RV}_{b}^{US}}{I}\hat{r}_{b}^{M}(\boldsymbol{\tau}) - \hat{P}(\boldsymbol{\tau})\right]$ is the policy's macro effect on expected consumption, and the second term $\hat{C}^{T}(\boldsymbol{\tau}) \equiv \left[\frac{wL}{I}\hat{w}^{T}(\boldsymbol{\tau}) + \sum_{b}\frac{\overline{RV}_{b}^{US}}{I}\hat{r}_{b}^{T}(\boldsymbol{\tau}) + \frac{TR}{I}\widehat{TR}(\boldsymbol{\tau})\right]$ is its treatment effect.

We can also use our estimates to calculate the macro and treatment effects on expected real wage and aggregate TFP. To calculate the effects on expected real wage, we simply take our estimate for the effect on expected nominal wage in equation (E2) and subtract off the estimated effect on expected price level: $\hat{w}(\tau) - \hat{P}(\tau)$.

Lastly, we calculate the effect on expected aggregate TFP by subtracting $\hat{P}(\tau)$ from the left- and right-hand sides of equation (E3), weighting by the bin's employment share, and summing across all bins.

$$\widehat{\text{TFP}}(\boldsymbol{\tau}) \equiv \sum_{b} s_{b} \widehat{\text{TFPR}}_{b}(\boldsymbol{\tau}) - \hat{P}(\boldsymbol{\tau})$$

$$= \left(\sum_{b} s_{b} \widehat{\text{TFPR}}_{b}^{M}(\boldsymbol{\tau}) - \hat{P}(\boldsymbol{\tau}) \right) + \sum_{b} s_{b} \widehat{\text{TFPR}}_{b}^{T}(\boldsymbol{\tau}),$$
(E7)

where the first term $\widehat{\text{TFP}}^{M}(\boldsymbol{\tau}) \equiv \left(\sum_{b} s_{b} \widehat{\text{TFPR}}_{b}^{M}(\boldsymbol{\tau}) - \hat{P}(\boldsymbol{\tau})\right)$ is the policy's macro effect on expected TFP, and the second term $\widehat{\text{TFP}}^{T}(\boldsymbol{\tau}) \equiv \sum_{b} s_{b} \widehat{\text{TFPR}}_{b}^{T}(\boldsymbol{\tau})$ is its treatment effect.

E.2 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). In their setup, the free-trade equilibrium is inefficient because firms do not internalize productivity spillovers and therefore underinvest in new technology. Protection exacerbates this inefficiency by protecting small, inefficient firms and reducing their incentive to innovate. The reduction in (future) technological spillovers reduces firms' incentives to innovate, and productivity slows due to a "macro" effect common to all firms. An attractive feature of the Perla et al. (2021) model is that it has the property that the impact of trade on the economy can be summarized by examining movements in the ratio of the average profitability of firms relative to the minimum profits of firms ($\overline{\pi}_{rat}$). Thus, a researcher who knows how a trade shock moved relative profits could use their model to assess the growth implications. We

therefore use our estimates of the impact of the trade war on the expected cash-flow of firms to infer changes in firms' expected profits and calibrate their model to estimate the effects of the trade war on growth and welfare. 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

$$\overline{U} = \frac{\rho \ln c + g}{\rho^2},\tag{E8}$$

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

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

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

$$d\ln\overline{U} = \frac{d\overline{U}}{\overline{U}} = \overline{U}^{-1} \left(\frac{d\ln c}{\rho} + \frac{dg}{\rho^2} \right),$$
(E9)

where

$$d\ln c = d\ln\left(1 - \tilde{L}\right) + \frac{1}{\sigma - 1}d\ln\Omega + \frac{1}{1 - \sigma}d\ln\lambda_{ii}.$$
(E10)

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 ($\overline{\pi}_{rat} \equiv \pi_{ave}/\overline{\pi}_{min}$) 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 ($d\overline{\pi}_{rat}$):

$$d\ln\left(1-\tilde{L}\right) = -\lambda_{ii}\left(\sigma - \frac{1+\theta-\sigma}{\theta\left(1-\chi\right)}\lambda_{ii}\right)^{-1}\frac{1+\theta-\sigma}{\theta\left(1-\chi\right)}\frac{d\overline{\pi}_{rat}}{\overline{\pi}_{rat}-1}$$
(E11)

$$d\ln\Omega = -\left(\frac{(1-\chi)\,\theta\sigma}{1+\theta-\sigma}\lambda_{ii}^{-1} - 1\right)^{-1}\frac{(1-\chi)\,\theta\sigma}{1+\theta-\sigma}\lambda_{ii}^{-1}\frac{d\overline{\pi}_{rat}}{\overline{\pi}_{rat} - 1} \tag{E12}$$

$$d\ln\lambda_{ii} = \frac{-d\overline{\pi}_{rat}}{\overline{\pi}_{rat} - 1}.$$
(E13)

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

$$dg = dg = \frac{\rho \left(1 - \chi\right)}{\chi \theta} d\overline{\pi}_{rat}.$$
(E14)

Thus, if we substitute equations (E10)-(E14) into equation (E9), we can write the change in utility as a function of the policy induced change in the profit ratio ($d\overline{\pi}_{rat}$) and the model parameters.

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

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

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

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

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

$$d\ln \pi_{ave} = \sum_{b} s_{b} \hat{r}_{b} \left(\boldsymbol{\tau} \right), \tag{E15}$$

where s_b and $\hat{r}_b(\tau)$ are defined in Appendix E.1 of our paper. The minimum profit is determined by model parameters alone (see equation (G.19) of their Online Appendix), so $d \ln \pi_{min} = 0$. Equation (E15) implies that the trade-war events affected average firm profits by $d \ln \pi_{ave} = -0.056$, which reduces the profit ratio by $d\overline{\pi}_{rat} = -0.104$. Substituting this into equation (E14) 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 8.1% ($d \ln \overline{U} = -0.081$).