Trade Protection, Stock-Market Returns, and Welfare*

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September 29, 2021

Abstract

We show that the specific factors model can be used to rigorously map stock price movements into expected movements in productivity, wages, and welfare. We also prove that the effective rate of protection equals revenue TFP. Using our framework, we find that the U.S.-China trade-war announcements caused large declines in U.S. stock prices, expected TFP, and expected inflation and caused dollar appreciation and a jump in uncertainty as measured by the VIX. The expected decline in U.S. welfare is 7.8 percentage points, which is much larger than the predictions of static models but in line with those of dynamic models.

JEL CLASSIFICATION: F13 F14 F16
KEYWORDS: Protection, Event Studies, Adjustment Costs

*This paper supersedes an earlier unpublished paper, "The Effect of the U.S.-China Trade War on U.S. Investment." We thank George Alessandria, Kirill Borusyak, Dave Donaldson, Ethan Ilzetzki, Peter Neary, Peter Schott, Jon Vogel, and Michael Waugh for many useful comments. We thank Richard Crump for sharing inflation expectations data and Daniel Lewis for sharing the economic surprise data. We also thank Yingjie (Angela) Wu and Dongcheng Yang for providing excellent research assistance. The views expressed in this paper are those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of New York or the Federal Reserve System.

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1 Introduction

Trade models differ sharply in their predictions about the gains from trade. Canonical trade models typically have the property that the free-trade equilibrium is efficient, so trade protection only has small, second-order effects on welfare. By contrast, dynamic models often have the property that there are productivity spillovers across firms that are not internalized, which means that protection can have large, first-order effects on productivity and welfare in the long run. Testing which approach is more reasonable is difficult because dynamic effects may take years to materialize, and it is difficult to know whether any observed shift in productivity over a long time period is due to the change in protection or some other policy change. In this paper, we show that stock price data can be used to identify the effects of a policy measure on *expected* profits, productivity and welfare under the assumption that stock price movements on the day of a new tariff announcement are principally driven by the news of new protection. 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 with announcements of new trade protection implies that market participants expected the trade war to lower U.S. welfare by 7.8 percent, which we show is just under the value we obtain from calibrating Perla et al. (2021)'s dynamic model.

The structure we use to link movements in stock prices to expected movements in productivity and welfare builds on two seminal papers in the literature. First, we use the structure of Jones (1975)'s specific factors model, which proved that there is a theoretical relationship between the effective rate of protection (ERP), wages, and the returns to a specific factor. We demonstrate that one can invert Jones's model and write changes in nominal variables (wages and the ERP) as a function of the returns to the specific factor. Second, we use an insight proven in Grossman and Levinsohn (1989) that shows that stock price changes can be interpreted as expected movements in returns to firm-specific factors. Taken together these two results mean that movements in stock prices tell us about changes in expected returns to specific factors, wages, and ERP. Finally, 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.

Our method also provides a way to estimate 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 the 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. Lower marginal costs, however, imply that there must also be 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 in 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 develop a method for exactly decomposing the effect of a trade-war announcement on expected TFP and welfare into its effect on macro variables and treatment variables. 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 show that the differential abnormal returns of importers, exporters, and firms selling in China during event windows likely capture the treatment effects of protection. 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. Thus, we provide a rigorous approach to solving the problem of how to decompose ERP first raised by Corden (1966).[1]

We apply this methodology to the 2018-2019 U.S.-China trade war. One challenge with using stock-price data to infer movements in the broader economy is that the sample of listed firms over-weights large firms relative to the overall U.S. distribution of firms. We deal with this problem by re-weighting the stock returns for firm-size and industry cells to match those reported in national data and then assuming that within-cell average returns in stock-market data match those in the U.S. national data. We identify U.S. and Chinese tariff event dates as the earliest tariff 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 one-day, three-day, or five-day event windows. We find that during a three-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,

[1] 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].

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 latent macro variables.

While our method doesn't provide guidance on which macro variables drove the market, we do show that there were large movements in several macro variables that are strongly correlated (in terms of magnitude and significance) with our latent macro variables. For example, our event study shows that tariff announcements drove one measure of uncertainty—the VIX—up by 114 percent. The announcements also caused a 3.3 percent appreciation in the dollar. In total, the impact of the announcement on the latent macro variables was so large relative to usual movements in these variables that our placebo test easily rejects the hypothesis that it arose from random movements in these variables. Moreover, as in 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.

In order to compute the impact of these announcements on U.S. welfare, we also 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 those of 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 10-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.

Our baseline results show that the drop in stock prices implies that market participants expect TFP to fall by 9.5 percent and welfare to fall 7.8 percent. Decomposing the welfare loss into the macro component—the way in which a policy affects all firms through macro variables—and the more conventional treatment effect, we find the macro effect matters the most, accounting for 7.2 percentage points of the welfare decline, and only 0.6 percentage points is due to the differential impact on treated firms. The relationship between ERP and TFP sheds light on what is underlying these large effects. Since expected 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 expected firm-level TFP. In our setup, the large drop in expected TFP drives down expected wages. This drop in expected wages provides intuition for the decline in measured expected inflation. Moreover, we show that the expected TFP changes exhibit a significant negative relationship with trade exposure measures. This result is consistent with the findings of empirical studies of the effect of liberalization on productivity, which have also found that protection has economically significant effects on TFP.[2]

Our estimate of the decline in welfare is larger than that typically estimated using static trade models. For example Amiti et al. (2019), estimate a welfare loss of 0.4 percent of GDP due to the trade war.[3] By contrast, Sampson (2016), Buera and Oberfield (2020), and Perla et al. (2021) argue that one can obtain much larger estimated impacts of trade if one allows for productivity spillovers that enable trade protection to have a first-order effect on welfare. We explore this formally by calibrating the Perla et al. (2021) model to show that it provides a mapping between trade induced movements in stock prices and welfare. Seen through the lens of their model, the stock-price movements imply that there will be a 9.0 percentage point drop in U.S. welfare: a number close to our baseline estimate. This result suggests that markets anticipate welfare effects that are similar in magnitude to those modeled by Perla et al. (2021).

Related Literature Our paper is related to the vast empirical trade literature over the last two decades showing that trade liberalizations have big effects on per capita income and productivity. These studies have shown that *firm-level* TFP is very sensitive to 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 Khandelwal (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 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 studies 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.

Our work is also closely related to the voluminous literature on stock-market event studies that use trade data (Grossman and Levinsohn (1989), Hartigan et al. (1986), Breinlich (2014), Fisman et al. (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 general equilibrium model to interpret the data. Greenland et al. (2020) is particularly relevant in that they show that positive firm abnormal returns in response to lower trade uncertainty, through the granting of permanent normal trade relations in 2000, led to increases in firm employment, sales, productivity and profits six years later. Our approach yields a theoretical foundation for these regressions, and their regressions validate our assumption that movements in share prices are tightly linked to movements in future

[2]For example, Amiti and Konings (2007) estimate the elasticity of firm-level TFP with respect to input tariffs to be -1.2 in Indonesia 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, and Brandt et al. (2017) and Brandt et al. (2019) estimate the elasticity to be -2.3 in Chinese data.

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

accounting profits and other non-financial variables.

The specific factors model, which forms the basis of our approach, has also been used extensively in empirical estimation in recent years (c.f., Topalova (2010), Kovak (2013), and Dix-Carneiro and Kovak (2017)). These papers have shown that many of the large effects of trade policy changes on wages often take a decade to be fully apparent in the data. Our paper provides a complementary way of thinking about the long-term effects of a policy change in terms of expected wages.

We also contribute to the burgeoning literature on understanding the importance of protection for 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.

Finally, our work is related to the 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 et al. (2021) 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 is a set of potential entrants into the market indexed by ℓ 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_ℓ (the specific factor) that enables it to produce a product f at a given marginal cost of $c_f^\ell(w, r_\ell, q_1, ..., q_n)$, where the arguments correspond to ~~the wage (w)~~, returns to firm ℓ's specific factor r_ℓ, and a set of intermediate inputs, each produced at a price q_i. Successful entrants will hire L_ℓ workers in order to produce y_ℓ 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_ℓ) and unit cost functions ($c_f^\ell(w, r_\ell, q_1, ..., q_n)$) 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., $p_f > c_f^\ell (w, 0, q_1, ..., q_n)$, and in this case it earns $r_\ell V_\ell = \left(p_f - c_f^\ell (w, 0, q_1, ..., q_n)\right) y_\ell > 0$ on its production plan. Since the entry condition only depends on the common market price for the good (p_f) and $c_f^\ell (w, 0, q_1, ..., q_n)$, without loss of generality, we can rank the potential entrants by the unit cost of their production plans, i.e.,

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

Entrants 2 and higher will not produce if $p_f^1 \leq c_f^2 (w, 0, q_1, ..., q_n)$. Therefore, potential entrant 1 will optimally produce at the limit price of $p_f^1 = c_f^2 (w, 0, q_1, ..., q_n)$, 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 ℓ notation and refer to firm 1 producing good f as "firm f," its price as p_f, and its unit cost as $c_f (w, r_f, q_1, ..., q_n)$.

