

# Trade Protection, Stock-Market Returns, and Welfare\*

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## Abstract

We show that the specific factors model can be used to derive a rigorous link between movements in stock prices and productivity, wages, employment, output, and welfare. We also prove that the commonly used measure of effective rate of protection equals the dual measure of revenue TFP, providing a theoretical foundation for why many studies have found that trade liberalization significantly increases firm-level productivity growth. Our method enables us to trace a tariff announcement's effect on TFP through its impact on macro variables (e.g., exchange rates) and through its effect on the relative prices of imports. We apply this framework to understanding the implications of the U.S.-China trade war. Our results show that the trade-war announcements caused large declines in U.S. stock prices, expected TFP, and expected inflation largely by moving macro variables, but also by causing declines in the returns of firms trading with China. We find that markets expect the trade war to lower U.S. welfare by 7.8 percentage points over the long run.

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# 1 Introduction

In a seminal paper, [Grossman and Levinsohn \(1989\)](#) showed that stock price changes reflect expected movements in returns to firm-specific factors. In this paper, we show that under the same specific factors setup, one can use stock-price movements as sufficient statistics to compute expected movements in firm-level employment, output, wages, effective rates of protection (ERP), productivity, and welfare. To do this, we exploit an insight in [Jones \(1975\)](#) that there exists a theoretical relationship between the effective rate of protection (ERP), wages, and the returns to a specific factor. We show that one can invert Jones’s model and write changes in nominal variables (wages and the ERP) as a function of stock-price changes. Knowledge of the movements of relative factor prices, then enables us to compute expected movements in employment and output. We also show that one can compute the welfare impact of a policy if one estimates two additional variables: the change in tariff revenue induced by the policy, and the movements in expected consumer prices induced by the policy. We apply this framework to understanding the implications of the U.S.-China trade war. We find that the large drop in U.S. equity prices on days in which there were announcements of new trade protection implies that market participants expected the trade war to lower U.S. welfare by 7.8 percent.

Our method also provides a way of estimating the effects of a policy announcement on expected productivity using the observed impact on stock prices. Our starting point is the definition of the change in the ERP used in [Corden \(1966\)](#), [Jones \(1975\)](#), and [Ethier \(1977\)](#): the “proportional change in value added per unit.” [[Ethier \(1977\)](#) p. 238] This definition implies that if tariffs raise a firm’s output price, the ERP will rise, and if tariffs raise its input prices the ERP will fall. We then prove a simple relationship: under the assumption that the share of total expenditures on intermediates in total costs is constant, the percent change in ERP equals the percent change in the firm’s output price plus the percent change in the firm’s total factor productivity (TFP). The intuition is that holding fixed the output price, higher TFP means the marginal cost of production must fall, but this implies that there is more money available for workers and owners, which means that value added per unit output must also rise. In other words, ERP is just revenue TFP.

This relationship between output prices, TFP, and factor prices is related to that of [Feenstra and Hanson \(1999\)](#), who derive a similar, but different relationship. In their paper, all factors receive identical returns, which requires them to introduce an error term in order to satisfy the zero-profit condition empirically. In contrast, the zero-profit condition always holds in the specific factors model because price or TFP movements cause all expenses other than those for labor and materials to accrue to the specific factor, obviating the need for an error term. Thus, in our dual approach, revenue TFP is the residual needed to make the zero-profit condition hold, just as in the primal approach where revenue TFP is the residual needed to make sales growth consistent with input growth. Under the identifying assumption that stock-price movements on the day of the trade-war announcements capture movements in the expected returns to specific factors, expected movements in revenue TFP are uniquely determined without estimation.

We also provide a method for decomposing the effect of a trade announcement on TFP and welfare through its affect on macro variables and its direct treatment effect. This provides a rigorous approach to solving a problem first posed by [Corden \(1966\)](#) who argued

that the trade policy impact on the ERP should be divided into two components: protection's impact on macro variables that move due to changes in policy and its effect on the treated relative to the untreated goods.<sup>1</sup> For example, a tariff announcement might matter for the ERP of a firm because some firms need to pay tariffs while others do not (the "treatment effect"), but also because a tariff announcement might change exchange rates, economic policy uncertainty, or other macro variables (the "macro effect"). We show that we can identify both of these channels by using a conventional factor model coupled with an event study. We identify the macro effect by assuming that during a narrow event window, movements in the latent macro variables (unexplainable by standard "economic surprise" variables) capture the macro impact of the policy announcements in those windows. Similarly, we assume that the differential abnormal returns of importers, exporters, and firms selling in China during event windows capture the treatment effects. Finally, movements in returns that are unexplainable by either macro or treatment variables capture factors unrelated to the policy announcement (e.g., idiosyncratic information about the firm). Since we prove that revenue TFP is a linear function of stock price movements, this decomposition of stock returns also lets us linearly decompose estimated movements in revenue TFP as well.

In order to map the theory into data for the U.S. economy, we need to make adjustments for the fact that financial data oversamples large firms and that stock returns tell us about the expected returns of a firm, not the current returns. Both of these issues turn out to be simple to deal with. We average the Compustat returns for firm-size and industry cells that match those reported in national data and then estimate the U.S. impacts under the assumption that within-cell average returns in Compustat data match those in the U.S. data. We deal with the second problem by assuming that the zero-profit conditions are satisfied in terms of expected returns and expected price movements. Thus, trade announcements tell us about *expected* movements in returns to firm-specific factors, wages, and revenue TFP. This enables us to address important issues found in [Topalova \(2010\)](#), [Kovak \(2013\)](#), and [Dix-Carneiro and Kovak \(2017\)](#), who showed that many of the large effects of trade policy changes on wages often take a decade to be fully apparent in the data.

We apply this methodology to the 2018-2019 U.S.-China trade war. We identify U.S. and Chinese tariff event dates as the earliest announcement date in the media using Factiva and Google search. We find that the U.S.-China trade-war announcements are associated with large stock-price declines regardless of whether we look at impacts over 1-day, 3-day, or 7-day event windows. We find that during a 3-day window around each of the trade-war announcements stock prices fell 12.9 percent in total: a \$3.7 trillion loss in market value. When we filter the data through our factor and event-study models, we find that 11.9 percentage points of this decline can be attributed to the trade war with 9.2 percentage points of the drop due to the announcement's impact on macro variables (e.g., policy uncertainty). The impact of the announcement on macro variables is so large

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<sup>1</sup>In the words of [Corden \(1966\)](#), "an activity is only truly protected if the net result of the protective structure combined with the appropriate exchange rate adjustment is to raise the value added of that activity. This is the concept of *total protection*. The direction of change in output or value added depends not only on protection relative to non-traded goods, but also on protection relative to other traded goods." [p. 226, emphasis in the original]

that we can reject at standard levels of significance the hypothesis that it arose due to trade-war announcements coinciding with other announcements. Similar to [Huang et al. \(2019\)](#), we find that direct exposure to importing, exporting, and selling in China also have statistically and economically significant effects on firm stock returns even using a sample of many more event dates.

In order to compute the impact of these announcements on U.S. welfare, we need an estimate of how the trade war affected tariff revenues and consumer prices. The first variable can be computed by well-established methodologies such as [Fajgelbaum et al. \(2020\)](#). Estimating how trade protection affects aggregate consumer prices, however, is difficult to specify theoretically in standard trade models because they lack a theory of the price level. Fortunately, we can overcome this limitation by using financial data. The impact of a trade policy announcement on the price level over a ten-year horizon can be estimated from changes in expected rates of inflation from Treasury inflation protected securities (TIPS) around an announcement date following the methodology developed by [Abrahams et al. \(2016\)](#). Our analysis of the impact of the tariff announcements on inflationary expectations indicates that they caused a 1.3 percentage point drop in the price level over a 10-year horizon. This decline in the price level is not something that is predicted in standard trade models, which are only concerned with relative prices. However, it is consistent with work by [Comin and Johnson \(2020\)](#), who argue that increased globalization is inflationary. With these estimates in hand, we obtain our estimates of the impact of trade announcements on real wages and welfare.

Since revenue TFP and returns to specific factors are two sides of the same equation in the specific factors model, the model predicts that the observed declines in the returns of firms could only have arisen from the trade war's adverse impact on firm-level TFP. In our setup, the large drop in TFP caused by the trade war depressed wages and may help explain why our estimate implied consumer price changes based on TIPS premia fell as well. If we benchmark this decline using data on cross-country productivity from the Penn World Tables version 10.0, markets expect the U.S.-China decoupling to reduce the level of U.S. TFP to that of Switzerland. Moreover, we show that the implied TFP changes exhibit a significant negative relationship with trade exposure measures. This result is consistent with the findings of the reduced form studies of liberalization and productivity, which also has found economically significant effects of protection on TFP.<sup>2</sup>

Finally, we analyze the impact of the trade war on welfare. Our baseline results show that the 9.2 percent decline in expected TFP are expected to cause a 7.8 percentage point decline in welfare. This welfare decline is much larger than that typically computed in trade models focusing on distortions arising because some firms pay tariffs and others do not. However, our setup lets us decompose the welfare loss into the macro component, which is typically left out of trade policy analyses, and the more conventional treatment effect. We find that 7.2 percentage points of the decline is due to the macro effect and only 0.6 percentage points is due to the treatment effect (the relative price distortion). Since

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<sup>2</sup>For example, [Amity and Konings \(2007\)](#) estimate the elasticity of firm-level TFP with respect to input tariffs of -1.2 in Indonesian for firms that import their inputs. There were also gains to non-importers but these were smaller, so the average elasticity across all firms was -0.44. [Topalova and Khandelwal \(2011\)](#) estimate the elasticity to be -0.5 in Indian data, [Brandt et al. \(2017\)](#) and [Brandt et al. \(2019\)](#) estimate the elasticity to be -2.3 in Chinese data.

[Amiti et al. \(2019\)](#), using a conventional methodology, estimate a welfare loss of 0.4 percent of GDP due to the trade war, our estimate of the treatment effect is very much in line with conventional analyses.<sup>3</sup> Thus, if we confine ourselves to leaving out the macro effects of trade-war announcements our results are not far from standard estimates, especially considering that many estimates assume that protection has no productivity effect on firms.

## 1.1 Related Literature

Our paper is related to the large reduced form literature that has developed over the last two decades showing that trade has large effects on per-capita income and productivity. In particular, a large literature has developed showing that firm-level TFP is very sensitive to the ERP and protection more generally (c.f. [Amiti and Konings \(2007\)](#); [Bloom et al. \(2016\)](#); [Brandt et al. \(2017, 2019\)](#); [De Loecker \(2011\)](#); [Pavcnik \(2002\)](#); [Topalova and Khan-delwal \(2011\)](#); [Trefler \(2004\)](#)). We also identify large impacts of trade policy on revenue TFP, but our identification is based on using stock-price data filtered through a general equilibrium model. Our paper is also related to the large macro literature evaluating the impact of trade on income that has also found evidence of large impacts of trade on productivity and income (c.f., [Frankel and Romer \(1999\)](#); [Alcalá and Ciccone \(2004\)](#); [Feyrer \(2019\)](#)). These papers find that the elasticity of per capita income with respect to trade ranges from 0.5 to 3 and that most of the effect arises through trade's impact on productivity. Although our work also finds large impacts of trade on productivity and welfare, an important difference between our work and the macro work is that we build these estimates up from firm-level data on stock prices and use a structural general equilibrium setup to obtain our estimates.

We also contribute to the burgeoning literature on understanding the importance of protection on the economy through macro or policy uncertainty channels ([Baker et al. \(2016\)](#); [Pierce and Schott \(2016\)](#); [Handley and Limão \(2017\)](#); [Caldara et al. \(2019\)](#); [Greenland et al. \(2020\)](#)). Like these papers, our paper also suggests that trade policy announcements can have impacts that arise through uncertainty or changing the macro environment, but we differ in our use of financial data to identify the shocks and the use of a general equilibrium model. Our paper is also related to work on the China shock. For example, [Autor et al. \(2013\)](#), and [Caliendo et al. \(2019\)](#) show how trade with China affected U.S. employment, wages and welfare, but our work focuses on trade policy announcements.

Our work is closely related to the large literature on stock market event studies that are based on trade data ([Grossman and Levinsohn \(1989\)](#), [Hartigan et al. \(1986\)](#), [Breinlich \(2014\)](#), [Moser and Rose \(2014\)](#), [Breinlich et al. \(2018\)](#), [Crowley et al. \(2019\)](#), [Huang et al. \(2019\)](#), and [Greenland et al. \(2020\)](#)). We differ in the use of a structural model to interpret the data. In important new work, [Greenland et al. \(2020\)](#) also show that positive firm abnormal returns in response to the granting of permanent normal trade relations in 2000 led to increases in firm employment, sales, and labor productivity six years later. Since our approach yields a theoretical foundation for these regressions, and while not enough

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<sup>3</sup><https://libertystreeteconomics.newyorkfed.org/2019/05/new-china-tariffs-increase-costs-to-us-households.html#more>



time has elapsed since the trade war for us to run similar specifications, we see their work as complementary to ours.

Finally, our work is related to the large literature documenting the impact of the trade war on prices (c.f., [Amiti et al. \(2020\)](#); [Fajgelbaum et al. \(2020\)](#); [Flaaen et al. \(2020\)](#); [Amiti et al. \(2019\)](#); [Cavallo et al. \(2021\)](#)). These papers have found that during the U.S.-China trade war, tariff passthrough into firm input prices was close to complete, consistent with our finding that higher U.S. tariffs negatively affected importers. Cavallo, Gopinath, Neiman, and Tang (2020) found that Chinese tariffs depressed U.S. exporter prices, also consistent with our findings of negative abnormal returns for firms exporting to China following Chinese retaliation events.

## 2 Theory

We develop the theory in two steps. The first involves developing a non-parametric mapping between movements in stock returns and wages, employment, output, and welfare. The second explores the link between the ERP and TFP.

### 2.1 From Stock Prices to Wages, Real Economic Activity, and Welfare

We assume that there are a set of potential entrants into the market indexed by  $\ell$  and that labor is mobile, so if a potential entrant enters the market it will need to pay workers a wage of  $w$ . Each potential entrant has production plan  $V_\ell$  (i.e., the specific factor) that enables it to produce a product  $f$  at a given marginal cost of  $c_f^\ell(w, r_\ell, q_1, \dots, q_n)$ , where the arguments correspond to the wage ( $w$ ), returns to firm  $\ell$ 's specific factor  $r_\ell$ , and a set of intermediate inputs, each produced at a price  $q_i$ . Successful entrants will hire  $L_\ell$  workers in order to produce  $y_\ell$  units of output. We assume that the amount of the specific factor employed by each firm is fixed and that each production plan corresponds to a different constant-returns-to-scale production function.

We follow [Bernard et al. \(2003\)](#) and assume that each successful entrant is a Bertrand competitor in its market. Before entry, all endowments of the specific factor ( $V_\ell$ ) and unit cost functions ( $c_f^\ell(w, r_\ell, q_1, \dots, q_n)$ ) are known and potential entrants can choose whether or not to produce. If a potential entrant chooses not to enter, it receives a return of zero on its specific factor (i.e., its production plan is worthless). Since the amount of each specific factor is fixed, a potential entrant will enter only if it can make a positive return on its specific factor, i.e.,  $p_f > c_f^\ell(w, 0, q_1, \dots, q_n)$ , and in this case it earns  $r_\ell V_\ell = (p_f - c_f^\ell(w, 0, q_1, \dots, q_n)) y_\ell > 0$  on its production plan. Since the entry condition only depends on the common market price for the good ( $p_f$ ) and  $c_f^\ell(w, 0, q_1, \dots, q_n)$ , without loss of generality, we can rank the potential entrants by the unit cost of their production plans, i.e.,

$$\ell' > \ell \iff c_f^{\ell'}(w, 0, q_1, \dots, q_n) > c_f^\ell(w, 0, q_1, \dots, q_n). \quad (1)$$

Entrants 2 and higher will not produce if  $p_f^1 \leq c_f^2(w, 0, q_1, \dots, q_n)$ . Therefore, potential entrant 1 will optimally produce at the limit price of  $p_f^1 = c_f^2(w, 0, q_1, \dots, q_n)$ , which means it will be the sole producer of the good. Since potential entrant 1 will be the only producer of good  $f$ , we will drop the  $\ell$  notation and refer to firm 1 producing good  $f$  as “firm  $f$ ”, its price as  $p_f$ , and its unit cost as  $c_f(w, r_f, q_1, \dots, q_n)$ .