As in Jones (1975), we impose the full-employment conditions on labor and each firm's specific factor:

$$\sum_f a_{Lf} y_f = L, \text{ and} \tag{2}$$

$$a_{Vf} y_f = V_f, \tag{3}$$

where $L \equiv \sum_f L_f$ and the unit input requirements for labor and the specific factor are given by a_{Lf} and a_{Vf}. Since $a_{Lf} y_f = L_f$, 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_{Vf}) is inversely proportional to firm output (y_f). Similarly, we assume that the factor intensity of production (a_{Vf}/a_{Lf}) is determined by relative factor prices and the elasticity of substitution between the specific factor and labor (σ):

Definition

$$\hat{a}_{Vf} - \hat{a}_{Lf} = \sigma \left(\hat{w} - \hat{r}_f\right), \tag{4}$$

where r_f is the return to the firm-specific factor 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 returns to firm-specific factors, 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. 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 changes 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, Jones was concerned about mappings from changes in the ERP into factor prices. Here, we invert the logic in Jones to show that knowing the returns to specific factors pins down changes in wages and employment. This property will prove useful when we turn to the empirics because measuring movements in ERP due to a policy is extremely difficult, whereas it is straightforward to use stock prices to measure movements in returns to specific factors ($\hat{r}_f$). Second, 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 wage and employment changes using only information on changes in the returns to specific factors.[4] Wages move one for one with the employment-weighted average of share prices.[5]

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

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

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

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

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

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

Proof. See Appendix A.2.2 □

[4] By contrast, implementing the Jones approach would require us to know 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 σ typically falls between 0.4 and 0.7.

[5] 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 monotonically rising in average productivity.

The assumption that intermediate input expenditures are a constant fraction of sales will be satisfied if production is multiplicatively separable into a composite intermediate input and 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

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

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

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

2.2 ERP and Productivity

In this section, we provide the link between ERP and productivity, which enables us 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 specific factor can be written as

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

where

$$\varphi_f \equiv \frac{L_f}{\theta_{Vf}} \Big/ \sum_{f'}\frac{L_{f'}}{\theta^V_{f'}}, \tag{9}$$

θ_{Lf} and θ_{Vf} are the wage bill and payments to the specific factor expressed as a share of value added:

$$\theta_{Lf} \equiv \frac{wL_f}{p_f y_f\left(1-\sum_i \omega_{if}\right)}, \text{ and } \theta_{Vf} \equiv \frac{r_f V_f}{p_f y_f\left(1-\sum_i \omega_{if}\right)}, \tag{10}$$

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

$$\hat{p}^e_f \equiv \frac{\hat{p}_f - \sum_i \omega_{if}\hat{q}_{fi}}{1-\sum_i \omega_{if}}. \tag{11}$$

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. 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. If other firms have higher output prices or lower input prices on average, their marginal revenue product of labor will rise, which will raise the economy-wide wage and lower the returns to the firm's specific factor. Two important properties of the mapping between ERP and factor prices, which we will use later, are that it is linear and homogeneous of degree 1, which means that factor prices will not change if the ERP does not change. Moreover, 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 ($\sum_i \omega_{if}\hat{q}_{fi}$).

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 (ω_{if}). Fortunately, there is an easy workaround to the problem. As we prove in the following proposition, movements in the returns to the specific factor provide a sufficient statistic for the ERP.

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

$$\hat{p}^e_f = \theta_{Vf}\hat{r}_f + \theta_{Lf}\sum_{f'}\frac{L_{f'}}{L}\hat{r}_{f'} \tag{12}$$

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

$$\widehat{TFPR}_f \equiv \hat{p}_f + \widehat{TFP}_f = \hat{p}^e_f, \tag{13}$$

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 ERP ($\hat{p}^e_f$) 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, we show that if we can observe movements in the returns to the specific factors, we can use these data to form sufficient statistics that identify movements in wages and ERP.

The second part of the proposition provides a theoretical foundation for the robust empirical finding that tariff-induced increases in the 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.[6] 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 we need a means of measuring the returns to specific factors. 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. Finally, we need a means of assessing the impact of a policy on the aggregate price level in order to compute the welfare impact. We address each of these challenges in the next three sections.

3.1 Specific Factors and Stock Prices

Following Grossman and Levinsohn (1989), we use movements in stock prices as a means of measuring how returns on past firm-specific investments are expected to respond to policy announcements. Stock prices are well suited for this purpose because firm market value equals the expected present value of future firm profits. Therefore, movements stock prices tell us about changes in the expected future value of firm-specific capital (both tangible and intangible). We incorporate this change by slightly modifying the model presented in the previous section. We assume that firms produce in two periods which we denote by period subscripts $s \in \{1, 2\}$. Each period has an identical entry and equilibrium structure as the one we described in the previous section, but we also assume that the amount of labor in the economy, the amount of each specific factor, and the cost functions of each firm and potential entrant are unchanging across time periods. We also assume that output is not storable, so production must equal consumption in each period. As before, wages are set to clear the labor market within each period. The firm's profits (returns to the specific factor) in each period are given by $r_{fs}V_f = (p_{fs} - c_f(w_s, 0, q_{1s}, ..., q_{ns}))\, y_{fs}$. The L identical consumers (workers) in the economy are each endowed with a unit of labor and own an equal share of each firm. Within each period, firms first observe output and input prices, then produce, pay workers, and distribute profits as dividends. This structure means that equations (2) and (3) will hold in each period, and we can use equation (4) as well as all of our propositions to determine changes in variables conditional on observing movements in r_{fs}.

Next, we establish the link between changes in r_{fs} and policy changes. Let $\boldsymbol{\tau}$ denote a vector of policies that could be announced by the government between the end of period 1 and the start of period 2 that cause a movement in the ERP. After these policy announcements are made, the economy is also buffeted by a series of idiosyncratic price shocks, so

[6] Following Hsieh and Klenow (2009), we define TFPR as the change in value added net of changes in labor and capital inputs.

that at the start of period 2, the change in the ERP is given by

$$\hat{\mathbf{p}}^{\mathbf{e}} = \hat{\mathbf{p}}^{\mathbf{e}}(\boldsymbol{\tau}) + \hat{\mathbf{p}}^{\mathbf{I}}, \tag{14}$$

where each element of $\hat{\mathbf{p}}^{\mathbf{e}}$ is a vector whose elements are the log change in the ERP of each firm (with each element given by $\hat{p}^e_f \equiv \ln\left(p^e_{f2}/p^e_{f1}\right)$); $\hat{\mathbf{p}}^{\mathbf{e}}(\boldsymbol{\tau})$ is the vector of log changes in ERP due to the policy shift; and $\hat{\mathbf{p}}^{\mathbf{I}}$ is a vector of log changes in ERP due to idiosyncratic information unrelated to the policy. We assume that movements in ERP due to idiosyncratic information are mean zero, so $E\left[\hat{\mathbf{p}}^{\mathbf{I}}\right] = \mathbf{0}$. Similarly, in the absence of a change in policy ($\boldsymbol{\tau} = \mathbf{0}$), there will be no policy-induced price changes, so $\hat{\mathbf{p}}^{\mathbf{e}}(\mathbf{0}) = 0$. Equation (8) tells us that for any firm f there is a linear mapping between the change in the rate of return for its specific factor $\hat{r}_f \equiv \ln(r_{f2}/r_{f1})$ and the vector of price changes of all firms ($\hat{\mathbf{p}}^{\mathbf{e}}$), so we can write movements in the returns to the specific factor as

$$\hat{r}_f = r_f\left(\hat{\mathbf{p}}^{\mathbf{e}}(\boldsymbol{\tau})\right) + \nu_f, \tag{15}$$

where $r_f(\cdot)$ is the linear mapping between movements in ERP and returns to the specific factor given in equation (8); and $\nu_f \equiv r_f\left(\hat{\mathbf{p}}^{\mathbf{I}}\right)$ is the movement in returns to specific factors due to idiosyncratic factors. Moreover, since the linear mapping is homogeneous of degree 1 in the ERP, we also have $r_f(\mathbf{0}) = 0$, which follows from the fact that if all input and output prices are unchanged, factor prices will also be unchanged. This result implies that ν_f must also be mean zero:

$$E[\nu_f] = E\left[r_f\left(\hat{\mathbf{p}}^{\mathbf{I}}\right)\right] = r_f\left(E\left[\hat{\mathbf{p}}^{\mathbf{I}}\right]\right) = r_f(\mathbf{0}) = 0. \tag{16}$$

This result in combination with equation (15) enables us to simplify notation by setting $E[\hat{r}_f|\boldsymbol{\tau}] = E[r_f(\hat{\mathbf{p}}^{\mathbf{e}}(\boldsymbol{\tau}))]$. We can also show that in the absence of a policy change there will be no movement in the expected returns to the specific factors:

$$E[\hat{r}_f|\mathbf{0}] \equiv E\left[r_f(\hat{\mathbf{p}}^{\mathbf{e}}(\mathbf{0})) + r_f\left(\hat{\mathbf{p}}^{\mathbf{I}}\right)\right] = 0, \tag{17}$$

which means that expected prices will be identical in the two periods, so $E[r_{f2}|\mathbf{0}] = r_{f1}$.