As in Jones (1975), we can impose the full-employment conditions:

$$\sum_f a_{L_f} y_f = L, \text{ and} \quad (2)$$

$$a_{V_f} y_f = V_f, \quad (3)$$

where  $L \equiv \sum_f L_f$  and the unit input requirements for labor and capital are given by  $a_{L_f}$  and  $a_{V_f}$ . Since  $a_{L_f} y_f = L_f$ , the first full-employment condition (2) stipulates that firm-level employment will adjust with firm-level production. In contrast, the second full-employment condition (3) stipulates that the amount of the specific factor ( $V_f$ ) is fixed, so the unit-input requirement of the specific factor ( $a_{V_f}$ ) is inversely proportional to firm output ( $y_f$ ). Similarly, we assume that the factor intensity of production ( $a_{V_f}/a_{L_f}$ ) is determined by relative factor prices and the elasticity of substitution between capital and labor ( $\sigma$ ):

$$\hat{a}_{V_f} - \hat{a}_{L_f} = \sigma (\hat{w} - \hat{r}_f), \quad (4)$$

where  $r_f$  is the return to the firm-specific factor (i.e., the stock price) and hats over variables indicate log changes. We are now ready to prove our first proposition linking stock prices to wages.

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

*Proof.* See Appendix A.2.1 □

The intuition behind the first equation in Proposition 1 is that the full-employment condition implies that changes in factor returns cannot yield an increase in the aggregate demand for labor. However, the aggregate demand for labor will only remain constant if the change in relative wages ( $\hat{w} - \hat{r}_f$ ) are zero “on average,” i.e., changes in wages ( $\hat{w}$ ) equal a firm-size weighted change in the average of the returns to the specific factor ( $\sum_f \frac{L_f}{L} \hat{r}_f$ ). The second line follows immediately from this equation and the fact that the amount of the specific factor is fixed, so the left-hand side of equation (4) is just  $\hat{L}_f$ .

Proposition 1 is based on the structure of Jones (1975) but differs in a number of respects from his canonical model. First, while it is difficult to know how to measure the returns to an industry specific factor, stock-market returns capture the returns to a firm-specific factors. Second, Jones was concerned about mappings from goods prices into factor prices. Here, we invert the logic in Jones to show that knowing the returns to specific factors pins down wages. Third, by assuming that there is one elasticity of substitution between labor and capital, we simplify the expressions in his canonical model and are able to construct a sufficient statistic for computing the impact of the movements

in stock prices on wages without doing any estimation.<sup>4</sup> Wages move one for one with the employment-weighted average of share prices.<sup>5</sup> Fourth, and most importantly, our method suggests that there is a much simpler way of estimating the wage impacts of a policy change than the one proposed by Jones. His approach (in the general case) requires knowing a policy's impact on the ERP of every every industry, which requires a researcher to observe all price changes in the economy as well as the full input-output structure, whereas our approach only requires observing firm employment and stock-price changes. Finally, we obtain a simple expression of how each firm's employment shifts conditional only on observing its stock prices—the movement in employment is proportional to the the abnormal return of the firm.<sup>6</sup> Again, we have a sufficient statistic for understanding the employment movements.

Cost minimization implies that the unit-input requirements can be written as  $a_{Lf} = \frac{\partial c_f}{\partial w}$ , and  $a_{Vf} = \frac{\partial c_f}{\partial r_f}$ , and  $a_{if} = \frac{\partial c_f}{\partial q_i}$ , so we have

$$a_{Lf}w + a_{Vf}r_f + \sum_i a_{if}q_i = p_f, \quad (5)$$

where  $p_f$  is the firm price. It will also prove useful to define  $\omega_{Lf}$ ,  $\omega_{Vf}$ , and  $\omega_{if}$  the expenditures of firm  $f$  on labor, the specific factor, and input  $i$  expressed as a share of total revenue. We now can obtain an expression for a mapping between relative stock-price movements and output changes.

**Proposition 2.** *If the expenditures on intermediate inputs is 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  $\omega_{Lf}$  and  $\omega_{Vf}$  denote the payments to labor and specific factors as a share of revenue.

*Proof.* See Appendix [A.2.2](#) □

Propositions 1 and 2 indicate that knowledge of stock returns, the labor and capital input shares, and the elasticity of substitution between capital and labor is sufficient to identify nominal wage movements, as well as employment and output movements. The assumption that intermediate input expenditures is a constant fraction of sales will be satisfied if production is multiplicatively separable into a composite intermediate input and

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<sup>4</sup>By contrast, implementation of the Jones approach would require us knowing the full set of firm-level elasticities. While the assumption of a single elasticity of substitution is more restrictive, other studies have often adopted even more restrictive assumptions, e.g., assuming that  $\sigma = 1$  (c.f., Kovak 2013). [Knoblach and Stöckl \(2020\)](#) conduct a meta-analysis of 49 studies and find that the value of  $\sigma$  typically falls between 0.4 and 0.7.

<sup>5</sup>At first, it may seem surprising that wages rise one for one with average returns to the specific factor, however, this result is present in other models in which firms have positive operating profits. For example, in Melitz (2003), both per worker welfare and average firm profits are both monotonically rising in average productivity.

<sup>6</sup>Abnormal returns in event studies are usually computed as the difference between the firm return and the market capitalization weighted average of the stock returns, but in our case it is the difference between the firm return and the employment weighted average.



other factors of production. A Cobb-Douglas production function would satisfy this, but one could also have richer production technologies in which there are arbitrary elasticities of substitution between labor and capital and among intermediate inputs, so long as the elasticity of substitution between labor and the composite intermediate (and between capital and the composite intermediate) is one.

Finally, our theory also lets us compute the welfare effects. Income in this economy consists of payments to factors plus tariff-revenue ( $TR$ ) (i.e.,  $I = w \sum_f L_f + \sum_f r_f V_f + TR$ ). Welfare therefore can be written as

$$\ln W = \ln \left( w \sum_f L_f + \sum_f r_f V_f + TR \right) - \ln P, \quad (6)$$

where  $P$  is the price index for consumption. Totally differentiating equation (6) yields

$$\hat{W} \equiv d \ln W = \frac{wL}{I} \hat{w} + \sum_f \frac{r_f V_f}{I} \hat{r}_f + \frac{TR}{I} \widehat{TR} - \hat{P}. \quad (7)$$

combining this with the result in Proposition (1) yields

$$\hat{W} = \frac{wL}{I} \left( \sum_f \frac{L_f}{L} \hat{r}_f \right) + \sum_f \frac{r_f V_f}{I} \hat{r}_f + \frac{TR}{I} \widehat{TR} - \hat{P}$$

where  $\hat{P}$  is the change in consumer prices.

Computing welfare changes using financial data requires two additional pieces of information: the change in tariff revenues and the movement in consumer prices. There are many reasonable methods that have been developed to obtain estimates for the changes in tariff revenues, and as we'll see the impacts on welfare through tariffs are small compared to the other terms. The impact of a trade announcement on consumer prices can also easily be inferred from financial data. In Section 3.2, we will show how one can estimate this variable from spreads on treasury inflation-protected securities (TIPS).

## 2.2 Trade Policy and Productivity

In this section, we provide the link between movements in stock prices, effective rates of protection, output prices, and productivity to provide the channels through which protection affects stock prices as well as how to map stock price movements into movements in revenue TFP. The starting point for developing a structural approach for mapping policy changes into stock price movements is to recall a result from Jones (1975), which proved that the movement in the returns to each factor can be written as

$$\hat{r}_f = \left( \varphi_f + \frac{1}{\theta_{Vf}} \sum_{f' \neq f} \varphi_{f'} \right) \hat{p}_f^e - \frac{\theta_{Lf}}{\theta_{Vf}} \sum_{f' \neq f} \varphi_{f'} \hat{p}_{f'}^e, \text{ and } \hat{w} = \sum_f \varphi_f \hat{p}_f^e, \quad (8)$$

where

$$\varphi_f \equiv \frac{L_f}{\theta_{Vf}} / \sum_{f'} \frac{L_{f'}}{\theta_{V_{f'}}}, \quad (9)$$

$\theta_{L_f}$  and  $\theta_{V_f}$  are the wage bill and payments to the specific factor expressed as a share of value added:

$$\theta_{L_f} \equiv \frac{wL_f}{p_f y_f (1 - \sum_i \omega_{if})}, \text{ and } \theta_{V_f} \equiv \frac{r_f V_f}{p_f y_f (1 - \sum_i \omega_{if})}, \quad (10)$$

and  $\hat{p}_f^e$  is the firm's ERP, which is defined as

$$\hat{p}_f^e \equiv \frac{\hat{p}_f - \sum_i \omega_{if} \hat{q}_{fi}}{1 - \sum_i \omega_{if}}. \quad (11)$$

Thus, if we know how a policy affects the ERP, we can infer the implied movement in the return to wages and the specific factor. The ERP is rising in the firm's output price ( $\hat{p}_f$ ) and falling in its average input price ( $\sum_i \omega_{if} \hat{q}_{fi}$ ).

The first term in equation (8) captures the direct link between a firm's return and its ERP. Intuitively, the return on a firm's specific factor will rise if its ERP rises and fall if the ERPs of other firms rise. The reason why increases in the ERPs of other firms depress a firm's share price comes from the fact that if on average other firms have higher output prices or lower input prices, the value of the marginal product of labor for these firms will rise, which raises the economy-wide wage and lowers the returns to the firm's specific factor. All else equal, if protection raises a firm's output price or lowers its average input price, this will serve to raise the return of its specific factor.

A major empirical challenge to implementing the Jones (1975) approach in our dataset (and in many other datasets) is that it is impossible to use equation (11) to compute the ERP directly because it requires observing firm-level output prices ( $\hat{p}_f$ ), input prices ( $\hat{q}_i$ ), and the full firm-level input-output matrix ( $\omega_{if}$ ). Fortunately, there is an easy workaround to the problem. As we prove in the following proposition stock price movements provide a sufficient statistic for the ERP.

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

$$\hat{p}_f^e = \theta_{V_f} \hat{r}_f + \theta_{L_f} \sum_{f'} \frac{L_{f'}}{L} \hat{r}_{f'} \quad (12)$$

and if the share of total expenditures on intermediate inputs is a constant fraction of firm sales, then

$$\widehat{TFPR}_f \equiv \hat{p}_f + \widehat{TFP}_f = \hat{p}_f^e, \quad (13)$$

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

*Proof.* See Appendix A.2.3 □

Proposition 3 is key for understanding the difference between the prior literature's approach to the problem and ours. Jones (1975) was concerned with how a researcher who *observed* a change in the effective rate of protection ( $\hat{p}_f^e$ ) could infer the implications for factor prices ( $\hat{w}$  and  $\hat{r}_f$ ). A voluminous theoretical literature then developed showing that it was difficult to *rigorously* link movements in tariffs to movements in the ERP without knowing the passthrough of a vector of tariffs into every price in an economy as required

by equation (11). Empirical implementation of the Jones (1975) model therefore forced researchers to make strong assumptions about input-output structures, tariff passthrough rates into *every* price in the economy, and whether tariffs affect aggregate prices or just relative prices. By contrast, our approach starts with what is observable in stock-price data—firm-level returns ( $\hat{r}_f$ )—and shows that one can use these data to form sufficient statistics that identify movements in wages and effective rates of protection.

The second part of the proposition provides a theoretical foundation for the robust empirical finding that tariff-induced increases in ERP are associated with increases in TFP (c.f., Amiti and Konings (2007), Topalova and Khandelwal (2011), Brandt et al. (2017), and Brandt et al. (2019)). Proposition 3 proves that the ERP is simply revenue TFP.<sup>7</sup> The intuition for this result stems from the zero profit condition, which implies that  $\hat{p}_f^e = \theta_{Vf}\hat{r}_f + \theta_{Lf}\hat{w}$ . The left-hand side will only be positive if aggregate payments to factors rise, which can only happen if a firm’s revenue is growing faster than its costs, i.e., TFPR is rising. This proposition also helps to situate our paper among a variety of other studies. For example, Feenstra and Hanson (1999) use a Heckscher-Ohlin setup in which changes in value-added prices and TFP are set equal to changes in returns to capital and labor. Their specification requires an error term because they assume that the returns to capital do not vary across industries (equivalent to assuming  $\hat{r}_f = \hat{r}$  in our setup).

### 3 Empirical Implementation

We face a number of challenges in moving from the theory to the data. The first is that stock price movements may occur for reasons other than a policy announcement (e.g., economic surprises or idiosyncratic news about a firm). We therefore need a way of identifying the component of a firm’s stock-price movements that can be attributed to the policy alone. Second, the set of listed firms is not representative, so we need a way to apply our estimates based on our sample of listed firms to the broader economy. We address these issues in Section 3.1. Section 3.2 provides a method for using interest rate premia in order to measure the impact of the policy change on all consumer prices, which is a necessary input into computing welfare.

#### 3.1 Identifying Policy Impacts

We assume that a policy announcement is a vector of policies ( $\tau$ ). It is therefore important to make a distinction between the observed movements in firm returns ( $\hat{r}_{ft}$ ) and the expected ones based on the policy change ( $E[\hat{r}_f|\tau]$ ). Proposition 1 tells us that the wage change due to a policy announcement can be written as the labor weighted average of the returns, thus the expected wage change due to a policy change can be written as

$$E[\hat{w}|\tau] = \sum_f \frac{L_f}{L} E[\hat{r}_f|\tau]. \quad (14)$$

Equation (14) requires us to be able to compute the movement in the expected returns of firms due to the tariff. We assume that the returns are additively log separable into macro and treatment effects:

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<sup>7</sup>Following Hsieh and Klenow (2009), we define TFPR as the change in value added net of changes in labor and capital inputs.

$$\hat{r}_{ft} = \hat{r}^M(\boldsymbol{\delta}(\boldsymbol{\Phi}_t, \boldsymbol{\tau}_t), \boldsymbol{\beta}_f) + \hat{r}^T(\mathbf{Z}_f, \boldsymbol{\tau}_t) + \nu_{ft}, \quad (15)$$

where  $\boldsymbol{\delta}(\boldsymbol{\Phi}_t, \boldsymbol{\tau}_t) = (\delta_{1t}, \dots, \delta_{Kt})$  is a  $K \times 1$  vector of macro variables (exchange rates, policy uncertainty, etc.) that may be affected by a vector of macro variables unrelated to the event ( $\boldsymbol{\Phi}_t$ ) as well as policy announcements ( $\boldsymbol{\tau}_t$ );  $\boldsymbol{\tau}_t$  is a vector of policies announced on a day  $t$ ;  $\boldsymbol{\beta}_f$  is a vector of firm characteristics that matter for how macro variables affect firms;  $\mathbf{Z}_f$  is another vector of firm characteristics (which may or may not be different from  $\boldsymbol{\beta}_f$ ) that affects how a policy impacts firms directly (e.g., an importer paying a tariff as opposed to having a tariff change some macro variable); and  $\nu_{ft}$  is a mean-zero error term that captures time-varying, firm-specific productivity shocks. In this setup,  $\hat{r}_{ft}^M = \hat{r}^M(\boldsymbol{\delta}(\boldsymbol{\Phi}_t, \boldsymbol{\tau}_t), \boldsymbol{\beta}_f)$  captures how macro variables affect the returns to specific factors, and  $\hat{r}_{ft}^T = \hat{r}^T(\mathbf{Z}_f, \boldsymbol{\tau}_t)$  captures the movements in the returns that would normally be captured in an event study, i.e., “treatment effects” of a policy announcement that cannot be captured by macro variables. Our structure allows the set of firm characteristics ( $\boldsymbol{\beta}_f$ ) to change how macro shocks ( $\boldsymbol{\delta}(\boldsymbol{\Phi}_t, \boldsymbol{\tau}_t)$ ) affect firm returns (for example, exporters might be affected by exchange rate movements differently than importers), and a potentially different set ( $\mathbf{Z}_f$ ) to affect importers through  $\hat{r}^T(\mathbf{Z}_f, \boldsymbol{\tau}_t)$ . For example, a U.S. tariff might lead to a change in  $\boldsymbol{\delta}(\boldsymbol{\Phi}_t, \boldsymbol{\tau}_t)$  by altering exchange rates, causing stock returns ( $\hat{r}^M(\boldsymbol{\delta}(\boldsymbol{\Phi}_t, \boldsymbol{\tau}_t), \boldsymbol{\beta}_f)$ ) to vary by firm. However, this tariff change might also differentially affect firms even after controlling for the exchange rate movement, and this “treatment effect” would be captured by  $\hat{r}^T(\mathbf{Z}_f, \boldsymbol{\tau}_t)$ . If there is a tariff announcement on day  $j$  we have  $\boldsymbol{\tau}_j \neq \mathbf{0}$ , and the announcement will move firm returns by shifting macro variables ( $\boldsymbol{\delta}(\boldsymbol{\Phi}_t, \boldsymbol{\tau}_t)$ ) and/or differentially affecting the returns of firms. Differentiating equation (15) gives us

$$\hat{r}_{ft} = \sum_{k=1}^K \sum_{i=1}^N \frac{\partial \hat{r}_{ft}^M}{\partial \delta_k} \frac{\partial \delta_k}{\partial \tau_{it}} d\tau_{it} + \sum_{i=1}^N \frac{\partial \hat{r}_{ft}^T}{\partial \tau_{it}} d\tau_{it}. \quad (16)$$