We now examine how movements in stock prices are related to movements in the returns to specific factors. Let $E_1[\cdot]$ denote the expectation at the end of period 1 (before the policy and idiosyncratic shocks are revealed), and let $E[\cdot|\boldsymbol{\tau}]$ be the expectation conditional on observing the policy shocks but not the idiosyncratic shocks (ν_f). Since the policies are not expected, $E_1[\boldsymbol{\tau}] = \mathbf{0} \neq \boldsymbol{\tau}$. The firm's value at the end of period 1 before any shocks are revealed equals its expected dividend payment in period 2 multiplied by the discount rate (ρ): $E[\rho r_{f2}V_f|E_1[\boldsymbol{\tau}]] = \rho V_f E[r_{f2}|\mathbf{0}] = \rho V_f r_{f1}$. Thus, the change in the market value of the firm is given by

$$\hat{r}^{MV}_f \equiv \frac{E[\rho r_{f2}V_f|\boldsymbol{\tau}] - E[\rho r_{f2}V_f|E_1[\boldsymbol{\tau}]]}{E[\rho r_{f2}V_f|E_1[\boldsymbol{\tau}]]} = \frac{E[r_{f2}|\boldsymbol{\tau}] - r_{f1}}{r_{f1}} = \frac{r_{f2} - r_{f1}}{r_{f1}} = \hat{r}_f, \tag{18}$$

last

where we move to the equality by making the assumption that the log change equals the percentage change. We now can use equation (15) to write

$$\hat{r}^{MV}_f = r_f\left(\hat{\mathbf{p}}^{\mathbf{e}}(\boldsymbol{\tau})\right) + \nu_f, \tag{19}$$

and

$$E\left[\hat{r}_f^{MV}|\boldsymbol{\tau}\right] = E\left[\hat{r}_f|\boldsymbol{\tau}\right]. \tag{20}$$

In other words, the movement in the market return of the firm before and after a policy announcement equals the expected change in the return of the specific factor due to the policy plus a mean zero error term. Thus, as long as we can compute the expected change in the market return due to the policy ($E\left[\hat{r}_f^{MV}|\boldsymbol{\tau}\right]$), we know how much the market thought the policy moved the return to the specific factor ($E\left[\hat{r}_f|\boldsymbol{\tau}\right]$).

An important feature of this structure is that we can use an estimate of how much the policy affected stock returns ($E\left[\hat{r}_f^{MV}|\boldsymbol{\tau}\right]$) along with the results in Section 2 to compute how the policy affected expected wages, TFP, and welfare. Proposition 1 and equation (20) imply

$$E\left[\hat{w}|\boldsymbol{\tau}\right] = \sum_f \frac{L_f}{L} E\left[\hat{r}_f^{MV}|\boldsymbol{\tau}\right]. \tag{21}$$

The zero profit condition in the Jones (1975) model requires that

$$\hat{p}_f^e = \theta_{Lf}\hat{w} + \theta_{Vf}\hat{r}_f. \tag{22}$$

Using the result from Proposition 3, equating ERP and TFPR, taking expectations and substituting in equations (20) and (21) provides a link between movements in expected TFPR and trade-war induced movements in stock prices:

$$E\left[\widehat{\text{TFPR}}_f|\boldsymbol{\tau}\right] = \theta_{Lf}\sum_f \frac{L_f}{L} E\left[\hat{r}_f^{MV}|\boldsymbol{\tau}\right] + \theta_{Vf} E\left[\hat{r}_f^{MV}|\boldsymbol{\tau}\right]. \tag{23}$$

3.2 Identifying Policy Impacts

We now turn to modeling the stochastic process determining stock returns. We know from equations (15) and (19) that we can model stock returns as a linear function of shocks to ERP ($r_f\left(\hat{\mathbf{p}}^{\mathbf{e}}\left(\boldsymbol{\tau}\right)\right)$) and an error term. We now make a functional form assumption for $r_f\left(\hat{\mathbf{p}}^{\mathbf{e}}\left(\boldsymbol{\tau}\right)\right)$. In particular, we assume that the stock returns on day t ($\hat{r}_{ft}$) are additively log separable into macro and treatment effects:

$$\hat{r}_{ft} = \hat{r}^M\left(\boldsymbol{\delta}\left(\boldsymbol{\Phi_t}, \boldsymbol{\tau_t}\right), \boldsymbol{\beta_f}\right) + \hat{r}^T\left(\boldsymbol{Z_f}, \boldsymbol{\tau_t}\right) + \nu_{ft}, \tag{24}$$

where $\boldsymbol{\delta}\left(\boldsymbol{\Phi_t}, \boldsymbol{\tau_t}\right) = \left(\delta_{1t}, ..., \delta_{Kt}\right)$ 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 ($\boldsymbol{\tau_t}$) on day t; $\boldsymbol{\beta_f}$ is a vector of firm characteristics that matter for how macro variables affect firms; $\boldsymbol{Z_f}$ is another vector of firm characteristics (which may or may not be different from $\boldsymbol{\beta_f}$) that affect how a policy affects firms directly (e.g., an importer paying a tariff as opposed to having a tariff change some macro variable); and ν_{ft} is a mean-zero error term that captures time-varying, firm-specific productivity shocks.

Equation (24) can be thought of as a high-frequency version of equation (15) in which the vector of ERP ($\hat{\mathbf{p}}^{\mathbf{e}}$) moves each day as a result of policy variables (τ), other macro variables ($\boldsymbol{\Phi_t}$) and idiosyncratic price shocks (ν_{ft}). In this setup, $\hat{r}_{ft}^M = \hat{r}^M\left(\boldsymbol{\delta}\left(\boldsymbol{\Phi_t}, \boldsymbol{\tau_t}\right), \boldsymbol{\beta_f}\right)$

captures how macro variables affect the returns to specific factors, and $\hat{r}^T_{ft} = \hat{r}^T(\boldsymbol{Z_f}, \boldsymbol{\tau_t})$ captures the movements in the returns that would normally be captured in an event study, i.e., "treatment effects" of a policy announcement.. 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 (24) gives us

$$\hat{r}_{ft} = \sum_{k=1}^{K} \sum_{i=1}^{N} \frac{\partial \hat{r}^M_{ft}}{\partial \delta_k} \frac{\partial \delta_k}{\partial \tau_{it}} d\tau_{it} + \sum_{i=1}^{N} \frac{\partial \hat{r}^T_{ft}}{\partial \tau_{it}} d\tau_{it}. \tag{25}$$

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 macro variables (δ_{kt}):[7]

$$E\left[\hat{r}^M\left(\boldsymbol{\delta}(\boldsymbol{\Phi_t}, \boldsymbol{\tau_t}), \boldsymbol{\beta_f}\right)\right] = \alpha_f + \sum_{k=1}^{K} \beta_{kf}\delta_{kt} \tag{26}$$

where α_f is a firm fixed effect, and β_{kf} is our estimate of $\frac{\partial \hat{r}^M_{ft}}{\partial \delta_k}$ in equation (25) and tells us the firm's sensitivity to latent variable k (its "loading"). Equation (26) 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 δ_{kt} equals 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 Ω^U, the set of Chinese events as Ω^C, and the combined set of U.S. and Chinese events as $\Omega^{UC} = \Omega^U \bigcup \Omega^C$. We define D^w_{jt} to be an indicator variable that is 1 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} ($i \in \{1, ..., N\}$) that specify firm characteristics (relevant only during an event window) 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. We assume that the impact of a tariff change on the expected differential return of a firm can be written as

$$E\left[\hat{r}^T_f | \boldsymbol{\tau_t}\right] = \sum_{j \in \Omega^{UC}} \sum_{i=1}^{N} \gamma_{ij} Z_{fi} D^w_{jt}, \tag{27}$$

where γ_{ij} is our estimate of $\frac{\partial \hat{r}^D_{ft}}{\partial \tau_{it}}$ during event window j.

[7] 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."