The first term in this expression captures the policy’s impact on the rate of return that arises from its effect on macro variables, and the second term captures its impact through other mechanisms (e.g., relative price movements not captured by exchange rates)

We next model the components of  $\hat{r}_{ft}$ . Since we do not know the set of macro variables that matter for understanding movements in stock returns, we assume that these movements can be described by a set of latent variables:<sup>8</sup>

$$E \left[ \hat{r}^M(\boldsymbol{\delta}(\boldsymbol{\Phi}_t, \boldsymbol{\tau}_t), \boldsymbol{\beta}_f) \right] = \alpha_f + \sum_{k=1}^K \beta_{kf} \delta_{kt} \quad (17)$$

where  $\alpha_f$  is a firm fixed effect,  $\beta_{kf}$  is our estimate of  $\frac{\partial \hat{r}_{ft}^M}{\partial \delta_k}$  in equation (16) and tells us the firm’s sensitivity to latent variable  $k$  (its “loading”). Equation (17) is standard in the asset pricing literature as it nests many common models. For example, the capital asset pricing model (CAPM) is a restricted version of this model in which one of the  $\delta_{kt}$  equals

<sup>8</sup>In order to avoid confusion between the term “factor” as used in statistics and the term “factor” as used in “specific factors model,” we will continue to define a “factor” as a factor of production and refer to the econometric term “factor” as a “latent variable.”

the market return. Thus, our choice of this structure enables us to nest many popular methods of modeling asset price movements.

In order to specify the functional form for the treatment effects, we need to establish some notation for the policy announcements. We define the set of U.S. events as  $\Omega^U$ , the set of Chinese events as  $\Omega^C$ , and the combined set of U.S. and Chinese events as  $\Omega^{UC} = \Omega^U \cup \Omega^C$ . In our baseline specification, we will make the standard assumption that an event on day  $j$  causes stock prices to react on day  $j - 1$ ,  $j$ , and  $j + 1$ , so the length of our event window is  $w = 3$ . We will also consider shorter and longer event windows in which stock prices only move on the day of the event ( $w = 1$ ) or extend from the day before the event to five trading days afterwards ( $w = 7$ ). We define  $D_{jt}^w$  to be an indicator variable that is one if day  $t$  falls within an announcement event window for event  $j$  and zero otherwise. During the event window, we assume that there is a set of treatment variables  $Z_{fi}$  ( $i \in \{1, \dots, N\}$ ) that specify firm characteristics that might yield differential returns, e.g., whether a firm is an importer from China, an exporter to China, or the share of its revenues that accrues from China, *etcetera*. We assume that the impact of a tariff change on the expected differential return of a firm can be written as

$$E[\hat{r}_f^T | \tau_t] = \sum_{j \in \Omega^{UC}} \sum_{i=1}^N \gamma_{ij} Z_{fi} D_{jt}^w, \quad (18)$$

where  $\gamma_{ij}$  is our estimate of  $\frac{\partial \hat{r}_f^D}{\partial \tau_{it}}$  during event window  $j$ .

A key feature of equation (18) is that it is isomorphic to equation (17). In particular, we can think of  $D_{jt}^w$  as latent variables that only matter during an event window, and  $\theta_t$  and  $\gamma_{ij} Z_{fi}$  as their loadings. This isomorphism means that we can use standard factor analysis to identify the general latent variables and then use an event study based on the residuals from the factor analysis to identify the event effects. To see this formally, note that if we substitute equations (17) and (18) into equation (15), we obtain

$$\hat{r}_{ft} = \alpha_f + \sum_{k=1}^K \beta_{kf} \delta_{kt} + \epsilon_{ft}, \quad (19)$$

where

$$\epsilon_{ft} \equiv \sum_{j \in \Omega^{UC}} \sum_{i=1}^N \gamma_{ij} Z_{fi} D_{jt}^w + \theta_t D_{jt}^w + \tilde{\nu}_{ft}, \quad (20)$$

$$\nu_{ft} \equiv \theta_t D_{jt}^w + \tilde{\nu}_{ft}, \text{ and } E[\nu_{ft}] = 0. \quad (21)$$

Here,  $\theta_t$  is a parameter to be estimated and  $\tilde{\nu}_{ft}$  is an error that is mean zero on each day. The reason we include  $\theta_t$  comes from our specification of the moment condition (21). Since we assume that  $E[\nu_{ft}] = 0$ , our estimation procedure will impose the moment condition that  $\frac{1}{FT} \sum_f \sum_t \hat{\nu}_{ft} = 0$ , where  $F$  denotes the number of firms,  $T$  denotes the number of days, and  $\hat{\nu}_{ft}$  our estimate of  $\nu_{ft}$  given in equation (21). However, this does not imply that  $\frac{1}{F} \sum_f \hat{\nu}_{ft} = 0$ , so the value of  $\theta_t$  is given by  $\theta_t = \frac{1}{F} \sum_f \hat{\nu}_{ft}$ . In other words,  $\theta_t$  captures the fact that even mean-zero errors need not sum to zero on any given day.



We now make some identifying assumptions. Following the factor analysis and event study literatures, we assume that  $E[\epsilon_{ft}] = E[\nu_{ft}] = 0$ . We also assume that the latent variables ( $\delta_{kt}$ ) matter for stock prices “in general”, but the expected relative price effects of tariff announcements only matter during some finite event window. [Bai and Ng \(2002\)](#) show that this is tantamount to assuming that the latent variables have positive variances in the limit as the sample size approaches infinity, i.e.,

$$\lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=1}^T (\delta_{kt} - \delta_k)^2 > 0, \quad (22)$$

where  $\delta_k \equiv \frac{1}{T} \sum_t \delta_{kt}$ . Since the  $D_{jt}^w$  are only non-zero during the event window and the number of events is finite, we also know that  $\lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=1}^T (D_{jt}^w - D_j^w)^2 = 0$ , where  $D_j^w \equiv \frac{1}{T} \sum_t D_{jt}^w = 0$ . In other words, the  $D_{jt}^w$  will not be identified as latent variables. We therefore will correctly identify the number and values of latent variables as well as the values of all of their parameters in equation (19) since the terms on the right-hand side of equation (20) will appear in the error term of equation (19). This enables us to use the residuals from this equation ( $\hat{\epsilon}_{ft}$ ) as the dependent variable in an event study to identify the remaining parameters.

Equation (18) gives us the expectation of the differential impact of a policy announcement,  $\tau_t$ , on a firm with characteristics  $Z_f$ . Thus, as long as we know the distribution of firm characteristics, we can construct the expected differential returns for firms in the economy. In order to compute wage changes, though, we also need to know how the announcement-induced macro movements affected firms. While we know from our estimation of equation (19) how to compute the impact of movements in macro factors on returns ( $E[\hat{r}^M | \tau_t]$ ), we need to isolate the impact from tariff movements. In order to do this, we assume that movements in macro factors ( $\delta_k(\Phi_t, \tau_t)$ ) can be decomposed into movements due to economic surprise variables unrelated to the tariff announcement ( $ES_{1t}, ES_{2t}, \dots, ES_{\bar{N}t}$ ) and another component  $\delta_k(\tau_t)$  that is due to movements in the policy:

$$\delta_{kt} = \alpha'_k + \sum_{i=1}^{\bar{N}} \phi_{ik} ES_{it} + \delta_k(\tau_t), \quad (23)$$

where  $\alpha'_k$  and  $\phi_{ik}$  are parameters to be estimated,  $\bar{N}$  is the number of economic surprises. We then can identify  $\delta_k(\tau_t)$  by regression  $\delta_{kt}$  on the economic surprise variables and setting  $\delta_k(\tau_t)$  equal to the error term. This procedure lets us isolate the impact of the tariff change on firm returns through the macro effect due to the policy change during a set of  $j$  events ( $\tau$ ) as

$$E[\hat{r}_f^M | \tau] = \sum_k \sum_j \sum_t \beta_{kf} \delta_k(\tau_t) D_{jt}^w, \quad (24)$$

where we drop the  $t$  subscript on  $\tau$  to indicate that we are computing the effect of all policy announcements. Similarly, if we sum across all days within an event window and across all events, we can use equation (18) to write

$$E [\hat{r}_f^T | \boldsymbol{\tau}] \equiv \sum_t E [\hat{r}_f^T | \boldsymbol{\tau}_t] = \sum_t \sum_{j \in \Omega^{UC}} \sum_{i=1}^N \gamma_{ij} Z_{fi} D_{jt}^w, \quad (25)$$

which gives us

$$E [\hat{r}_f | \boldsymbol{\tau}] = E [\hat{r}_f^M | \boldsymbol{\tau}] + E [\hat{r}_f^T | \boldsymbol{\tau}]. \quad (26)$$

With estimates of how the announcement affects expected firm returns, we have enough information to compute their expected impact on wages. If we substitute equations (24), (25), and (26) into equation (14), we obtain an expression that gives us expected wage movements as a function of firm characteristics:

$$\begin{aligned} E [\hat{w} | \boldsymbol{\tau}] &= \sum_f \frac{L_f}{L} E [\hat{r}_f^M | \boldsymbol{\tau}] + \sum_f \frac{L_f}{L} \left( \sum_{j \in \Omega^{UC}} \sum_{i=1}^N \sum_t \gamma_{ij} Z_{fi} D_{jt}^w \right) \\ &= \sum_f \frac{L_f}{L} E [\hat{r}_f^M | \boldsymbol{\tau}] + \left[ \sum_{j \in \Omega^{UC}} \sum_{i=1}^N \sum_t \gamma_{ij} D_{jt}^w \left( \sum_f \frac{L_f}{L} Z_{fi} \right) \right], \end{aligned} \quad (27)$$

where the term in the last square brackets is  $E [\hat{r}_f^T | \boldsymbol{\tau}]$ . Here,  $E [\hat{w} | \boldsymbol{\tau}]$  should be thought of as the change in expected earnings of a worker with a unit endowment of labor after the announcement of the tariff.

Since the Compustat sample of firms is not representative of the size distribution of U.S. firms, we need to re-weight the data before implementing equation (27). We assume that we can define bins based on a narrow range of firm employment within a sector such that the average returns among listed firms in a bin equals the average returns for all firms in that bin. We also will explore alternative assumptions in Section 5.3. We know the share of employment by firm size for the U.S. by bin  $b$ , so  $L_b/L$  is the share of U.S. workers employed in firm-size bin  $b$  in the U.S. economy. We set the expected rate of return for firms in size bin  $b$  ( $E [\hat{r}_b | \boldsymbol{\tau}, f \in \Omega_b]$ ) as equal to the average rate of return for publicly listed firms in the same bin in the Compustat sample:

$$E [\hat{r}_b | \boldsymbol{\tau}] = E [\hat{r}_f | \boldsymbol{\tau}, f \in \Omega_b]. \quad (28)$$

We use an identical procedure to compute the the expected returns due to the macro shock by bin ( $E [\hat{r}_b^M | \boldsymbol{\tau}]$ ) and the differential shock by bin ( $E [\hat{r}_b^T | \boldsymbol{\tau}]$ ). We then have

$$E [\hat{w} | \boldsymbol{\tau}] = \sum_b w_b \left( E [\hat{r}_b^M | \boldsymbol{\tau}] + E [\hat{r}_b^T | \boldsymbol{\tau}] \right), \quad (29)$$

where  $w_b$  is the share of employees in bin  $b$  and  $\sum_b w_b = 1$ .

Our framework also enables us to determine how the trade war affected the revenue TFP of U.S. firms. In the Jones (1975) model, we have

$$\hat{p}_f^e = \theta_{L_f} \hat{w} + \theta_{V_f} \hat{r}_f. \quad (30)$$

Using Proposition 3 and taking expectations gives

$$E \left[ \widehat{\text{TFPR}}_f | \boldsymbol{\tau} \right] = \theta_{L_f} E [\hat{w} | \boldsymbol{\tau}] + \theta_{V_f} E [\hat{r}_f | \boldsymbol{\tau}]. \quad (31)$$

This expression lets us understand how the trade war affected the expected revenue TFP of firms and thus gives us a window into how the trade war affected the relative productivities of different types of firms. Moreover, we can also decompose movements in TFPR into those caused by macro forces and those caused by the treatment effect

$$\begin{aligned} E \left[ \widehat{\text{TFPR}}_{b'} | \boldsymbol{\tau} \right] &= \left\{ \theta_{L_b} \sum_b w_b \left( E [\hat{r}_b^M | \boldsymbol{\tau}] + E [\hat{r}_b^T | \boldsymbol{\tau}] \right) + \theta_{V_{b'}} E [\hat{r}_{b'}^M | \boldsymbol{\tau}] \right\} + \theta_{V_b} E [\hat{r}_{b'}^T | \boldsymbol{\tau}] \\ &= \theta_{L_b} \sum_b w_b \left( E [\hat{r}_b^M | \boldsymbol{\tau}] + E [\hat{r}_b^T | \boldsymbol{\tau}] \right) + \theta_{V_{b'}} E [\hat{r}_{b'}^M | \boldsymbol{\tau}] + \theta_{V_b} E [\hat{r}_{b'}^T | \boldsymbol{\tau}] \\ &= \left( \theta_{V_{b'}} E [\hat{r}_{b'}^M | \boldsymbol{\tau}] + \theta_{L_b} \sum_b w_b E [\hat{r}_b^M | \boldsymbol{\tau}] \right) + \left( \theta_{V_b} E [\hat{r}_{b'}^T | \boldsymbol{\tau}] + \theta_{L_b} \sum_b w_b E [\hat{r}_b^T | \boldsymbol{\tau}] \right), \end{aligned} \quad (32)$$

where the first term captures the impact of a policy announcement on TFP that happens through macro variables, and the second term captures the impact of the tariff through relative price effects that cannot be captured by macro movements.

### 3.2 Measuring Welfare, Price, Real Wage, and TFP Effects

The estimation procedures described thus far enable us to measure all of the nominal variables in the equilibrium as well as the movements in real variables, so we now address how to identify movements in consumer prices and therefore real wages and welfare. We use estimates of the 5- and 10-year expected inflation rates from [Abrahams et al. \(2016\)](#), which were 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 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  $B$ -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 day before) is

$$E \left[ \hat{P} | \boldsymbol{\tau} \right] = \sum_j \sum_t \left[ Y (\hat{\pi}_t^Y - \hat{\pi}_{t-1}^Y) \right] D_{jt}^w. \quad (33)$$

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.

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

$$Y \left( \hat{\pi}_t^Y - \hat{\pi}_{t-1}^Y \right) = \alpha^Y + \sum_{i=1}^{\bar{N}} \beta_i^Y ES_{it} + \epsilon_t^\pi, \quad (34)$$

and then run the following regression:

$$\hat{\epsilon}_t^\pi = \alpha^\pi + \gamma^\pi \sum_{j \in \Omega^{UC}} D_{jt}^w + \epsilon'_t, \quad (35)$$

where  $\alpha^\pi$  and  $\gamma_j^\pi$  are parameters to be estimated. In this specification,  $\gamma^\pi$  tells us the average change in inflationary expectations 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

$$E \left[ \hat{P} | \tau \right] = wJ\gamma^\pi, \quad (36)$$

where  $J$  is the number of events.

In order to compute the change in welfare (equation 7), we also need estimates of the announcements on tariff revenues and the CPI ( $\hat{P}$ ). The method for computing  $\hat{P}$  was described in the previous section. We compute the change in tariff revenue ( $TR \times \widehat{TR}$ ) due to the trade-war announcements by using the import demand elasticities estimated in Fajgelbaum et al. (2020) to estimate import quantities (based on Census data) after the levying of the tariffs and multiplied the implied import levels by the amount of the tariff increase. We set  $TR$  equal to the total tariff revenues collected in 2017, and  $I$  equal to total U.S. value added generated by the private sector as reported in the input-output tables for same year. In order to compute the implied tariff revenue generated by the tariffs, we need to construct the counterfactual change in imports that would arise if the only change were the tariffs against China:

$$\widehat{\text{Imports}}_h = \text{Imports}_{h,17} - \sigma \Delta\tau_h \text{Imports}_{h,17}, \quad (37)$$

where  $\text{Imports}_{h,17}$  is the value of imports in 2017 in Harmonized Tariff System code  $h$ ,  $\sigma = 2.3$  is the elasticity of import demand estimated in Fajgelbaum et al. (2020), and  $\Delta\tau_h$  is the change in U.S. tariffs. We then set  $\widehat{TR} = TR^{-1} \sum_h \widehat{\text{Imports}}_h \Delta\tau_h$ .

In order to compute welfare, we need to also make an adjustment for the fact that we do not observe the returns of all firms. We do this by noting that the expected change in welfare due to a policy announcement ( $E \left[ \hat{W} | \tau \right]$ ) can be computed by taking expectations of equation (7):

$$E \left[ \hat{W} | \tau \right] = \frac{wL}{I} E \left[ \hat{w} | \tau \right] + \sum_f \frac{r_f V_f}{I} E \left[ \hat{r}_f | \tau \right] + \frac{TR}{I} \widehat{TR} - E \left[ \hat{P} | \tau \right]. \quad (38)$$

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

$$E \left[ \hat{W} | \tau \right] = \frac{wL}{I} E \left[ \hat{w} | \tau \right] + \sum_b \frac{r_b V_b}{I} E \left[ \hat{r}_b | \tau \right] + \frac{TR}{I} \widehat{TR} - E \left[ \hat{P} | \tau \right]. \quad (39)$$

In this expression, we need a means of measuring  $r_b V_b / I$ , 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 ( $\overline{RV}_b$ ).<sup>9</sup> We then write the payments to the specific factor in the U.S. as

$$\overline{RV}_{b'}^{US} = \frac{N_{b'}^U \overline{RV}_{b'}}{\sum_b N_b^U \overline{RV}_b} RV^{US}, \quad (40)$$

where  $N_b^U$  is the number of firms in bin  $b$  in the U.S. We then can write the welfare impact as

$$E[\hat{W}|\tau] = \frac{wL}{I} E[\hat{w}|\tau] + \sum_b \frac{\overline{RV}_b^{US}}{I} E[\hat{r}_b|\tau] + \frac{TR}{I} \widehat{TR} - E[\hat{P}|\tau]. \quad (41)$$

We can also use equation (29) and (26) to rewrite this equation into the welfare changes due to macro and treatment effects:

$$\begin{aligned} E[\hat{W}|\tau] &= \frac{wL}{I} \sum_b w_b (E[\hat{r}_b^M|\tau] + E[\hat{r}_b^T|\tau]) + \sum_b \frac{\overline{RV}_b^{US}}{I} (E[\hat{r}_b^M|\tau] + E[\hat{r}_b^T|\tau]) + \frac{TR}{I} \widehat{TR} \\ &= \left\{ \frac{wL}{I} \sum_b w_b E[\hat{r}_b^M|\tau] + \sum_b \frac{\overline{RV}_b^{US}}{I} E[\hat{r}_b^M|\tau] - E[\hat{P}|\tau] \right\} \\ &\quad + \left\{ \frac{wL}{I} \sum_b w_b E[\hat{r}_b^T|\tau] + \sum_b \frac{\overline{RV}_b^{US}}{I} E[\hat{r}_b^T|\tau] + \frac{TR}{I} \widehat{TR} \right\}, \end{aligned} \quad (42)$$

where the first term in braces captures the macro effect of the announcement and the second term captures the treatment effect. In this formula, we group together expected movements in returns to the specific factor due to macro factors ( $E[\hat{r}_b^M|\tau]$ ) with movements in the expected consumer price index ( $E[\hat{P}|\tau]$ ) because we tend to think that both of these are driven by macro fundamentals. The second term, therefore, captures losses due to some firms' differential exposure to changes in trade costs ( $E[\hat{r}_b^T|\tau]$ ) as well as the tariff revenues generated by the import tariffs ( $\widehat{TR}$ ).

We can also perform an analogous decomposition of real wages and TFP. If we subtracted the expected price changes from both sides of equation (27) and make the transition to binned data as in equation (28), we obtain

$$E[\hat{w}|\tau] - E[\hat{P}|\tau] = \left( \sum_b w_b E[\hat{r}_b^M|\tau] - E[\hat{P}|\tau] \right) + \sum_b w_b E[\hat{r}_b^T|\tau], \quad (43)$$

where the first term is the impact of the tariff announcement on real wages through the macro factors and the second term is the impact of the tariff announcement on real wages arising from the treatment effects of protection on importers and firms selling in China. Lastly, we can neutralize the effect of secular movements in inflation on revenue TFP by subtracting  $E[\hat{P}|\tau]$  from the left- and right-hand sides.

<sup>9</sup>We use the median to reduce the importance of outliers in the data.



$$E [\widehat{\text{TFP}}_{i,t} | \tau] \equiv E [\widehat{\text{TFPR}}_{i,t} | \tau] - E [\hat{P} | \tau] = \left( \theta_{Vb} E [\hat{r}_b^M | \tau] + \theta_{Lb} \sum_b w_b E [\hat{r}_b^M | \tau] - E [\hat{P} | \tau] \right) + \left( \theta_{Vb} E [\hat{r}_b^T | \tau] + \theta_{Lb} \sum_b w_b E [\hat{r}_b^T | \tau] \right). \quad (44)$$

In this expression, the first term in parentheses is the macro effect on TFP and the second term is the treatment effect.

## 4 Data

### 4.1 Data Sources and Variable Construction

Our analysis requires data on stock returns, inflationary expectations, exposure to China, balance sheet items, and event dates. Our stock return data are from the Center for Research in Security Prices (CRSP) provided by Wharton Research Data Services (WRDS), for every trading day in 2016-2019. When we merge the Compustat data with the CRSP data for a balanced panel of firms that report stock returns on every day and employment in 2017, we obtain a sample of 2,859 firms that cover all sectors. We set  $\hat{r}_{i,t}$  to be the log change in the firm's stock price.<sup>10</sup>

A commonly used measure of inflation expectations is the difference in yields on a Treasury and a Treasury Inflation-Protected security, however in addition to inflation expectation this could contain inflation and liquidity risk. We obtained our measures of inflationary expectations from Richard Crump who updated the estimates generated in [Abrahams et al. \(2016\)](#), using a methodology that isolates the inflation expectations component.

We also collected data on important macroeconomic or firm specific surprises that coincided with our event windows. Our 65 economic surprise variables encompass all major price, monetary policy, and macroeconomic data releases used in economic forecasting and were provided by Daniel Lewis (see appendix for details). These variables equal the difference between a data release and the Bloomberg median of economists' forecast on the previous day (see [Lewis et al. \(2019\)](#) for methodology). Additionally, for each firm in our sample, we obtained the dates of its individual announcements that could have influenced its abnormal returns from the Capital IQ Key Developments database.<sup>11</sup> To ensure that our results are not contaminated by these firm announcements, when we estimate equation (20) we exclude the abnormal returns of firms that made an announcement between one day before the start of an event window and one day after the event window ended.

We consider three ways in which firms are exposed to China: importing, exporting, and foreign sales (either through exporting or subsidiaries). It is important to capture

<sup>10</sup>When a company issues multiple classes of stocks, we combine their returns by taking their weighted average, weighted by each stock's share of market capitalization within the firm.

<sup>11</sup>These announcements include those that relate to buybacks (announcements, cancellations), dividends (affirmations, increases, decreases), earnings calls, stock splits, mergers and acquisitions (announcements, cancellations), and follow-on equity offerings.

indirect imports that are ultimately purchased by U.S. firms because many firms do not import directly from China but instead obtain Chinese inputs through their subsidiaries or the U.S. subsidiaries of foreign firms. For example, Apple Computer’s exposure to China can arise through direct imports, imports obtained by its subsidiary (Beats Electronics), or from the purchase of iPhone’s from the U.S. subsidiary of Foxconn. In order to identify the supply chains, we use DUNS numbers from Dun & Bradstreet to merge importers from Datamyne to a list of firms and their subsidiaries from Capital IQ. We use a firm-name match to link firms, subsidiaries, and their suppliers that are reported in Datamyne, Compustat, Bloomberg, and FactSet and identify which firms are trading with China directly or indirectly through their network or suppliers. After matching firms with identical names in two or more datasets, we manually compared firms with similar names to identify whether they are matches. We define “China Revenue Share” to be the share of a firm’s revenues in 2018 (either obtained through sales of subsidiaries or exports) that arise from sales in China as reported in FactSet.<sup>12</sup>

The Datamyne data used to identify U.S. firms that import from China or export to China has a number of limitations. First, the product-level reported is more aggregated than the Harmonized Tariff System 8-digit level that U.S. tariffs are set at. While some of the Datamyne data is at the Harmonized System (HS) 6-digit level, much of it is at the far more aggregated HS2-digit level, making it impossible to know what share of a firm’s trade was affected by tariffs. We therefore opt to use a binary exposure measure. Our “China Import” dummy is one if the firm or its supply network imported from China in 2017 and zero otherwise. We also construct a “China Export” dummy analogously for exports. Second, the Datamyne data only covers seaborne trade. The U.S. Census data reveals that in 2017, 62 percent of all imports from China and 58 percent of exports to China are conducted by sea, so although we capture over half of the value of U.S. China trade, the China import and export dummies are likely to miss some U.S. firms that trade with China. On the export side, any exporters that are not reflected in the export dummy are included in the China revenue share variable. To check for missing importers, we also include a robustness check where we replace the importer dummy with a large firm dummy equal to one for all firms with more than 1000 employees from Compustat.

These data show that the supply chain information is critical in understanding firms’ exposure to international trade. From Table 1, we see that only 10 percent of the firms in our sample import directly from China, and only 2 percent export directly to China. However, if we take into account subsidiaries, these numbers rise to 24 and 4 percent, respectively. When we add in imports by all firms in the supply chain, we see that 29

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<sup>12</sup>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 is 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 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 appendix.

Table 1: China Trade Exposure of Listed U.S. Firms

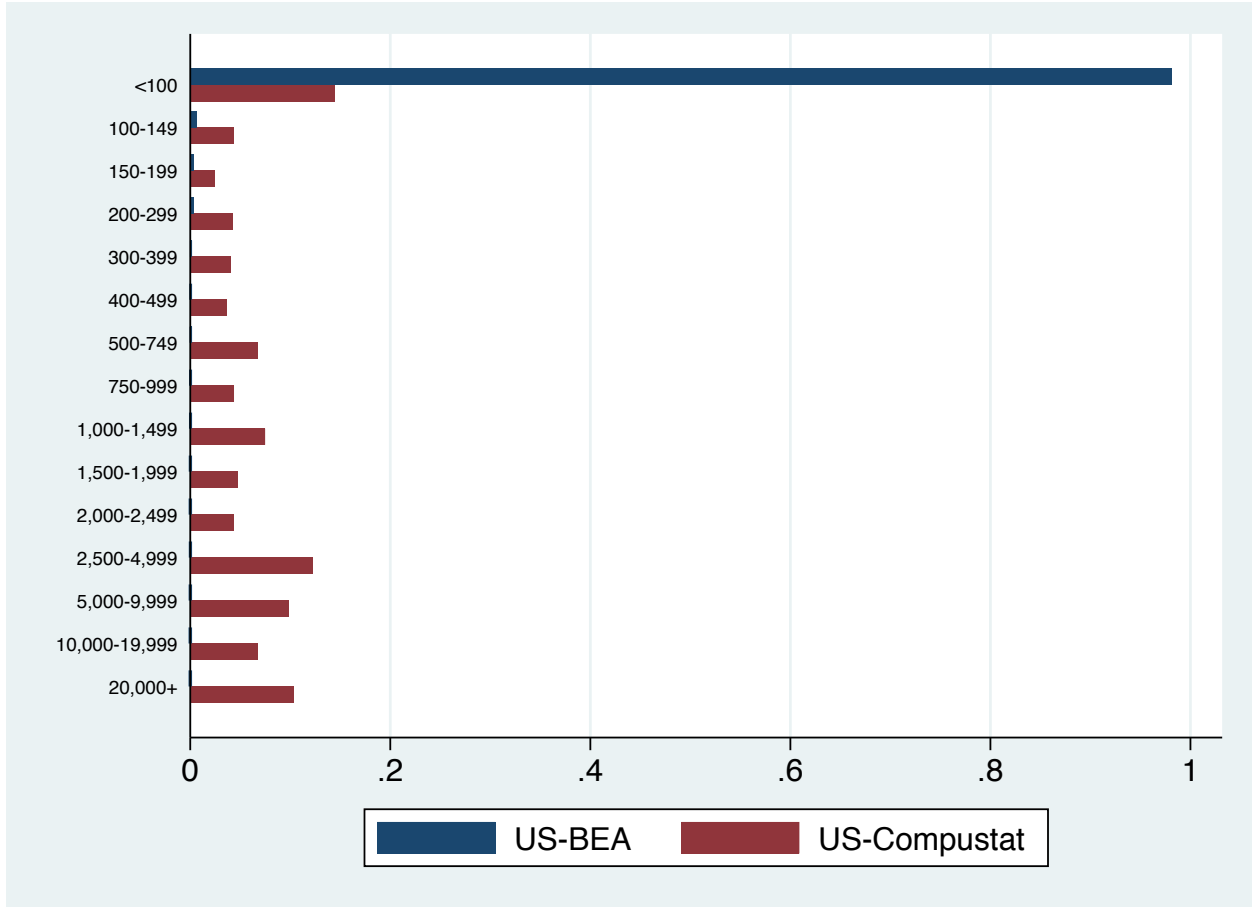
	Mean
Firm imports from China	0.10
Firm or subsidiary imports from China	0.24
Firm, subsidiary, or supplier imports from China	0.29
Firm exports to China	0.02
Firm or subsidiary exports to China	0.04
Firm sells in China via exports or affiliates	0.43
Average share of revenue from Chinese exports or affiliate sales	0.04
Firm exposed to China through imports, exports, or affiliate sales	0.53
Number of Firms: 2,859	

Note: This table reports the means of indicator variables that are one if a firm satisfies the listed criterion, as well as the mean of the continuous Chinese revenue share variable.

percent of all listed firms in the U.S. import directly or indirectly from China. In the last row of the table, we construct a variable, “Firm Exposed to China” if any firm in the firm’s network exported to or imported from China or if the firm had positive revenues from China (possibly from affiliate sales). We see that 53 percent of all firms were exposed to China through one or more of these channels.

We obtained employment data from a number of sources. The firm-level employment data for the listed firms in our sample is 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 National Establishment Time Series (NETS) for 2014 (the most recent year available to us), which provides data at the establishment basis for U.S. firms. We merged the NETS data with the Compustat data by DUNS number to obtain the domestic firm employment. We also created an indicator for whether the firm was a multinational using information from Compustat’s geographic segments data. We assumed that the Compustat employment numbers accurately reflected 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 one if the firm was an exporter, and the share of foreign revenues for the firm from FactSet (see Appendix for details). 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. As a comparison with the national employment data, provided by the Statistics of U.S. Businesses (SUSB, U.S. Census Bureau), this procedure leads us to estimate that our sample of Compustat firms employs 29.2 million workers domestically or 22.7 percent of the number of people employed in the SUSB data. The economy-wide distribution of the number of employees working for firms of a given size category, from

Figure 1: Distribution of Number of Firms by Employment Size bins



Note: Source of data is the Statistics of U.S. Businesses (SUSB, U.S. Census Bureau). The vertical axis indicates the employment size bins, and the horizontal axis is the share of U.S. firms.