A key feature of equation (27) is that it is isomorphic to equation (26). In particular, we can think of D_{jt}^{w} as latent variables that only matter during an event window, and $\gamma_{ij} Z_{if}$ 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 (26) and (27) into equation (24), we obtain

$$\hat{r}_{ft} = \alpha_f + \sum_{k=1}^{K} \beta_{kf} \delta_{kt} + \epsilon_{ft}, \tag{28}$$

where

$$\epsilon_{ft} \equiv \sum_{j \in \Omega^{UC}} \sum_{i=1}^{N} \gamma_{ij} Z_{fi} D_{jt}^{w} + \theta_t D_{jt}^{w} + \tilde{\nu}_{ft}, \tag{29}$$

$$\nu_{ft} \equiv \theta_t D_{jt}^{w} + \tilde{\nu}_{ft}, \text{ and } E\left[\nu_{ft}\right] = 0. \tag{30}$$

Here, θ_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 θ_t comes from our specification of the moment condition (30). Since we assume that $E\left[\nu_{ft}\right] = 0$, 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 $\hat{\nu}_{ft}$ is our estimate of ν_{ft} given in equation (30). However, this does not imply that $\frac{1}{F} \sum_f \hat{\nu}_{ft} = 0$, so the value of θ_t is given by $\theta_t = \frac{1}{F} \sum_f \hat{\nu}_{ft}$. In other words, θ_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 $E\left[\epsilon_{ft}\right] = E\left[\nu_{ft}\right] = 0$. We also assume that the latent variables (δ_{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.,

$$\lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \left(\delta_{kt} - \delta_k\right)^2 > 0, \tag{31}$$

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 $\lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \left(D_{jt}^{w} - D_{j}^{w}\right)^2 = 0$, 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 (28), since the terms on the right-hand side of equation (29) will appear in the error term of equation (28). 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 (27) gives us the expectation of the differential impact of a policy announcement, $\boldsymbol{\tau_t}$, on a firm with characteristics $\boldsymbol{Z_f}$. Thus, as long as we know these 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 (28) how to compute the impact of movements in macro factors on returns ($E\left[\hat{r}^M|\boldsymbol{\tau_t}\right]$), we need to isolate the impact from tariff announcements. In order to do this, we assume that movements in macro factors ($\delta_k(\boldsymbol{\Phi_t}, \boldsymbol{\tau_t})$) can be decomposed into movements due to economic surprise variables unrelated to the tariff announcement ($ES_{1t}, ES_{2t}, ..., ES_{\overline{N}t}$) and another component $\delta_k\left(\boldsymbol{\tau_t}\right)$ that is due to movements in the policy:

$$\delta_{kt} = \alpha'_k + \sum_{i=1}^{\overline{N}} \phi_{ik} ES_{it} + \delta_k\left(\boldsymbol{\tau_t}\right), \tag{32}$$

where α'_k and ϕ_{ik} are parameters to be estimated, and $\overline{N}$ is the number of economic surprises. We then can identify $\delta_k\left(\boldsymbol{\tau_t}\right)$ by regressing δ_{kt} on the economic surprise variables and setting $\delta_k\left(\boldsymbol{\tau_t}\right)$ equal to the error term.

Now that we have identified all of the key parameters, we can compute the cumulative impact of the announcements on expected firm returns ($E\left[\hat{r}_f|\boldsymbol{\tau}\right]$). The expected cumulative macro effect due to the policy change during a set of j events ($\boldsymbol{\tau}$) is given by

$$E\left[\hat{r}^M_f|\boldsymbol{\tau}\right] = \sum_k \sum_j \sum_t \beta_{kf}\delta_k\left(\boldsymbol{\tau_t}\right) D^w_{jt}, \tag{33}$$

where we drop the t subscript on $\boldsymbol{\tau}$ when we want 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 (27) to write

$$E\left[\hat{r}^T_f|\boldsymbol{\tau}\right] \equiv \sum_t E\left[\hat{r}^T_f|\boldsymbol{\tau_t}\right] = \sum_t \sum_{j\in\Omega^{UC}} \sum_{i=1}^{N} \gamma_{ij} Z_{fi} D^w_{jt}, \tag{34}$$

which gives us

$$E\left[\hat{r}_f|\boldsymbol{\tau}\right] = E\left[\hat{r}^M_f|\boldsymbol{\tau}\right] + E\left[\hat{r}^T_f|\boldsymbol{\tau}\right]. \tag{35}$$

Since we know how the announcement affected the expected returns of firms, we have enough information to compute their expected impact on wages. If we substitute equations (33), (34), and (35) into equation (21), we obtain an expression that gives us expected wage movements as a function of firm characteristics:

$$\begin{aligned} E\left[\hat{w}|\boldsymbol{\tau}\right] &= \sum_f \frac{L_f}{L} E\left[\hat{r}^M_f|\boldsymbol{\tau}\right] + \sum_f \frac{L_f}{L}\left(\sum_{j\in\Omega^{UC}} \sum_{i=1}^{N} \sum_t \gamma_{ij} Z_{fi} D^w_{jt}\right) \\ &= \sum_f \frac{L_f}{L} E\left[\hat{r}^M_f|\boldsymbol{\tau}\right] + \left[\sum_{j\in\Omega^{UC}} \sum_{i=1}^{N} \sum_t \gamma_{ij} D^w_{jt}\left(\sum_f \frac{L_f}{L} Z_{fi}\right)\right], \end{aligned} \tag{36}$$

where the term in the last square brackets is $E\left[\hat{r}^T_f|\boldsymbol{\tau}\right]$. Here, $E\left[\hat{w}|\boldsymbol{\tau}\right]$ 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.

Sampling Issues Since the sample of firms that report stock prices is not representative of the size distribution of U.S. firms, we need to re-weight the data before implementing equation (36). 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. In our baseline specification, we set the expected rate of return for all U.S. firms in size bin b ($E\left[\hat{r}_b|\boldsymbol{\tau}, f \in \Omega_b\right]$) as equal to the average rate of return for publicly listed firms in the same bin:

$$E\left[\hat{r}_b|\boldsymbol{\tau}\right] = E\left[\hat{r}_f|\boldsymbol{\tau}, f \in \Omega_b\right]. \tag{37}$$

We also will explore alternative assumptions in Section 5.3. We use an identical procedure to compute the expected returns due to the macro shock by bin ($E\left[\hat{r}_b^M|\boldsymbol{\tau}\right]$) and the differential shock by bin ($E\left[\hat{r}_b^T|\boldsymbol{\tau}\right]$). We then have

$$E\left[\hat{w}|\boldsymbol{\tau}\right] = \sum_b w_b \left(E\left[\hat{r}_b^M|\boldsymbol{\tau}\right] + E\left[\hat{r}_b^T|\boldsymbol{\tau}\right]\right), \tag{38}$$

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

Similarly, we can also decompose movements in TFPR into the macro and treatment effects:

$$\begin{aligned} E\left[\widehat{\text{TFPR}}_{b'}|\boldsymbol{\tau}\right] &= \left\{\theta_{Lb}\sum_b w_b \left(E\left[\hat{r}_b^M|\boldsymbol{\tau}\right] + E\left[\hat{r}_b^T|\boldsymbol{\tau}\right]\right) + \theta_{Vb'} E\left[\hat{r}_{b'}^M|\boldsymbol{\tau}\right]\right\} + \theta_{Vb} E\left[\hat{r}_{b'}^T|\boldsymbol{\tau}\right] \\ &= \theta_{Lb}\sum_b w_b \left(E\left[\hat{r}_b^M|\boldsymbol{\tau}\right] + E\left[\hat{r}_b^T|\boldsymbol{\tau}\right]\right) + \theta_{Vb'} E\left[\hat{r}_{b'}^M|\boldsymbol{\tau}\right] + \theta_{Vb} E\left[\hat{r}_{b'}^T|\boldsymbol{\tau}\right] \\ &= \left(\theta_{Vb'} E\left[\hat{r}_{b'}^M|\boldsymbol{\tau}\right] + \theta_{Lb}\sum_b w_b E\left[\hat{r}_b^M|\boldsymbol{\tau}\right]\right) + \left(\theta_{Vb} E\left[\hat{r}_{b'}^T|\boldsymbol{\tau}\right] + \theta_{Lb}\sum_b w_b E\left[\hat{r}_b^T|\boldsymbol{\tau}\right]\right), \end{aligned} \tag{39}$$

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.

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

$$E\left[\hat{P}|\boldsymbol{\tau}\right] = \sum_j \sum_t \left[Y\left(\hat{\pi}_t^Y - \hat{\pi}_{t-1}^Y\right)\right] D_{jt}^w. \tag{40}$$

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

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

$$Y\left(\hat{\pi}_t^Y - \hat{\pi}_{t-1}^Y\right) = \alpha^Y + \sum_{i=1}^{\overline{N}} \beta_i^Y ES_{it} + \epsilon_t^\pi, \tag{41}$$

and then run the following regression:

$$\hat{\epsilon}_t^\pi = \alpha^\pi + \gamma^\pi \sum_{j\in\Omega^{UC}} D_{jt}^w + \epsilon_t', \tag{42}$$

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

$$E\left[\hat{P}|\boldsymbol{\tau}\right] = N^w J \gamma^\pi, \tag{43}$$

where N^w is the number of days in the window; and 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. 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 multiplying 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 the 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: $\widehat{\text{Imports}}_h = \text{Imports}_{h,17} - \sigma\Delta\tau_h \text{Imports}_{h,17}$, where $\text{Imports}_{h,17}$ is the value of imports in 2017 in the 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 ($E\left[\hat{W}|\boldsymbol{\tau}\right]$) can be computed by taking expectations of equation (7):

$$E\left[\hat{W}|\boldsymbol{\tau}\right] = \frac{wL}{I}E\left[\hat{w}|\boldsymbol{\tau}\right] + \sum_f \frac{r_f V_f}{I}E\left[\hat{r}_f|\boldsymbol{\tau}\right] + \frac{TR}{I}\widehat{TR} - E\left[\hat{P}|\boldsymbol{\tau}\right]. \tag{44}$$

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

$$E\left[\hat{W}|\boldsymbol{\tau}\right] = \frac{wL}{I}E\left[\hat{w}|\boldsymbol{\tau}\right] + \sum_b \frac{r_b V_b}{I}E\left[\hat{r}_b|\boldsymbol{\tau}\right] + \frac{TR}{I}\widehat{TR} - E\left[\hat{P}|\boldsymbol{\tau}\right]. \tag{45}$$