U.S. Census, is shown in Figure 1, alongside the publicly-listed firm-size distribution in the Compustat sample. As we see, the publicly listed firm distribution is skewed towards larger firms relative to the overall U.S. distribution, which motivates our reweighting of the returns by the U.S. employment distribution, so as not to overweight the returns of large firms.

In order to construct the labor and capital share variables ( $\theta_{L_f}$  and  $\theta_{V_f}$ ), 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 dropped firms for which this value was not positive.<sup>13</sup> 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  $w L_f / (p_f y_f)$  and  $\sum_i \omega_{i,f}$ . To do this, we set  $LSHARE_f$  and  $MSHARE_f$  equal to 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

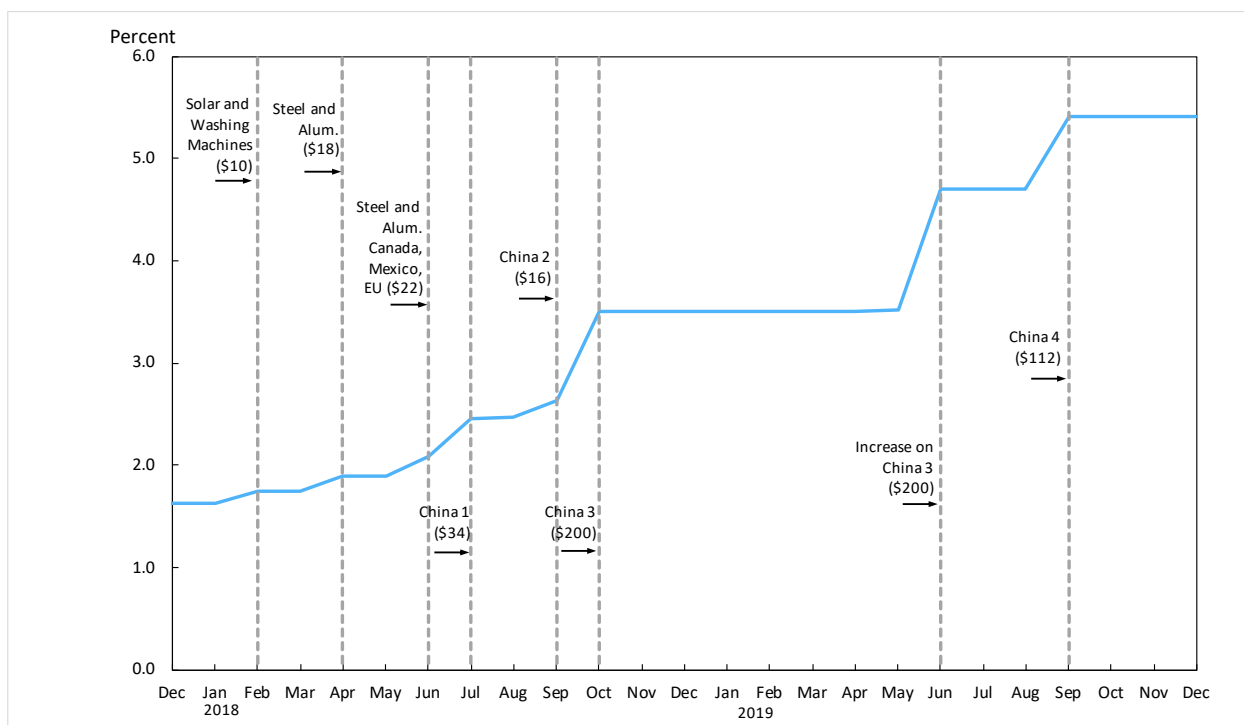
<sup>13</sup>Ordinary income after depreciation equals firm revenue less cost of goods sold, and expenses related to marketing, administration, depreciation. Labor costs appear in the cost of goods sold and the market and administration expenses lines. We also tried an alternative measures of  $r_f V_f$  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 one. 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 had constructed these variables we used equation (10) to construct  $\theta_{L_f}$  and  $\theta_{V_f}$ . In order to compute  $\overline{RV}_b$ , 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  $\overline{RV}_b = \alpha_i + \beta \text{EMP}_b$ , where  $\alpha_i$  is an industry dummy and  $\beta$  is a parameter, and  $\text{EMP}_b$  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.

Figure 2: Average U.S. Tariffs by Wave of the 2018-2019 Trade War



Note: Authors' calculations based on data from the U.S. Census Bureau; U.S. Trade Representative (USTR); U.S. International Trade Commission. Tariffs on the 10-digit Harmonized Tariff Schedule (HTS) product code by country, weighted by 2017 annual import value. Dashed vertical lines indicate the implementation of each of the eight major waves of new tariffs during 2018-2019; tariffs implemented after the 15th of the month counted for the subsequent month. Four tranches of tariffs were imposed on China, designated by 1, 2, 3, and 4. Import values associated with each line correspond to headline numbers, not 2017 values, which are a little lower. Numbers in parentheses correspond to the value of imports covered by the new tariffs in billions.

## 4.2 Trade War Announcements

Figure 2 shows the new U.S. tariffs levied on China by the U.S. during 2018 and 2019. For each of these tariff events we identified the earliest announcement date in the media



using Factiva and Google search. In addition, we also used the same method to identify the earliest announcement dates for each date that China imposed retaliatory tariffs on U.S. exports. The figure shows that the average rate of tariffs on all U.S. imports rose by close to 4 percentage points due to the fact that tariffs on a wide range of Chinese imports reached 25 percent by the end of the period.

Our method identifies 11 trade-war announcement dates, comprising six U.S. tariff events and five China retaliation events, summarized in Table 2. Our first event is the January 22, 2018 announcement of U.S. tariffs on solar panels and washing machines that were implemented on February 7, 2018 on China, and in this case more broadly on other countries too. The second event date, the announcement of steel and aluminum tariffs on February 28, 2018, also more broadly applied, was imposed on March 3, 2018. All of the subsequent U.S. tariff events only apply to China. On May 29, 2018 the U.S. announced a 25 percent tariff on \$50 billion of Chinese imports. Although this was implemented in two tranches on two separate dates (\$34 billion on July 7, 2018 and \$16 billion on August 23, 2018), we include this as only one event as what is important for our purposes is the first time it was announced. All of the 11 events are listed in Table 2 in date order, with more details and links to the announcement of each event provided in the Appendix. Our approach to choosing event dates has the advantage of being comprehensive and objective.

Table 2: Stock Returns on Event Dates

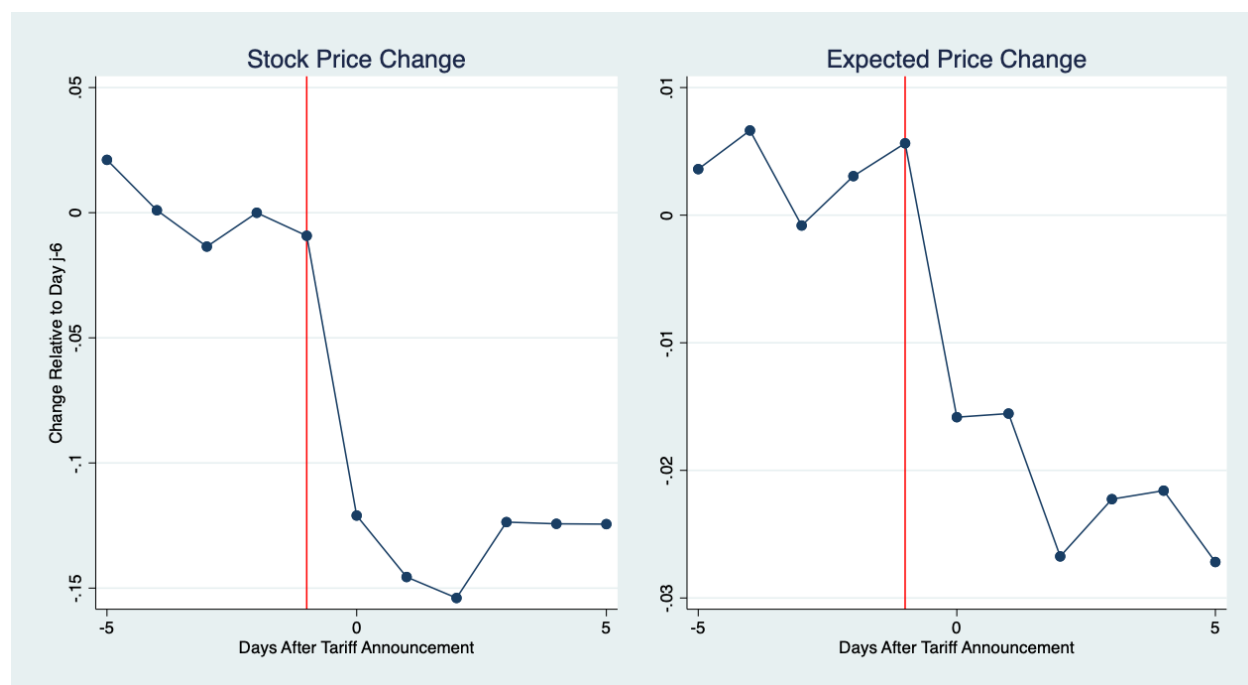
Event Group	Event Date	$R_t$ (%)	$\sum_{t-1}^{t+1} R_t$ (%)	Description
US	22Jan18	0.75	1.56	US imposes tariffs on solar panels and washing machines
US	28Feb18	-1.07	-3.56	US will impose steel and aluminum tariffs
CHN	22Mar18	-2.57	-4.77	Trade war escalates as China says it will impose tariffs on 128 U.S. exports
US	29May18	-1.00	0.10	White House to impose 25% tariff on \$50 bn worth of Chinese goods
CHN	15Jun18	-0.10	0.08	China announces retaliation against US tariffs on \$50 bn of imports
US	19Jun18	-0.41	-0.28	US announces imposition of tariffs on \$200 bn of Chinese goods
CHN	02Aug18	0.59	0.83	China announces tariffs on \$60 bn of U.S. goods
US	06May19	-0.41	-1.00	US to raise tariffs on \$200 bn of Chinese goods up to 25%
CHN	13May19	-2.58	-1.34	China to raise tariffs on \$60 bn of US goods starting June 1
US	01Aug19	-1.00	-2.90	US will impose a fresh 10% tariff on another \$300 bn of Chinese goods
CHN	23Aug19	-2.64	-1.65	China retaliates with higher tariffs on soy, autos
US+CHN	all	-10.43	-12.94	

Note: This table shows market returns on and around trade-war events. "US" refers to events involving an announcement of U.S. tariffs on China; "CHN" refers to events involving Chinese retaliatory tariffs.  $R_t$  is the market return (in our sample of firms) on the day of the announcement.  $\sum_{t-1}^{t+1} R_t$  is the cumulative market return over a 3-day window beginning on the trading day before the announcement and extending two trading days after the announcement. The total 3-day return for the U.S. and Chinese events in this table does not exactly equal the value in subsequent tables because we are presenting raw data in this table and double count one day that appears in two event windows.

The data reveals that there were large and persistent movements in stock prices and inflationary expectations following these trade-war announcements. Table 2 presents the stock market return on each of these event dates. We see that the stock market fell on all of the event dates except one U.S. event date and one China event date, with a total drop of 10.4 percent over all of the events, and 12.9 percent over a three day window. These drops in the market imply substantial losses for U.S. firms—a factor that Proposition 1 suggests will tend to drive real wage decreases.

We explore the persistence of these stock market movements in Figure 3, which plots the change in stock prices relative to the level six trading days before each announcement cumulated across all firms and all event dates against the number of days before or after each event. The data reveal that in the five trading days before our events, stock price movements were quite small. Indeed, there is little evidence of anything out of the ordinary happening in the market before the announcements. However, on the announcement days, just as in Table 2, we see that there was a large decline of over ten percentage points. Moreover, it is also quite striking how persistent this decline is. Even if we track the market five trading days (or one week of calendar days) later, we see that the market did not recover. Thus, there is little evidence that markets overreacted and bounced back from their initial negative assessment of the trade war on expected returns.

Figure 3: Impact of Trade-War Announcements on Stock Prices and Expected Prices



Note: The stock-price plot shows the cumulative return of the stock market relative to its level six trading days before the trade-war announcements. The horizontal axis is normalized so that the announcement always happens on day 0. Days to the left of this point correspond to days before the announcement, and days following this point correspond to days after the announcement. In order to generate the price-change plot, for each day  $t$ , we compute the change in expectation on day  $t$  of the price level ten years in the future:  $E_t[\hat{P}^{10}] \equiv 10 \times (\hat{\pi}_t^{10} - \hat{\pi}_{t-1}^{10})$ , where the definitions of these variables are given in Section 3.2. We then compute the total change (summing across all events) for each day within a 10-day window around each event. Starting five days before event, we report the cumulative change in expected prices in the figure, so the point corresponding to -5 tells us the expected price change (summing across all events) five days before an event relative to 6 days before an event; the point corresponding to -4 tells us the expected price change four days before an event relative to 6 days before an event, and so on. Details on this procedure including the actual formulas used are provided in the Appendix.

Finally, we also can explore the impact that trade-war announcements have on expected price changes. In order to generate the price-change plot, for each day  $t$ , we compute the change in expectation on day  $t$  of the price level ten years in the future:  $E_t[\hat{P}^{10}] \equiv 10 \times (\hat{\pi}_t^{10} - \hat{\pi}_{t-1}^{10})$ , where the definitions of these variables are given in Section 3.2. We then compute the total change (summing across all events) for each day within a 10-day window around each event. Starting five days before event, we report

the cumulative change in expected prices in the figure, so the point corresponding to -5 tells us the expected price change (summing across all events) five days before an event relative to 6 days before an event; the point corresponding to -4 tells us the expected price change four days before an event relative to 6 days before an event, and so on. We plot the values in Figure 3 (See Appendix for details and formulas). We see that in the five days leading up to each announcement, the expected price level ten years later was within about 60 basis points of the level six days before the announcement. However, on the day of the announcements, the price level fell sharply: falling close to 200 basis points from the day before. Moreover, there appears to be no recovery in inflationary expectations. If anything, the data suggests inflationary expectations fell as time went on, indicating that just as we saw in the stock price data, the announcements were associated with a sharp and persistent decline in expected aggregate prices as well.

## 5 Results

In this section, we first present the results from estimating our factor model and event study. We then present our estimates of how these trade events affected wages and welfare.

### 5.1 Event Study Results

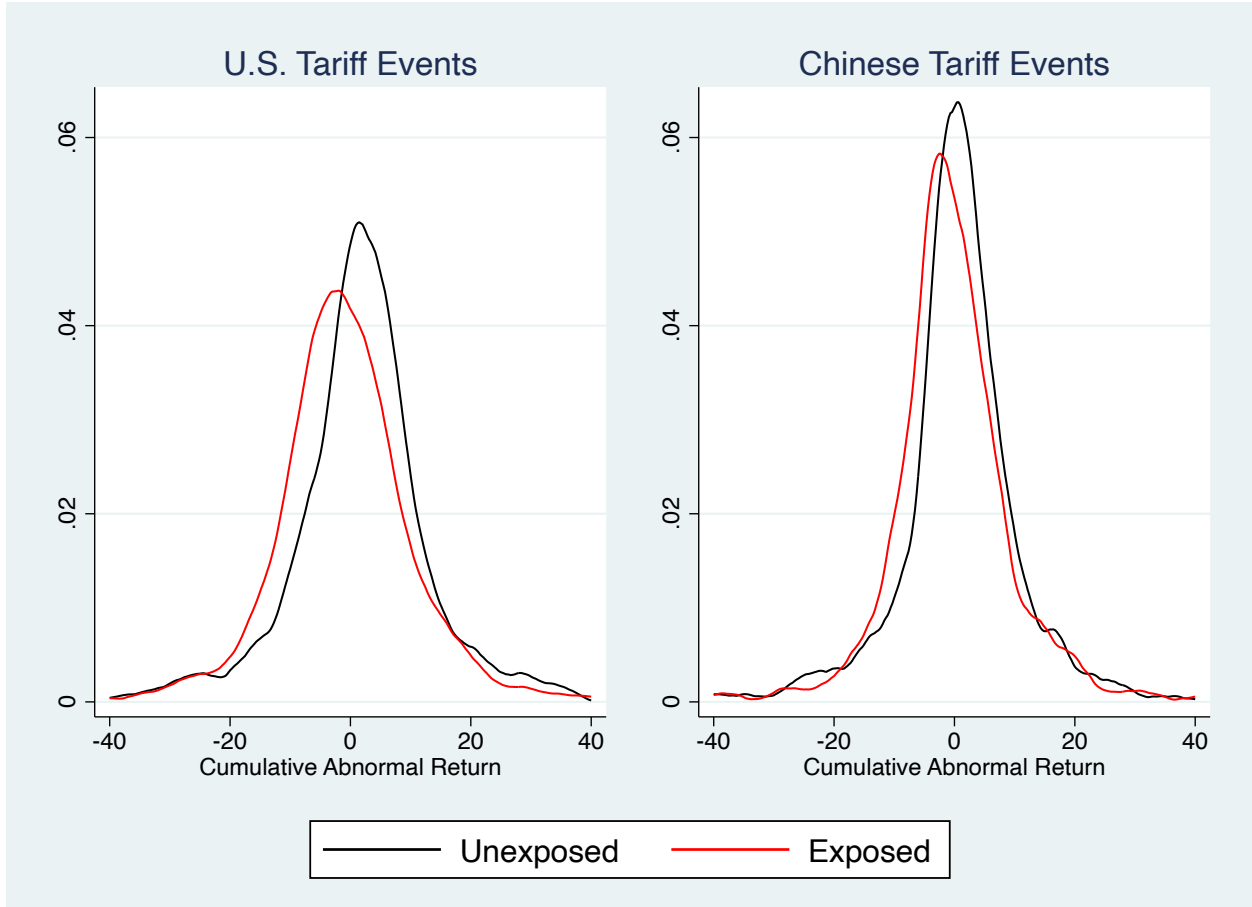
Using daily stock returns for all trading days between January 1, 2016 and December 31, 2019, we first estimate the number of general latent variables ( $K$ ) and the resulting factor model in equation (19) following the approach of Bai and Ng (2002) and Bai and Ng (2013). We follow Bai and Ng (2008), who recommend choosing the number of latent variables to minimize the following loss function when errors may be cross-sectionally correlated:

$$IC(K) = \ln(\mathcal{L}(K)) + K \left( \frac{F + T}{FT} \right) \ln(\min\{F, T\}), \quad (45)$$

where  $F$  is the number of firms;  $\mathcal{L}(K)$  is the log likelihood function based on the estimation of equation (19); and  $T$  is the number of days. Each additional factor adds 2,859  $\beta_{kf}$  parameters (one for each firm). The first factor is similar to what would be obtained in a classic CAPM setup. Based on this loss function, we use four factors in our baseline. The first factor accounts for 11.1 percent of the variance, but additional factors account for much less, with the next three factors accounting for 1.7, 1.5, 0.9 percent of the variance, respectively. Thus, macro variables explain 15.2 percent of the variation in the returns over the sample period, and any, single potentially omitted macro factor can explain no more than 0.9 percent of the variance.

In order to visualize how the tariff announcements affected the relative price component of each firm's returns depending on whether they were exposed or unexposed (as defined in Table 1), we plot the kernel densities of the error terms in equation (19) using a 3-day window around each event  $j$  ( $\epsilon_{fj} \equiv 100 \times \sum_{t=j-1}^{j+1} \epsilon_{ft}$ ) for both sets of firms in Figure 4. We define the set of exposed firms to include firms that import from, export to, or have some positive revenues in China. We see that the distribution of abnormal returns for firms exposed to China during U.S. tariff announcement events is to the left of firms

Figure 4: Dispersion in Returns (3-Day Windows)



Note: This figure portrays kernel density plots of cumulative abnormal returns of firms exposed to China (red) and unexposed (black) during 3-day windows around trade-war announcements. Exposed firms are firms that export to, import from, or have positive revenues in China.

that were not exposed. Similarly, we see that announcements of Chinese tariff retaliation produce a similar pattern, with the distribution of abnormal returns for exposed firms lying to the left of the distribution for unexposed firms. These patterns suggest that tariff announcements tended to reduce the abnormal returns of exposed firms.

We identify the relative effects of tariffs on the abnormal returns of exposed firms by estimating equation (19) using a three-day event window ( $w = 3$ ), where we regress the abnormal return (multiplied by 100) on the firm exposure variables across all eleven events, allowing separate coefficients for each firm type in each event. Table 3 presents the results for each of the six U.S. tariff events and Table 4 presents the estimated coefficients from the same regression for the five Chinese tariff retaliation events. The estimated coefficients under each event date correspond to the  $\hat{\gamma}_{ij}$  in equation (20), and we report the average value of these estimated coefficients across all U.S. events and all China events in the first column of each table. Thus, columns 2-7 of both tables are all estimated jointly. The coefficients should be interpreted as the average daily effect of the announcement on the returns of exposed firms during the event window relative to unexposed firms. For example, the coefficient of -0.18 on the China importer dummy in column 3 of

Table 3 implies that during the 3-day event window around the February 28, 2018 steel and aluminum announcement, firms that imported from China experienced declines in their abnormal returns that were on average 0.18 percentage points lower than other firms *every day* within within the three-day event window. Thus, their *cumulative* relative decline in stock prices was -0.54 ( $= 3 \times 0.18$ ) percentage points. The numbers in column 1 provide our estimate of the cumulative impact over all U.S. events and all days in the event windows ( $3 \sum_j \hat{\gamma}_{ij}$ ). For example, we can see from the first column of this table that the cumulative impact of the U.S. announcements was to lower the relative returns of U.S. importers by 1.72 percentage points relative to firms that did not import from China. Similarly, the relative returns of exporters was 2.46 percentage points lower than non-exporters, and firm’s selling in China saw their returns fall by 0.113 percentage points for every percentage point of revenue that they obtained from China. The coefficient on China Revenue Share implies that a firm with the average sales exposure to China corresponding to 4% of revenue, experienced an abnormal return of -0.4 percentage points across all of the U.S. events.

Table 3: Impact of U.S. Tariffs Announcements on Stock Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Cumulative	22Jan18	28Feb18	29May18	19Jun18	06May19	01Aug19
China Importer	-1.72*** (0.56)	-0.00 (0.07)	-0.18*** (0.07)	-0.02 (0.06)	-0.10 (0.07)	-0.12* (0.07)	-0.14 (0.09)
China Exporter	-2.46** (1.05)	0.02 (0.10)	0.03 (0.10)	-0.23*** (0.09)	-0.53*** (0.11)	-0.11 (0.12)	-0.01 (0.18)
China Revenue Share	-11.32*** (1.84)	-1.10*** (0.22)	-0.20 (0.22)	-0.22 (0.28)	-0.69*** (0.24)	-1.12*** (0.24)	-0.44* (0.26)

Note: This table presents the estimated coefficients on the U.S. events obtained from estimating equation (20); the estimated coefficients for the Chinese events are presented in Table 4. The dependent variable ( $\hat{\epsilon}_{ft} \times 100$ ) is the abnormal return obtained from estimating equation (19) with four factors multiplied by 100. China Importer is a dummy that equals one if the firm or any of its subsidiaries or suppliers imports from China. China Exporter is a dummy that equals one 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 80,674.

Table 3 suggests that U.S. tariff announcements had on average negative and significant impacts on the abnormal returns of importers, exporters, and firms selling in China more broadly. Although the effects are not precisely measured for every event and measure of exposure, thirteen of the fifteen event-day coefficients are negative, which indicates that typically firms exposed to China had negative abnormal returns relative to unexposed firms following U.S. tariff announcements. When we sum across all events, the cumulative effect is negative and significant for each type of exposure. Interestingly, U.S. tariff announcements caused negative abnormal returns not only for importing firms but also for firms exporting or selling in China more generally. These negative coefficients on the exporter or sales variables are likely due to three (not mutually exclusive) reasons. The first is that exporters may have anticipated that U.S. tariffs would provoke Chinese retaliatory tariffs, thereby lowering the abnormal return of exporters. Second, market participants may have anticipated that U.S. tariffs would also provoke Chinese retaliatory non-tariff barriers that could lower revenues obtained either by exporting or multi-national sales. Third, it is also possible that U.S. tariffs weakened the Chinese economy,



which could lower profits for U.S. firms selling there.

Table 4: Impact of Chinese Tariff Announcements on Stock Returns

	(1)	(2)	(3)	(4)	(5)	(6)
	Cumulative	22Mar18	15Jun18	02Aug18	13May19	23Aug19
China Importer	-0.54 (0.44)	0.09 (0.05)	0.00 (0.06)	0.00 (0.08)	-0.16** (0.07)	-0.11* (0.06)
China Exporter	-1.60** (0.70)	0.02 (0.09)	-0.08 (0.07)	-0.23* (0.13)	-0.10 (0.09)	-0.15* (0.08)
China Revenue Share	-11.54*** (1.91)	-0.69*** (0.23)	-0.59** (0.25)	-1.12*** (0.30)	-1.12*** (0.22)	-0.33 (0.42)

Note: This table presents the estimated coefficients on the Chinese events obtained from estimating equation (20); the estimated coefficients for the U.S. events are presented in Table 3. The  $R^2$  and number of observations are therefore the same as in Table 3. The dependent variable ( $\hat{\epsilon}_{ft} \times 100$ ) is the abnormal return obtained from estimating equation (19) with four factors multiplied by 100. China Importer is a dummy that equals one if the firm or any of its subsidiaries or suppliers imports from China. China Exporter is a dummy that equals one 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 \*  $p < 0.1$ .

Turning to the China announcements, column 1 of Table 4 shows that in general Chinese retaliation did not have a significant impact on the abnormal returns of firms importing from China, consistent with the idea that while U.S. tariff announcements provoked Chinese retaliation, Chinese retaliation did not provoke new U.S. tariffs. However, Chinese retaliation did produce negative returns for firms exporting to China on five out of the six events and for firms selling in China on all six occasions, though not always statistically significant. Overall, Chinese retaliation announcements led to a 1.6 percentage point drop in the abnormal returns of firms exporting to China and another 0.115 percentage point drop for every percentage point increase in a firm's sales in China. The results are economically significant as well. Since Bernard et al (2007) found that 79 percent of U.S. importers also export, it is worth considering the impact of the trade war on a firm exposed to China through multiple dimensions. We estimate that a firm that imported from and exported to China and obtained four percent of its revenue from sales to China would have had an abnormal return that amounted to -7.2 percent when we sum across all event days. The large magnitude of this result suggests that the trade war had a sizable economic impact on exposed firms.

We present a number of robustness tests in Table 5. Each of these specifications is based on estimating equation (20) using a different set of controls. However, in order to save space, we only report the cumulative results, so the columns in Table 5 are comparable with the first columns of Tables 3 and 4. Our coverage of firms selling in China is likely to be comprehensive because we can identify them either through the export dummy or the China revenue share variable. However, since we can only identify importers if they import goods by sea, our import variable is measured with error and potentially misses some firms that import by air. Bernard et al. (2007) have documented that importers are likely to be large firms. This is also true in our data where we find that 82 percent of importers have a thousand or more employees. In columns 1 and 2, we replace our im-

Table 5: Robustness Tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
China Importer			-1.42** (0.57)	-3.44*** (0.86)	-0.32 (0.75)	0.01 (1.24)	-3.05*** (0.59)	-1.04** (0.47)
Large Company	-1.97*** (0.52)	-0.39 (0.44)						
China Exporter	-2.62*** (1.01)	-1.76*** (0.67)	-2.50** (1.06)	-2.80 (2.02)	-2.01 (1.23)	0.23 (1.71)	-3.37*** (1.09)	-1.87** (0.78)
China Revenue Share	-11.29*** (1.84)	-11.55*** (1.91)	-10.09*** (1.91)	-19.90*** (3.28)	-16.95*** (2.42)	0.73 (5.64)	-14.11*** (2.00)	-12.31*** (1.88)
Industry Protected			-0.37 (1.28)					
N	80,674	80,674	80,674	29,356	29,356	82,080	80,674	80,674
Event	U.S.	China	U.S.	U.S.	China	Placebo	U.S.	China
Window Size	3	3	3	1	1	3	3	3
Model	4-factor	4-factor	4-factor	4-factor	4-factor	4-factor	CAPM	CAPM

Note: This table presents the results from estimating equation (20) for all U.S.-China tariff events. The dependent variable ( $\hat{\epsilon}_{ft} \times 100$ ) is the abnormal return obtained from estimating equation (19) with four factors multiplied by 100. Large Company dummy equals 1 if a firm had more than 1000 employees in 2017. China Importer is a dummy that equals one if the firm or any of its subsidiaries or suppliers imports from China. China Exporter is a dummy that equals one 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. Industry Protected is a dummy that equals one if a U.S. tariff was announced in the firm's 6-digit NAICS industry. Standard errors are in parentheses. The point estimates are the estimated cumulative impact on all event days.

port dummy with a dummy that is one for firms with a thousand or more employees.<sup>14</sup> We find qualitatively similar results with the coefficient on the large dummy for the U.S. events being negative and significant as in column 1 of Table 3, and smaller and insignificant for the China events as in column 1 of Table 4.

Next, we explore whether import tariffs provide protection to firms in that industry by including a dummy equal to 1 if there was an announcement that a new tariff would be levied on imports in that NAICS 6-digit industry level, which would lead to positive abnormal returns for import-competing firms in those sectors. The insignificant negative coefficient in column 3 suggests that this is not the case. This finding can be understood by recalling the result of [Amiti et al. \(2019\)](#) showing that U.S. protection drove up domestic output and input prices in treated sectors relative to untreated ones. In particular, effective rates of protection could fall if the impact of the tariff on a firm's output price is less than the impact of other tariffs on the pricing of the firm's *domestic* intermediate input suppliers. Appendix table A.6, which reports the individual event date coefficients on the Industry Protected variable, highlights this mechanism in our data. It shows that while the only large, *multilateral* application of tariffs—the steel and aluminum tariffs—did cause the abnormal returns of steel and aluminum producers to rise significantly, U.S. tariffs did not help protected industries when they were *only applied bilaterally* against China. Thus, a natural interpretation of this result is that purely bilateral tariffs levied on China raised the prices of Chinese intermediate inputs but failed to afford firms with protection because they still faced competition in their output markets from other foreign suppliers.

<sup>14</sup>We cannot obtain significant results with both import and large dummies because they are very highly correlated.

Another potential challenge to our identification strategy arises from the possibility that there may be omitted variables that are affecting firms trading with China during our event windows. For example, while three-day windows allow us to take account of possible information leaks the day before the event or related clarifications after the event, they may also allow for confounding information releases around event days. While we try to control for this by sweeping out movements in latent variables due to economic surprises, it remains possible that we inadvertently missed some other announcements. We deal with this challenge to identification in two ways. First, in columns 4 and 5 of Table 5, we shorten our event windows to one day, so we only consider stock-price movements on the day of the announcement. The results are, if anything, stronger than what we observed using three-day windows. Second, it is also possible that our results are just due to bad luck—perhaps, we just happened to pick days in which other, non-trade-war related announcements caused the returns of firms exposed to China to fall abnormally. We test the plausibility of this idea by running a placebo test in which we randomly select eleven events out of all trading dates in 2016 to 2019 (excluding our event dates) and re-estimate our event study for each of these randomly chosen events. We repeated this exercise 1,000 times and report the mean coefficients with their associated standard errors in column 6 of Table 5. We find that all coefficients are insignificantly different from zero, which provides another way of rejecting the possibility that our results are just due to chance.

Finally, we also explore the role played by the factor model in the last two columns of Table 5. The CAPM setup is commonly used in event studies, but we eschewed its use because we did not want to constrain the way that macro factors affect stock prices. Nevertheless, we can see the role played by using a factor model by replacing it with a CAPM framework in which abnormal returns used in the event study are computed based on the CAPM setup. We present these results in columns 7 and 8. The results indicate that using a CAPM setup leads to larger relative effects of trade-war announcements on exposure variables. This finding is consistent with Corden (1966)'s idea that tariff announcements affect macro variables in ways other than through their impact on average market returns. Thus, by including a richer set of macro controls, we tend to obtain smaller estimates of the the trade war on treated firms relative to untreated firms.

## 5.2 Tariffs and the Price Level

The results presented thus far concern the impact of the trade war on the nominal returns of specific factors. Changes in inflationary expectations could move these returns without having any impact on real returns. For example, if all final goods prices rose on a day, equation (5) implies that it would also be an equilibrium if all factor and import prices rose by the same amount. Thus, the absolute movement in real returns for firms need not tell us about real wage changes. In order to pin down the impact of the tariff announcements on real wages, we need to identify the impact of the announcements on aggregate prices. We do so by estimating equation (35) and then using equation (36) to estimate the impact of the announcements on price level.