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 ($\overline{RV}_b$).[8] We then write the payments to the specific factor in the U.S. as

$$\overline{RV}^{US}_{b'} = \frac{N^U_{b'}\overline{RV}_{b'}}{\sum_b N^U_b \overline{RV}_b} RV^{US}, \tag{46}$$

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

$$E\left[\hat{W}|\boldsymbol{\tau}\right] = \frac{wL}{I}E\left[\hat{w}|\boldsymbol{\tau}\right] + \sum_b \frac{\overline{RV}^{US}_b}{I}E\left[\hat{r}_b|\boldsymbol{\tau}\right] + \frac{TR}{I}\widehat{TR} - E\left[\hat{P}|\boldsymbol{\tau}\right]. \tag{47}$$

We can also use equations (35) and (38) to rewrite this equation into the welfare changes due to macro and treatment effects:

$$\begin{aligned} E\left[\hat{W}|\boldsymbol{\tau}\right] &= \frac{wL}{I}\sum_b w_b\left(E\left[\hat{r}^M_b|\boldsymbol{\tau}\right] + E\left[\hat{r}^T_b|\boldsymbol{\tau}\right]\right) + \sum_b \frac{\overline{RV}^{US}_b}{I}\left(E\left[\hat{r}^M_b|\boldsymbol{\tau}\right] + E\left[\hat{r}^T_b|\boldsymbol{\tau}\right]\right) + \frac{TR}{I}\widehat{TR} \\ &= \left\{\frac{wL}{I}\sum_b w_b E\left[\hat{r}^M_b|\boldsymbol{\tau}\right] + \sum_b \frac{\overline{RV}^{US}_b}{I}E\left[\hat{r}^M_b|\boldsymbol{\tau}\right] - E\left[\hat{P}|\boldsymbol{\tau}\right]\right\} \\ &+ \left\{\frac{wL}{I}\sum_b w_b E\left[\hat{r}^T_b|\boldsymbol{\tau}\right] + \sum_b \frac{\overline{RV}^{US}_b}{I}E\left[\hat{r}^T_b|\boldsymbol{\tau}\right] + \frac{TR}{I}\widehat{TR}\right\}, \end{aligned} \tag{48}$$

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 ($E\left[\hat{r}^M_b|\boldsymbol{\tau}\right]$) with movements in the expected consumer price index ($E\left[\hat{P}|\boldsymbol{\tau}\right]$) 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 ($E\left[\hat{r}^T_b|\boldsymbol{\tau}\right]$) 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 subtract the expected price changes from both sides of equation (36) and make the transition to binned data as in equation (37), we obtain

[8] We use the median to reduce the influence of outliers in the data.

$$E\left[\hat{w}|\boldsymbol{\tau}\right]-E\left[\hat{P}|\boldsymbol{\tau}\right]=\left(\sum_b w_b E\left[\hat{r}_b^M|\boldsymbol{\tau}\right]-E\left[\hat{P}|\boldsymbol{\tau}\right]\right)+\sum_b w_b E\left[\hat{r}_b^T|\boldsymbol{\tau}\right], \tag{49}$$

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 $E\left[\hat{P}|\boldsymbol{\tau}\right]$ from the left- and right-hand sides.

$$E\left[\widehat{\text{TFP}}_{b'}|\boldsymbol{\tau}\right]\equiv E\left[\widehat{\text{TFPR}}_{b'}|\boldsymbol{\tau}\right]-E\left[\hat{P}|\boldsymbol{\tau}\right]=\left(\theta_{Vb'}E\left[\hat{r}_{b'}^M|\boldsymbol{\tau}\right]+\theta_{Lb}\sum_b w_b E\left[\hat{r}_b^M|\boldsymbol{\tau}\right]-E\left[\hat{P}|\boldsymbol{\tau}\right]\right)$$
$$+\left(\theta_{Vb}E\left[\hat{r}_{b'}^T|\boldsymbol{\tau}\right]+\theta_{Lb}\sum_b w_b E\left[\hat{r}_b^T|\boldsymbol{\tau}\right]\right). \tag{50}$$

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 trading day, we obtain a sample of 2,859 firms that cover all sectors. We set $\hat{r}_{ft}$ to be the log change in the firm's stock price.[9]

A commonly used measure of inflation expectations is the difference in yields on a Treasury security and a Treasury inflation-protected security, however in addition to inflation expectations this measure 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 the 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

[9]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.

influenced its abnormal returns from the Capital IQ Key Developments database.[10] To ensure that our results are not contaminated by these firm announcements, when we estimate equation (29) 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 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 iPhones 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 with 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 of 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, and we discuss issues related to the quality of the FactSet data in the Appendix.

The Datamyne data used to identify U.S. firms that import from China or export to China have a number of limitations. First, the product level reported is more aggregated than that in the Harmonized Tariff System 8-digit level at which U.S. tariffs are set. While some of the Datamyne data are 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 1 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 cover seaborne trade. The U.S. Census data reveal that in 2017, 62 percent of all imports from China and 58 percent of exports to China were 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 1 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.

[10] 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.

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 1 if a firm satisfies the listed criterion, as well as the mean of the continuous Chinese revenue share variable.

However, if we take subsidiaries into account, these numbers rise to 24 and 4 percent, respectively. When we add imports by all firms in the supply chain, we see that 29 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.

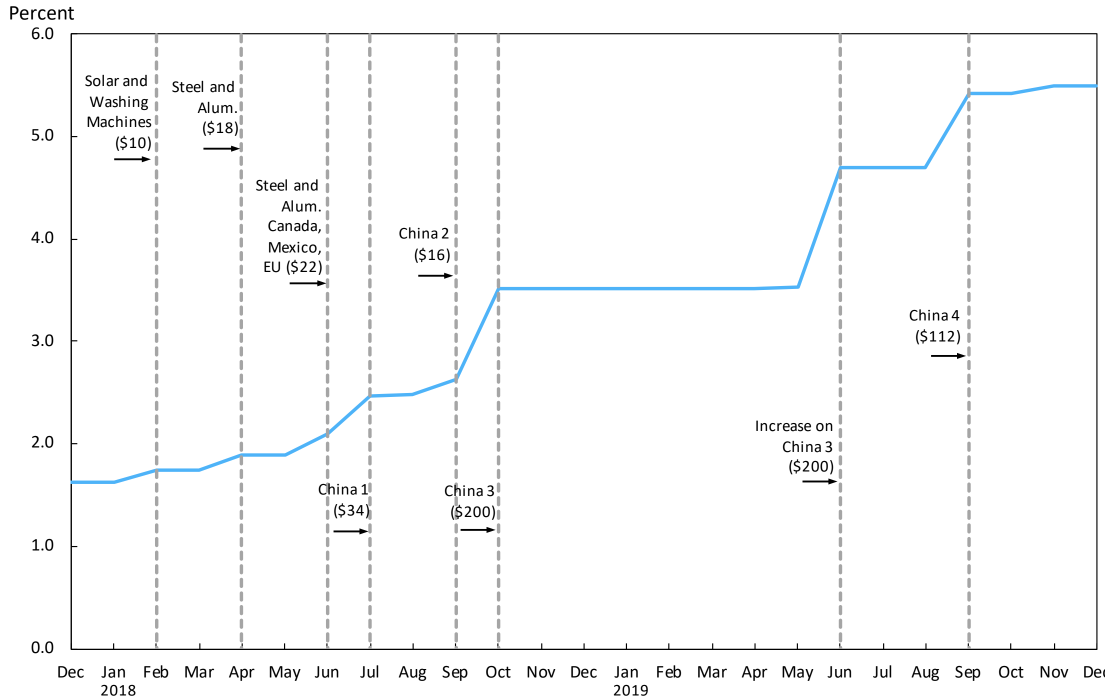
We obtained employment data from a number of sources. The firm-level employment data for the listed firms in our sample are from Compustat. However, one potential issue with using these data is that the reported employment is for the consolidated firm, and thus for multinationals it covers employment in the U.S. and in foreign subsidiaries, whereas our interest is in U.S. employment. We address this issue by supplementing the Compustat data with employment data from the National Establishment Time Series (NETS), which provides data on an establishment basis for U.S. firms. We merged the NETS data with the Compustat data by DUNS number to obtain the domestic firm employment. Based on this procedure, our sample of Compustat firms employs 29.2 million workers domestically or 22.7 percent of the number of people employed in the national employment data provided by the Statistics of U.S. Businesses (SUSB, U.S. Census Bureau). See Appendix for details.

4.2 Trade-War Announcements

Over the course of the the trade war, the U.S. implemented tariffs in waves, which we plot in Figure 1. The figure shows that the average rate of tariffs on all U.S. imports rose by approximately 4 percentage points as tariffs on a wide range of Chinese imports reached 25 percent by the end of the period.

For each of these new tariffs we identified the earliest announcement date in the media using Factiva and Google search. In addition, we also used the same method to iden-

Figure 1: Average U.S. Tariffs in the 2018-2019 Trade War



Note: Authors' calculations based on data from the U.S. Census Bureau, U.S. Trade Representative (USTR), and 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 new tariffs during 2018-2019; tariffs implemented after the 15th of the month are counted in the subsequent month. Four tranches of tariffs were imposed on China, designated by 1, 2, 3, and 4. Numbers in parentheses correspond to the value of imports covered by the new tariffs in billions.

tify the earliest announcement dates for each date that China imposed retaliatory tariffs on U.S. exports. 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, since what is important for our purposes is the first time it was announced. All 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.

The data reveal 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

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	U.S. imposes tariffs on solar panels and washing machines
US	28Feb18	-1.07	-3.56	U.S. 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 $50B worth of Chinese goods
CHN	15Jun18	-0.10	0.08	China announces retaliation against U.S. tariffs on $50B of imports
US	19Jun18	-0.41	-0.28	U.S. announces imposition of tariffs on $200B of Chinese goods
CHN	02Aug18	0.59	0.83	China announces tariffs on $60B of U.S. goods
US	06May19	-0.41	-1.00	U.S. to raise tariffs on $200B of Chinese goods up to 25%
CHN	13May19	-2.58	-1.34	China to raise tariffs on $60B of U.S. goods starting June 1
US	01Aug19	-1.00	-2.90	U.S. will impose a 10% tariff on another $300B of Chinese goods
CHN	23Aug19	-2.64	-1.65	China retaliates with higher tariffs on soy and 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 three-day window beginning on the trading day before the announcement and extending one trading day after. The total three-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.

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 the three-day windows (beginning the day before the announcement and extending one day after). These drops in the market imply substantial drops in expected profitability for U.S. firms—a factor that Proposition 1 suggests will drive decreases in the expected wage.

We explore the persistence of these stock-market movements in Figure 2, which plots the cumulative log change in average stock prices starting six trading days before each announcement 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 10 percent. Moreover, it is also quite striking how persistent this decline is. Even if we track the market five trading days later (approximately one week of calendar days), 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.

Finally, we also explore the impact that trade-war announcements have on other macro variables. We choose three that we think are likely related to trade-policy changes: changes in the expected price level, changes in exchange rates, and movements in uncertainty (as measured by the VIX). 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 10 years in the future: $E_t\left[\hat{P}^{10}\right] \equiv 10 \times \left(\hat{\pi}_t^{10} - \hat{\pi}_{t-1}^{10}\right)$, where the definitions of these variables are given in Section 3.3. 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 the 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 six days before an event; the point corresponding to -4 tells us the expected price change four days before an event relative to six days before an event, and so on. We plot the values in Figure 2 (See the Appendix for details and formulas). We see that in the five days leading up to each announcement, the expected price level 10 years later was within about 50 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 150 basis points from the day before. Moreover, there appears to be no recovery in inflationary expectations. If anything, the data suggest 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.

The lower two panels in Figure 2 present analogous plots for movements in the trade-weighted exchange rate and the VIX. The exchange rate index is measured in foreign currency per dollar, so higher values correspond to dollar appreciation. As conventional theory would predict, tariff announcements were associated with a 3.3 percent appreciation of the dollar. These trade announcements also caused a 115% increase in the value of VIX (see Appendix for regression results), consistent with a rise in uncertainty. There is also no evidence of speedy mean reversion as these changes persisted for at least 5 trading days after the events. Thus, tariff announcements had significant impacts on a variety of macro variables related to prices and uncertainty.

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.

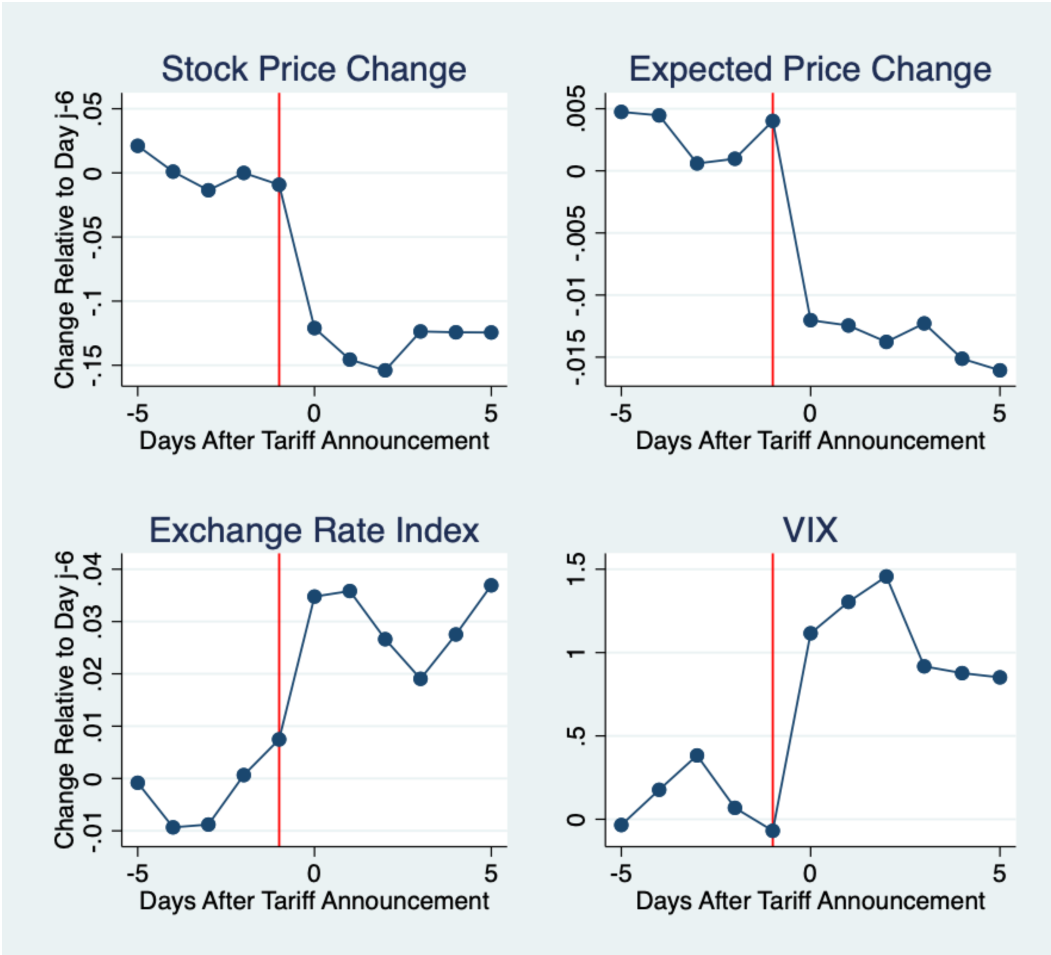
5.1 Event Study Results

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 (28). We use the procedure recommended in Bai and Ng (2008) to choose the number of latent variables to minimize the following loss function when errors may be cross-sectionally correlated:

$$IC(K) = \ln(\mathcal{L}(K)) + K\left(\frac{F+T}{FT}\right)\ln(\min\{F,T\}), \tag{51}$$

where F is the number of firms; $\mathcal{L}(K)$ is the log likelihood function based on the estimation of equation (28); and T is the number of days. Each additional latent variable (δ_{kt}) adds 2,859 β_{kf} parameters (one for each firm). Based on this loss function, we use four latent variables in our baseline.

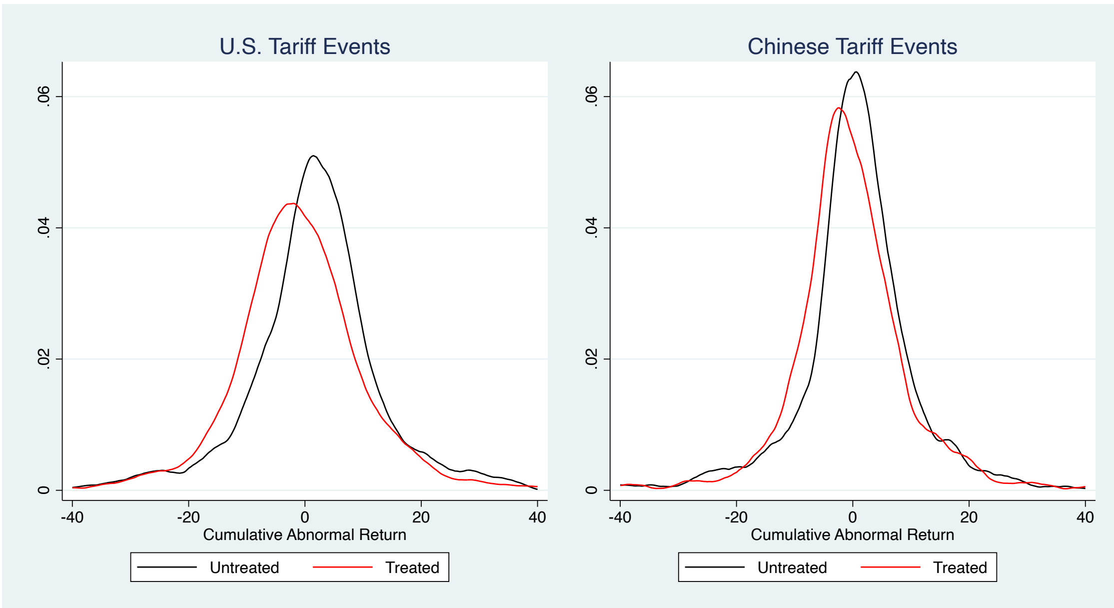
Figure 2: Impact of Trade-War Announcements



Note: Each chart shows the cumulative log change in average stock prices starting 6 trading days before each announcement. Details on this procedure including the actual formulas used are provided in the text and appendix. The exchange rate index is the Federal Reserve's Trade Weighted U.S. Dollar Index: Broad, Goods and Services). The exchange rate index is measured in foreign currency per dollar, so higher values correspond to dollar appreciation. Both the VIX and exchange-rate data were downloaded from FRED.