We report the results of our estimates of the trade war on the price level in Table 6. The estimates indicate that during each day in an announcement window, trade-war announcements were associated with a 0.029 percentage drop in the expected price level

Table 6: Impact of Trade-War Announcement on Inflation Expectations

	(1)	(2)	(3)	(4)
	5-year	5-year	10-year	10-year
Event Dummy	-0.029*	-0.076***	-0.038**	-0.092***
	(0.015)	(0.021)	(0.018)	(0.025)
Event Dummy $\times$ China Event Dummy		0.092***		0.105***
		(0.030)		(0.035)
$N$	989	989	989	989

Note: The dependent variable is the change in inflation expectations 5 years out in columns 1 and 2, and 10 years out in columns 3 and 4. The coefficients reflect the average effect across all event days.

five years later and a 0.038 percentage point drop ten years later. Given that we have eleven events spanning three days each, our results imply that the trade war lowered inflationary expectations so that prices were expected to be 1.0 percentage points lower five years later and 1.3 percentage points ten years later. In columns 2 and 4 we investigate whether it is U.S. or Chinese events that led to the decline in the expected U.S. inflation by interacting the event dummy with a dummy that is one if the announcement originated in China. We see that virtually all of the deflationary impact of tariffs comes from U.S. announcements, with Chinese events having no impact on the expected U.S. inflation. These results are consistent with the work of [Comin and Johnson \(2020\)](#) who argue that U.S. trade liberalization is inflationary.

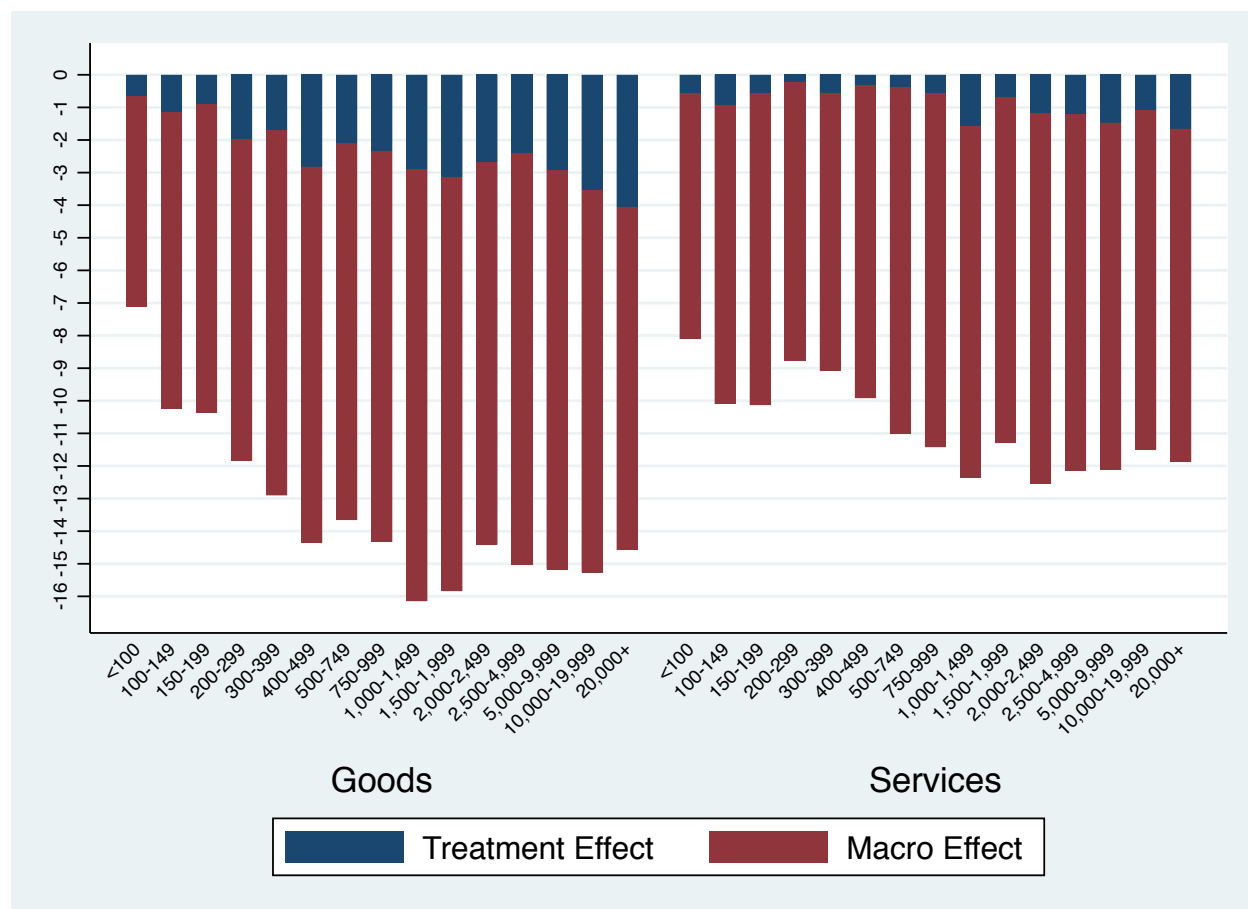
### 5.3 Productivity, Wage, and Welfare Effects

We can use the estimates we obtained in the last two sections to compute the macro and treatment effects on stock returns. We use equations (24) and (20) to compute the expected impacts of the tariffs on firm returns operating through the macro and treatment effects, and then follow the procedure described in the Data Section to compute the expected returns of firms in each bin. Figure 5 plots the distribution of expected returns ( $E[\hat{r}_b|\tau]$ ) due to the macro effect ( $E[\hat{r}_b^M|\tau]$ ), and expected returns due to the treatment effect ( $E[\hat{r}_b^T|\tau]$ ) by bin. The market-capitalization weighted average of the macro effect on stock prices ( $\sum_f w_f E[\hat{r}_f^M|\tau]$ ), is -9.2 percent and that of the treatment effect ( $\sum_f w_f E[\hat{r}_f^T|\tau]$ ) is -2.7 percent, so the total decline in the market that we attribute to the trade war ( $\sum_f w_f E[\hat{r}_f|\tau]$ ) is 11.9 percent. This is very close to the actual decline that we saw in Table 2 of 12.9 percent, which indicates that idiosyncratic firm-level shocks ( $\nu_{ft}$ ) do not matter much in aggregate on these days.

The figure also reveals that there were important differences in the impact of the trade-war on firms of different size and by sector. As expected, the treatment effect is biggest for firms producing goods and for firms employing a large number of workers. This probably reflects the fact that large firms selling goods are more likely to be buying from or selling in China. Interestingly, we observe a similar firm-size gradient for the macro effect, but we do not observe much of a difference between the macro effects of the announcements on producers of goods versus services for firms in a given size bin. This result is consistent with the idea that large firms are more likely to be globally engaged more broadly, so

general trade policy uncertainty surrounding the world trading system is more likely to affect larger firms. The most striking feature in this figure is the relative magnitude and pervasiveness of the macro effect. Consistent with the idea that the trade war created substantial policy uncertainty that hurt firms regardless of their exposure to China, we see that all categories of firms had substantial negative returns.

Figure 5: Expected Return Due to Tariff by Firm Employment



Note: The blue bars correspond to the predicted treatment effects in equation (25) with estimated coefficients from Tables 3 and 4, and the red bars correspond to the predicted macro effect from (24). These are converted to the bin level following the procedure described in the Data Section. The weights are adjusted to reflect the economy wide distribution, with data on employment distribution by sector-size from U.S. Census. Goods sectors are defined as all 2-digit NAICS industries 11, 21-23, and 31-33.

One concern with our estimate of the macro effect is that we may be capturing both the effect of the trade-war announcements and some other announcement that coincided with these days. As we explained in Section 3.1, we have already purged the estimates of the effect of any standard data release on stock prices. However, one still may wonder how likely is it that we would have identified a macro effect of this magnitude if we had just randomly picked eleven days between 2016 and 2019. In order to estimate this, we removed each event day from our sample along with the two prior and two subsequent days in order to create a sample of potential placebo event days in which no trade-war announcement occurred. We then randomly selected eleven placebo event days and their associated event windows, computed the macro effect, and repeated this procedure 1,000

times. We find that in contrast to the 9.2 percent decline in the market due to the macro effect that we estimate for the trade-war announcements, the average macro effect for the placebo event days was a 0.6 percent *increase* in stock prices. Moreover, out of the 1,000 placebo trials, less than 3 percent of the draws produced a macro effect of -8.3 percent or less. Thus, we can reject the hypothesis that the macro effect that we identify could have arisen by chance at conventional levels of significance.

In order to explore the underlying channels driving these large negative effects, we check whether greater protection lowers firm TFP, which has been consistently shown in the micro-level literature. Since Proposition 3 proves that revenue TFP is the same object as the effective rate of protection, we should expect import tariffs to lower the ERP and TFP of firms by raising their materials costs. Similarly, Chinese retaliation should lower ERP and TFP either by depressing output prices or making it more costly to sell in China. We use equation (31) to compute the movement in expected revenue TFP implied by the raw stock price movements during the event windows. If we regress these movements in firm-level expected TFP directly on our China exposure variables, we can interpret the coefficients as an estimate of how exposure to the trade war affected the market's expectation of the change in revenue TFP. Thus, we can see whether we observe the same links between protection and expected TFP that past studies have identified using primal TFP.

Table 7: Impact of U.S. Tariffs Announcements on TFPR

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Cumulative	22Jan18	28Feb18	29May18	19Jun18	06May19	01Aug19
China Importer	-0.52*** (0.04)	-0.01** (0.00)	-0.04*** (0.01)	0.01*** (0.00)	-0.05*** (0.01)	-0.06*** (0.00)	-0.02** (0.01)
China Exporter	-0.96*** (0.13)	-0.01* (0.01)	-0.02 (0.02)	-0.08*** (0.01)	-0.16*** (0.02)	-0.04*** (0.01)	-0.00 (0.02)
China Revenue Share	-4.64*** (0.45)	-0.30*** (0.03)	-0.21*** (0.05)	0.02 (0.01)	-0.34*** (0.03)	-0.51*** (0.05)	-0.21*** (0.04)

Note: The dependent variable is calculated as in equation (31). This table presents the average coefficient on each of the event days obtained from regressing TFPR as calculated in Proposition 3 on variables measuring exposure to the trade war. China Importer is a dummy that equals one if the firm or any of its subsidiaries or suppliers imports from China. China Exporter is a dummy that equals one 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. Standard errors are in parentheses. The number of observations is 58,076.

Before presenting the TFP results, we want to note an important theoretical difference between running the event-study specifications presented in Tables 3 and 4 with the abnormal returns as the dependent variable and running a specification in which we replace the dependent variable with TFP. As Corden (1966) originally argued, tariff announcements should affect returns through both macro and treatment effects. By focusing only on the latter, event-study regressions only capture a portion of the tariff's effect on returns, rendering identification of the full effect on the treated difficult. By contrast, the concept of firm-level TFP is immune to this problem because it includes both the macro and treatment effects, so we should expect regressions of TFP on protection to enable easier identification of the full treatment effect.

In Tables 7 and 8, we show that TFP is even more sensitive to protection than abnormal returns. As before, we continue to observe that protection has a statistically significant ef-



Table 8: Impact of Chinese Tariffs Announcements on TFP

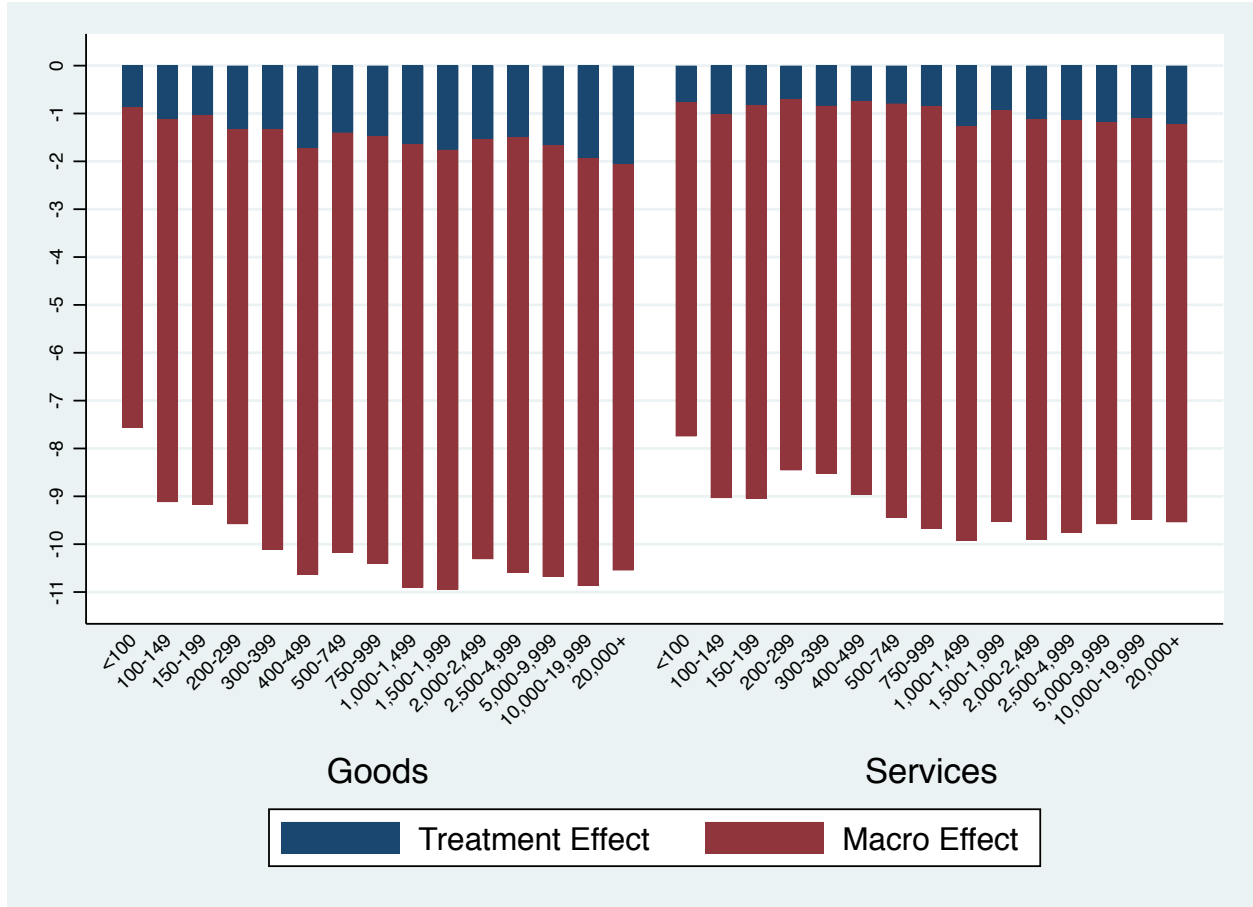
	(1)	(2)	(3)	(4)	(5)	(6)
	Cumulative	22Mar18	15Jun18	02Aug18	13May19	23Aug19
China Importer	-0.15*** (0.05)	-0.01 (0.01)	0.01*** (0.00)	0.02*** (0.00)	-0.04*** (0.00)	-0.04*** (0.01)
China Exporter	-0.61*** (0.11)	0.01 (0.02)	-0.04*** (0.00)	-0.07*** (0.00)	-0.02** (0.01)	-0.07*** (0.01)
China Revenue Share	-4.44*** (0.41)	-0.40*** (0.06)	-0.13*** (0.02)	-0.29*** (0.04)	-0.46*** (0.04)	-0.21*** (0.03)

Note: This table presents the average coefficient on each of the event days obtained from regressing TFP as calculated in Proposition 3 on variables measuring exposure to the trade war. China Importer is a dummy that equals one if the firm or any of its subsidiaries or suppliers imports from China. China Exporter is a dummy that equals one 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. Standard errors are in parentheses.

fect overall, but now we identify significant impacts of protection on expected TFP (as opposed to abnormal returns) on virtually all event days. 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 7), we see that these announcements led to significant declines in expected TFP of exposed firms in all but one case of U.S. protection. Similarly, Chinese retaliation announcements caused the expected TFP of U.S. exporters to fall significantly in four out of five cases and always had a significant negative impact on the expected TFP of firms selling in China. In order to give some sense of the economic magnitudes of these effect, we again consider the cumulative impact of these announcements on a firm that both imported from and exported to China and had a revenue of 4 percent coming from China (equal to the average). Such a firm would have experienced a 2.6 percentage point drop in its expected TFP.