As expected, each of these latent macro variables exhibits economically and statistically significant correlations with macro variables like exchange rate movements, changes in expected inflation, and the VIX (see Appendix for details). This result is consistent with our hypothesis that the forces that move our latent macro variables also move variables that are often central to macro models. While it is not possible to precisely link each latent variable with a particular measurable variable, as we show in Appendix A.8, the correlation between the first factor and the overall market return is 0.84, so it likely captures the sensitivity of firms to the forces that move the overall market (i.e., the forces that would be captured by the CAPM). The other factors also exhibit significant correlations with the macro variables portrayed in Figure 2, which is consistent with the notion that the latent variables are capturing the heterogeneous effects that macro variables can have on firms. The first latent variable accounts for 11.1 percent of the firm-level variance, but additional factors account for much less, with the next three factors accounting for 1.7, 1.5, and 0.9 percent of the variance, respectively. Thus, macro variables explain 15.2 percent of the variation in firm returns over the sample period, and any single potentially omitted macro factor can explain no more than 0.9 percent of the variance.

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



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

Turning to the treatment effects, Figure 3 shows how the tariff announcements affected the relative price component of firm returns depending on whether they were exposed or unexposed (as defined in Table 1). We plot the kernel densities of the cumulative abnormal returns given by the error terms in equation (28) using a three-day window around each event j ($\epsilon_{fj} \equiv 100 \times \sum_{t=j-1}^{j+1} \epsilon_{ft}$) for treated and untreated firms. We define the set of treated 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 that were not directly 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 tend to reduce the abnormal returns of treated firms relatively more.

We identify the relative effects of tariffs on the abnormal returns of exposed firms by estimating equation (28) using a three-day event window ($N^w = 3$), where we regress the abnormal return (multiplied by 100) on the firm exposure variables across all 11 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 (29), 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 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 three-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 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 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 those of non-exporters, and firm's selling in China saw their returns fall by 0.113 percentage point for every percentage point of revenue they obtained from China. The coefficient on China Revenue Share implies that a firm with the average sales exposure to China corresponding to 4 percent of revenue experienced an abnormal return of -0.4 percentage point across all of the U.S. events.

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

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

Note: This table presents the estimated coefficients on the U.S. events obtained from estimating equation (29); the estimated coefficients for the Chinese events are presented in Table 4. Day fixed effects are not reported. The dependent variable ($\hat{\epsilon}_{ft} \times 100$) is the abnormal return obtained from estimating equation (28) with four factors multiplied by 100. China Importer is a dummy that equals 1 if the firm or any of its subsidiaries or suppliers import from China. China Exporter is a dummy that equals 1 if the firm or its subsidiaries export to China. China Revenue Share is the share of the firm's revenue that comes from sales in China reported in percentage points. Column 1 presents the cumulative of the coefficients on each of the U.S. event days. Standard errors are in parentheses. Asterisks correspond to the following levels of significance: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. The number of observations is 80,674.

Table 3 suggests that in general U.S. tariff announcements had 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, 13 of the 15 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 four (not mutually exclusive) reasons. The first is that higher U.S. tariffs cause exchange rate appreciation, which will reduce the profitability of U.S. exporters and multinationals, as predicted by theory and we showed in Figure 2. Second, exporters may have anticipated that U.S. tariffs would provoke Chinese retaliatory tariffs, thereby lowering the abnormal return of exporters. Third, 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 multinational sales. Fourth, it is also possible that U.S. tariffs weakened the Chinese economy, which could lower expected profits for U.S. firms selling there.

Table 4: Impact of Chinese Tariff Announcements on Stock Returns

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

Note: This table presents the estimated coefficients on the Chinese events obtained from estimating equation (29); the estimated coefficients for the U.S. events are presented in Table 3. See the notes to Table 3 for variable definitions and details.

Turning to the Chinese 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 these results are 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 4 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 (29) 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

Table 5: Robustness Tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
China Importer			-1.42**	-1.15***	-0.11	0.01	-3.05***	-1.04**
			(0.57)	(0.29)	(0.25)	(1.24)	(0.59)	(0.47)
Large Company	-1.97***	-0.39						
	(0.52)	(0.44)						
China Exporter	-2.62***	-1.76***	-2.50**	-0.93	-0.67	0.23	-3.37***	-1.87**
	(1.01)	(0.67)	(1.06)	(0.67)	(0.41)	(1.71)	(1.09)	(0.78)
China Revenue Share	-11.29***	-11.55***	-10.07***	-6.63***	-5.65***	0.73	-14.11***	-12.31***
	(1.84)	(1.91)	(1.91)	(1.09)	(0.81)	(5.64)	(2.00)	(1.88)
Industry Protected			-0.36					
			(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 (29) for all U.S.-China tariff events. The dependent variable ($\hat{\epsilon}_{ft} \times 100$) is the abnormal return obtained from estimating equation (28) with four factors multiplied by 100 in columns 1-6, and we use the analogous abnormal return from the CAPM in the last two columns. Large Company dummy equals 1 if a firm had more than 1000 employees in 2017. China Importer is a dummy that equals 1 if the firm or any of its subsidiaries or suppliers import from China. China Exporter is a dummy that equals 1 if the firm or its subsidiaries export to China. China Revenue Share is the share of the firm's revenue that comes from sales in China reported in percentage points. Industry Protected is a dummy that equals 1 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.

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 import dummy with a dummy that is 1 for firms with a thousand or more employees.[11] 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, ERP 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

[11] We cannot obtain significant results with both import and large dummies because they are very highly correlated.

Table A.8, 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.

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 on 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 11 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. Third, it also might be the case that stock prices bounced back after their initial drops, so in the Appendix we also present results using five-day windows to show that we obtain similar results with longer windows.

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 our 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 trade war's effect 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 stock prices. Changes in inflationary expectations could move stock 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 stock 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 (42) and then using equation (43) to estimate the impact of the announcements on 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 × 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.

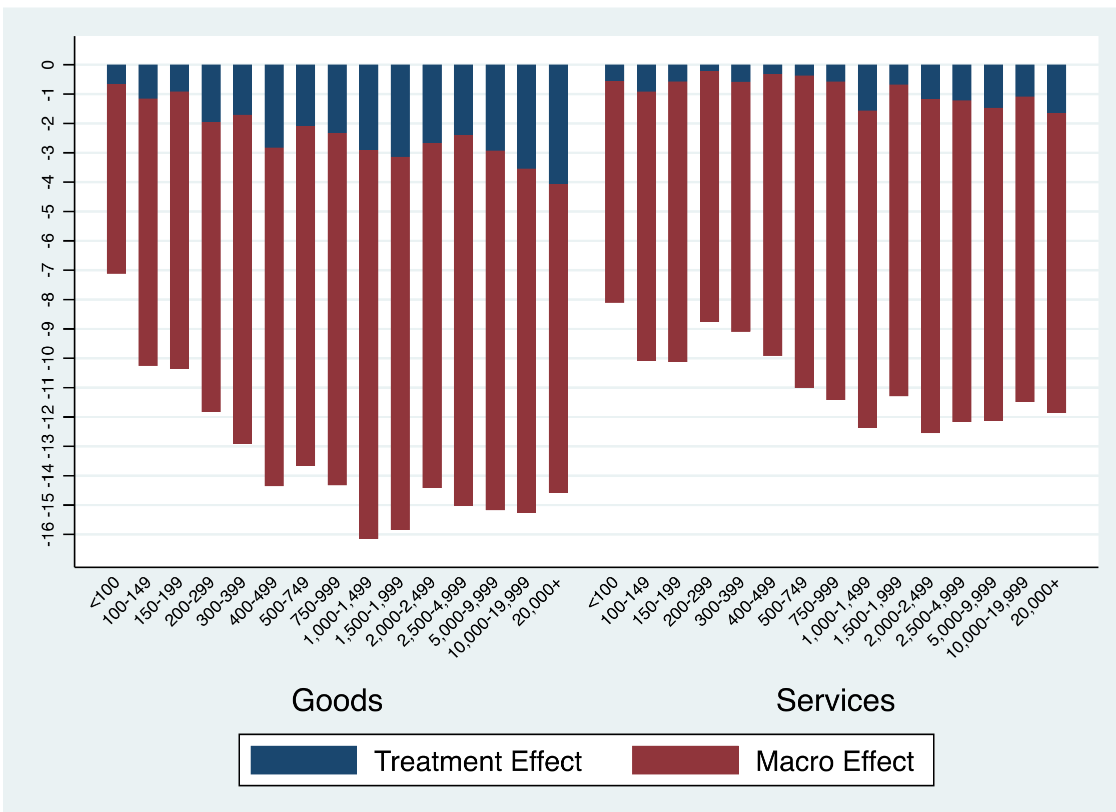
We report the results of our estimates of the trade war's effect on the expected future price level in Table 6. The estimates indicate that during each day in an announcement window, trade-war announcements were associated with a 0.029 percentage point drop in the expected price level five years later and a 0.038 percentage point drop ten years later. Given that we have 11 events spanning three days each, our results imply that the trade war lowered inflationary expectations so that prices were expected to be 0.96 percentage point lower 5 years later ($= 33 \times -0.029$) and 1.3 percentage points lower 10 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 1 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 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 (29) and (33) 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 4 plots the distribution of expected returns ($E\left[\hat{r}_b|\boldsymbol{\tau}\right]$) due to the macro effect ($E\left[\hat{r}_b^M|\boldsymbol{\tau}\right]$), and expected returns due to the treatment effect ($E\left[\hat{r}_b^T|\boldsymbol{\tau}\right]$) by bin. The market-capitalization weighted average of the macro effect on stock prices ($\sum_f w_f E\left[\hat{r}_f^M|\boldsymbol{\tau}\right]$), is -9.2 percent and that of the treatment effect ($\sum_f w_f E\left[\hat{r}_f^T|\boldsymbol{\tau}\right]$) is -2.7 percent, so the total decline in the market that we attribute to the trade war ($\sum_f w_f E\left[\hat{r}_f|\boldsymbol{\tau}\right]$) is 11.9 percent. This is very close to the actual decline of 12.9 percent that we saw in Table 2 , which indicates that idiosyncratic firm-level shocks (ν_{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 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, so general trade policy uncertainty surrounding the world trading system is more likely to affect them. 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 4: Expected Return Due to Tariff by Firm Employment