We can also use the observed movements in stock prices to infer the impact that the tariff announcements had on aggregate U.S. TFP based on equation (44). Figure 6 shows our estimates of the impact of the tariff announcements on the TFP of firms broken down by firm size. We find that the negative effect of trade-war announcements on expected TFP are rising with firm size until firms achieve a size of around 400 employees and then the impact of announcements on firm productivity levels off at around -10 percent. The main driver of this estimate is the fact that trade-war announcements caused the stock market to fall by 11.9 percent, which amounts to a \$3.3 trillion loss of firm value (equivalent to 16 percent of U.S. GDP in 2019). Seen through the lens of the specific factors model, the 12.9 percentage point decline in stock prices we observed was caused by a 9.5 percent decline in TFP. Firms employing less than a hundred workers experienced TFP declines that were typically three percentage points less than the declines for large firms. The model suggests that there are two complementary reasons why tariff announcements lowered the TFP of large firms by more. First, large manufacturers of goods are more dependent on trade, so the treatment effect rises in magnitude with firm size. Second, the macro effects—although similar for goods and services firms—also rise in magnitude with firm size. This second story is consistent with the finding in Figure 5 that macro factors drove the share prices of large, global firms down by relatively more following trade-war announcements.

Figure 6: Expected TFPR Due to Tariff by Firm Employment



Note: This plot shows estimates of revenue TFP (net of aggregate price movements) calculated according to equation (44) by firm size-sector bin.

We can use these estimates of  $E[\hat{r}_b^M|\tau]$ , and  $E[\hat{r}_b^T|\tau]$  to compute the impact of the trade war on expected real wages by using equation (43). We find that the trade war is expected to lower U.S. wages by 9.2 percent. These numbers are not out of line with estimates obtained from other large movements in trade barriers.<sup>15</sup> This economically significant decline arises from two channels. First, the adverse impacts of the trade war on productivity operating through the macro and treatment channels is expected to depress nominal wages by 10.5 percentage points relative to a benchmark without the trade war. However, this downward pressure on factor prices is also associated with an expected drop in the U.S. price level over a 10-year horizon as we saw in Table 6, and this offsets

<sup>15</sup>Given the stickiness of nominal wages, it might seem implausible that the trade war could reduce real wages by this amount. However, it is important to remember that this should be thought of as a long-run effect. For example, our estimates of the impact of the tariff announcements on the price level are based on data that allows for the impact to have up to 10 years to have an effect, thus the effects in any given year can still be small. Moreover, our point estimates are in line with estimates of the long-run impact of tariffs obtained in other studies. Kovak (2013) and Dix-Carneiro and Kovak (2017) estimate the impact of a Brazilian tariff liberalization on earnings and find that although there is little effect immediately afterwards, the impact is comparable in magnitude to our estimates ten years later.

1.3 percentage points of the decline.

Table 9: Welfare and Real Wage Effect

Description	Welfare			TFP	Real Wage
	Total	Macro	Treatment		
Size-Sector bins	-7.8	-7.2	-0.6	-9.5	-9.2
Bins based on size only	-7.7	-6.9	-0.8	-9.6	-9.5
Trade war has no impact on small firms	-5.0	-4.6	-0.4	-8.2	-7.8
Trade war only matters for listed firms	-3.9	-3.6	-0.2	-4.7	-1.6

We report the welfare implications of the trade war in Table 9. Equation (42) indicates that expected U.S. welfare fell by 7.8 percentage points as a result of the trade war. The macro effect accounts for about 7.2 percentage points of this drop, with the remaining 0.6 percent welfare loss due to the treatment effect. Taken together these results imply that the 7.8 percentage point decline in welfare arises mainly because the trade-war announcements induces adverse macro forces that serve to depress wages and firm returns. At first glance, our estimates may seem high compared to conventional measures, but in actuality the differences can largely be attributed to our ability to account for channels that are not typically included. For example, only 0.6 percentage points of the 7.8 percentage point decline in expected welfare is due to the treatment effect: the losses arising because some firms faced protection and others did not. For example, [Amiti et al. \(2019\)](#) estimate that the welfare loss due the trade war was \$79.1 billion, or 0.4 percent of GDP using a method that just looks at the treatment effect. Since this estimate and our treatment effect do not incorporate any potential macro losses, they are comparable.

Nevertheless, we explore a number of alternative specifications to see how different assumptions affect our results. In order to see how allowing for sectoral heterogeneity affects our results, we only use size bins to compute the welfare results instead of size-sector bins and report the results in the second row of Table 9. These results are qualitatively quite similar to our main specification. One of the biggest problems of using the Compustat data to approximate returns in the U.S. economy is that small firms in the Compustat data are likely to have significantly higher profitability than small firms in the U.S. economy. In order to make sure that these differences are not driving our results, we reran our welfare analysis imposing the assumption that the trade-war impact on the returns for firms employing fewer than 100 workers is zero. We report these results in the third row of the table. Not surprisingly, this restriction does lead to a smaller estimate of the the impact of the trade war on U.S. welfare, but we still arrive at the conclusion that the trade war lowered U.S. welfare by 5 percentage points. In the last row of the table, we consider an extremely conservative assumption: the trade war only affected listed firms. We impose this assumption by recomputing the estimated return in each cell by imposing the restriction that the average return for U.S. firms in the cell that were not listed always equals zero. Even when we impose this assumption, we still find that the trade war drove down U.S. welfare by 3.9 percent, which is about half of our baseline estimate. The reason we obtain large effects even when we assume that virtually all firms were unaffected by

the trade war is that listed firms constitute a large share of U.S. employment: 22.7 percent of the employment in our sample of industries is employed by listed firms. As a result, when expected profitability of listed firms declines sharply, as happened during the trade war, this has important implications for the expected welfare of Americans.

## 6 Conclusion

The specific factors model has largely been used by economists as a means of mapping trade-induced price changes into factor price movements. A key insight of this paper is that this logic can be reversed so that one can use movements in the returns to specific factors to identify movements in wages and ERP. We then apply this method to data by noting that stock price movements can be thought of movements in the expected returns to firm-specific factors. This fact lets us use the [Jones \(1975\)](#) model to obtain a mapping between expected returns to factors (as captured by stock-price movements) and expected movements in wages and ERP. Since we show that the change in the ERP is equivalent to a move in revenue TFP, this approach provides a means of analyzing the impact of trade on an economy in a general equilibrium setup in which we can use firm-level data to estimate how trade policy can induce changes in TFP. Our results indicate that markets expect the U.S.-China trade war to have large, negative impacts on U.S. wages and welfare. These effects are driven largely by the adverse effects of protection on productivity, and this study suggests that more work needs to be done to better understand why globalization is linked to firm-level productivity.

An important difference between our work and other studies of the impact of protection on welfare is that we use data based on market expectations of firm-level returns to identify these effects. An advantage of this approach is that market responses to policy announcements are rapid. Thus, a researcher trying to evaluate a policy can use this method without waiting for the data on the policy change to become available, which is an advantage when trying to evaluate large complex trade agreements in which it is difficult to model all the ways that a firm might be affected.

Finally, our work also suggests that there are important macro forces moving market expectations about firm-level TFP that are not captured by conventional differences-in-differences estimation and conventional trade models. While it is beyond the scope of this paper to identify precisely why trade-war announcements produce such large movements in stock prices, it is clear that much of the effect seems to be arising from the effect of trade on macro variables. Obvious candidates for these omitted macro factors are variables related to policy uncertainty, but establishing these connections is a topic for future work.

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# Online Appendix to “The Effect of U.S.-China Trade War on U.S. Investment” (Not for Publication)

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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. Section [A.5](#) presents sample statistics. We present the sources for each event in Section [A.31](#). Section [A.31](#) explains the details behind the construction of Figure 3. We provide links to sources for each of the first mentions of the tariff announcement in the U.S.-China trade war in Section [A.6](#). Section [A.8](#) replaces the FactSet measure of China Revenue Share used in the paper with the Compustat measure for 2017. Section [A.9](#) shows the results of including the Industry Protected dummy for each event.

## 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.** *In any specific factors model featuring an identical elasticity of substitution between labor and capital for all firms, 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:

$$\hat{y}_f = -\hat{a}_{Vf}, \quad (\text{A.1})$$

and

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

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

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

or

$$\hat{w} = \sum_f \frac{L_f}{L} \hat{r}_f - \frac{\hat{L}}{\sigma} \quad (\text{A.4})$$

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

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

or

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

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

$$\hat{L} = \sum_f \hat{L}_f L_f, \quad (\text{A.7})$$

we have

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

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

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

$$\hat{L} = \hat{L} L \implies \hat{L} = 0. \quad (\text{A.11})$$

which establishes that

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

□

## A.2.2 Proposition 1

**Proposition.** *If the share of expenditures on intermediate inputs is unaffected by the policy shock, the impact of a trade policy change on firm output is given by*

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

where  $\omega_{L_f}$  and  $\omega_{V_f}$  denote the payments to labor and specific factors as a share of revenue.

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

$$\omega_{L_f} \hat{a}_{L_f} + \omega_{V_f} \hat{a}_{V_f} + \sum_i \omega_{i_f} \hat{a}_{i_f} = 0. \quad (\text{A.13})$$

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

$$\hat{a}_{L_f} = -\frac{\omega_{V_f}}{\omega_{L_f}} \hat{a}_{V_f} \quad (\text{A.14})$$

Substituting this into equation (A.5) yields

$$-\hat{y}_f + \frac{\omega_{V_f}}{\omega_{L_f}} \hat{a}_{V_f} = \sigma (\hat{w} - \hat{r}_f). \quad (\text{A.15})$$

Substituting in equation (A.1) gives us

$$-\hat{y}_f - \frac{\omega_{V_f}}{\omega_{L_f}} \hat{y}_f = \sigma (\hat{w} - \hat{r}_f) \quad (\text{A.16})$$

$$\hat{y}_f + \frac{\omega_{V_f}}{\omega_{L_f}} \hat{y}_f = \sigma (\hat{r}_f - \hat{w}) \quad (\text{A.17})$$

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

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

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

Making use of our wage result from Proposition 1 gives us

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

□

### A.2.3 Proof of Proposition 3

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

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

and if the share of expenditures on intermediate inputs is unaffected by the policy shock, then  $\hat{p}_f^e$  equals the change in the firm's "value-added" total factor productivity: i.e., the change in a firm's value added holding fixed its labor and capital inputs.

*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  $\omega_{Lf}\hat{w} + \theta_{Vf}\hat{r}_f + (1 - \sum_i \omega_{if})\hat{y}_f = \sum_i \omega_{if}\hat{q}_i$ . If we divide both sides by  $(1 - \sum_i \omega_{if})$  and rearrange, we obtain:

$$\theta_{Lf}\hat{w} + \theta_{Vf}\hat{r}_f = \frac{\hat{p}_f - \sum_i \omega_{if}\hat{q}_i}{1 - \sum_i \omega_{if}}, \quad (\text{A.22})$$

Using Proposition 1, we can rewrite equation (A.22) as

$$\theta_{Lf} \sum_{f'} \frac{L_{f'}}{L} \hat{r}_{f'} + \theta_{Vf}\hat{r}_f = \frac{\hat{p}_f - \sum_i \omega_{if}\hat{q}_i}{1 - \sum_i \omega_{if}} \equiv \hat{p}_f^e. \quad (\text{A.23})$$

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

$$p_f y_f - \sum_i m_{if} q_i = L_f w + V_f r_f, \quad (\text{A.24})$$

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

$$p_f y_f - p_f y_f \sum_i \omega_{if} = L_f w + V_f r_f, \quad (\text{A.25})$$

or

$$p_f y_f \left(1 - \sum_i \omega_{if}\right) = L_f w + V_f r_f, \quad (\text{A.26})$$

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

$$(dp_f y_f + p_f dy_f) \left(1 - \sum_i \omega_{if}\right) = L_f dw + V_f dr_f + w dL_f + r_f dV_f. \quad (\text{A.27})$$

Dividing through by  $p_f y_f$  produces

$$(\hat{p}_f + \hat{y}_f) \left(1 - \sum_i \omega_{if}\right) = \omega_{L_f} \hat{w} + \omega_{L_f} \hat{L}_f + \omega_{V_f} \hat{r}_f + \omega_{V_f} \hat{V}_f. \quad (\text{A.28})$$

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

$$TFPR_f \equiv \hat{p}_f + \hat{y}_f - \theta_{L_f} \hat{L}_f - \theta_{V_f} \hat{V}_f = \theta_{L_f} \hat{w} + \theta_{L_f} \hat{r}_f = \hat{p}_f^e, \quad (\text{A.29})$$

where  $\theta_{L_f}$  and  $\theta_{V_f}$  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 the ERP is the same as TFP.  $\square$

### 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

The Compustat employment data overstates U.S. employment for multinationals because Compustat includes workers employed abroad. In this section, we provide further details on our estimates of U.S. employment for multinational firms in our sample. First, we 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.

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

## 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:  $\epsilon_{ft}$  is estimated from equation (19). The China Importer and China Exporter dummies equal one 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 one when a firm has at least 1,000 employees, sourced from Compustat. The Industry Protected Dummy is defined 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	<a href="#">washington post</a>
2018/2/28	2018/3/23	US	<a href="#">reuters</a>
2018/3/22	2018/4/2	China	<a href="#">nytimes</a>
2018/5/29	2018/7/6	US	<a href="#">npr</a>
2018/6/15	2018/7/6	China	<a href="#">npr</a>
2018/6/19	2018/9/24	US	<a href="#">wsj</a>
2018/8/2	2018/9/24	China	<a href="#">reuters</a>
2019/5/5	2019/5/10	US	<a href="#">dw</a>
2019/5/13	2019/6/1	China	<a href="#">cnbc</a>
2019/8/1	2019/9/1	US	<a href="#">cnbc</a>
2019/8/23	2019/9/1	China	<a href="#">cnbc</a>

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 3

### 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:

$$R_t = \alpha + \sum_{s=-5}^5 \beta_s D_{jts} + \epsilon_t. \quad (\text{A.30})$$

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

$$\psi_s \equiv 11 \sum_{k=-5}^s \hat{\beta}_k. \quad (\text{A.31})$$

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

### A.7.2 Price Change Plot

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

$$E_t [\hat{P}^{10}] = \alpha + \sum_{s=-5}^5 \beta_s D_{jts} + \epsilon_t \quad (\text{A.32})$$

where  $\alpha$  and  $\beta_s$  are parameters to be estimated, and  $\epsilon_t$  is an error term. We compute  $\psi_s$  as in equation (A.31) using these new estimates of  $\beta_s$  for  $s \in [-5, 5]$ .

## A.8 Robustness to Using 2017 Compustat Data to Measure Chinese Revenue Shares

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.4 and A.5 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 does well in capturing the foreign sales of larger firms but misses the sales of smaller firms that FactSet identifies through their 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.4: Impact of U.S. Tariffs Announcements on Stock Returns (2017 Compustat China Revenue Share)

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

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

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

## A.9 Disaggregated Industry Protected Specification

Table A.6: Robustness Tests (Industry Protected)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Cumulative	22Jan18	28Feb18	29May18	19Jun18	06May19	01Aug19
China Importer	-1.42** (0.57)	0.02 (0.07)	-0.19*** (0.07)	0.02 (0.06)	-0.07 (0.07)	-0.15** (0.08)	-0.09 (0.10)
China Exporter	-2.50** (1.06)	-0.00 (0.09)	0.02 (0.10)	-0.23*** (0.09)	-0.52*** (0.11)	-0.12 (0.12)	0.02 (0.18)
China Revenue Share	-10.09*** (1.91)	-0.83*** (0.22)	-0.19 (0.22)	-0.12 (0.28)	-0.65*** (0.25)	-1.17*** (0.24)	-0.40 (0.26)
Industry Protected	-0.37 (1.28)	-0.81*** (0.20)	1.08*** (0.33)	-0.17*** (0.06)	-0.08 (0.08)	0.11 (0.08)	-0.24* (0.13)