Note: The blue bars correspond to the predicted treatment effects in equation (34) with estimated coefficients from Tables 3 and 4, and the red bars correspond to the predicted macro effect from (33). Both are in percent. These are reported at the sector/firm employment bin level. The weights are adjusted to reflect the economy-wide distribution, with data on employment distribution by sector-size from the U.S. Census Bureau. 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 the discussion of equation (32), we have already purged the estimates of the effect of any standard data release on stock prices. However, one still may wonder how likely it is that we would have identified a macro effect of this magnitude if we had just randomly picked 11 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 to create a sample of potential placebo event days in which no trade-war announcement occurred. We then randomly selected 11 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 2 percent of the draws produced a macro effect of -9.2 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 expected future firm TFP, which is our counterpart to the productivity results in the micro literature and an important channel in dynamic models such as Perla et al. (2021). We use equation (23) 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. Tariff Announcements on TFPR

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

Note: The dependent variable is calculated as in equation (23). 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 1 if the firm or any of its subsidiaries or suppliers import from China. China Exporter is a dummy that equals 1 if the firm or its subsidiaries export to China. China Revenue Share is the share of the firm's revenue that comes from sales in China. Standard errors are in parentheses. The number of observations is 58,076.

In Tables 7 and 8, we show that TFP is even more sensitive to trade-war announcements than abnormal returns. As before, we continue to observe that protection has a statistically significant effect overall, but now we identify significant impacts of protection on expected TFP (as opposed to abnormal returns) on virtually all event days. For

Table 8: Impact of Chinese Tariff Announcements on TFPR

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

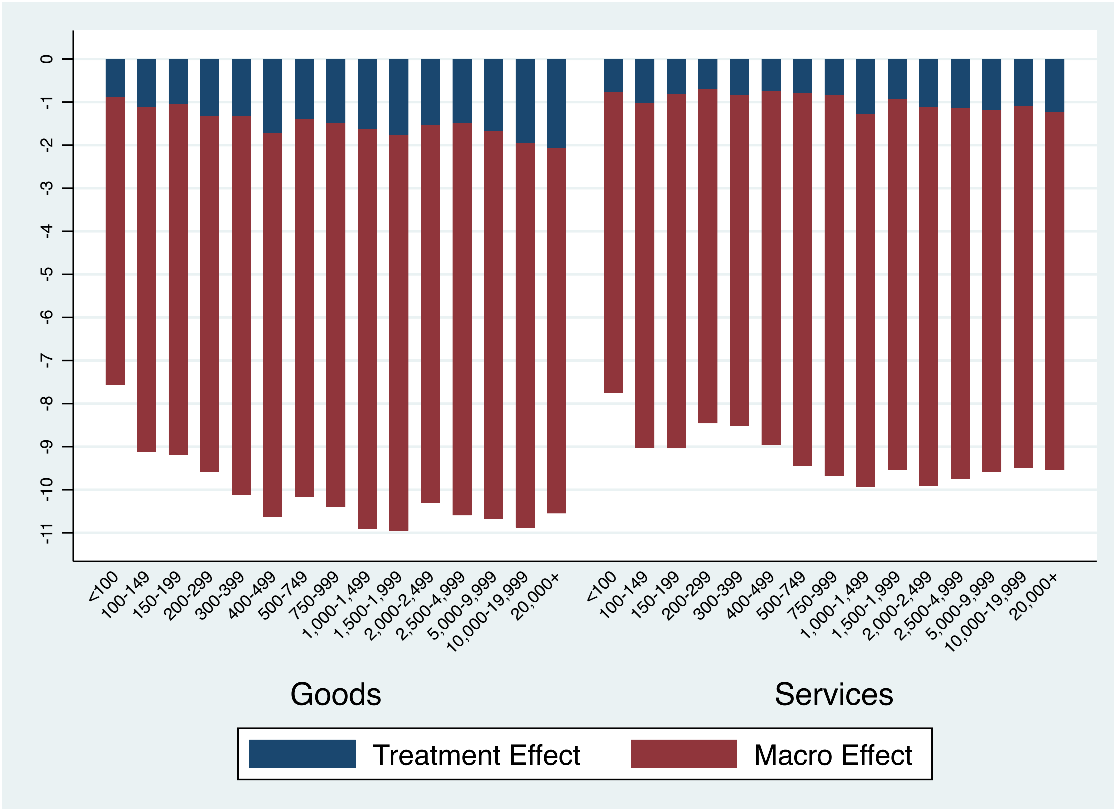
See the note to Table 7 for variable definitions and details.

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 effects, we again consider the cumulative impact of these announcements on a firm that both imported from and exported to China and had revenue of 4 percent coming from China (equal to the average). Such a firm would have experienced a 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 expected aggregate U.S. TFP based on equation (50). Figure 5 shows our estimates of the impact of the tariff announcements on the TFP of firms by firm size. We find that the negative effects 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 expected firm productivity levels off at around -10 percent. The main driver of this estimate is the 11.9 stock market decline caused by the trade war announcements, which amounted 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 expected TFP. Firms employing fewer than a hundred workers experienced expected TFP declines that were typically 3 percentage points less than the declines for large firms. The model suggests that there are two complementary reasons why tariff announcements lowered the expected 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 4 that macro factors drove the share prices of large, global, firms down by relatively more following trade-war announcements.

We can use these estimates of $E\left[\hat{r}_b^M|\boldsymbol{\tau}\right]$ and $E\left[\hat{r}_b^T|\boldsymbol{\tau}\right]$ to compute the impact of the trade war on expected real wages by using equation (49). 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

Figure 5: Expected TFP Due to Tariff by Firm Employment



Note: This plot shows estimates of revenue TFP (net of aggregate price movements) calculated according to equation (50) by firm size-sector bin. Both are reported in percent.

estimates obtained from other large movements in trade barriers.[12] 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 are 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 1.3 percentage points of the decline.

We report the welfare implications of the trade war in Table 9. Using equation (48), we find 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

[12]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 allow 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 10 years later.

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

that the 7.8 percentage point decline in welfare arises mainly because the trade-war announcements induce 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. This estimate is close to that of Amiti et al. (2019), who used a standard trade model and found that the welfare loss due the trade war was $79.1 billion, or 0.4 percent of GDP.

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 ensure that these differences are not driving our results, we reran our welfare analysis imposing the assumption that the trade war's 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 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 a conservative assumption: the trade war only affected listed firms. We implement this approach by recomputing the estimated return in each cell after imposing the restriction that the average return for U.S. firms in the cell that were not listed always equals zero. 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 22.7 percent of U.S. employment. As a result, when the expected profitability of listed firms declines sharply, as happened during the trade war, this has significant implications for the expected welfare of Americans.

5.4 Calibrating the Welfare Gain

In this section, we examine the plausibility of our estimates by viewing the stock price movements through the lens of a different model: Perla et al. (2021). Their model places much more structure on how trade costs affect firms, but it is a useful point of comparison because it can easily be rewritten in a form that allows a researcher who knows how a trade policy affected stock prices to compute the impact on growth and welfare (see Appendix (A.12) for details). In their setup, the free-trade equilibrium is inefficient because firms do not internalize productivity spillovers and therefore underinvest in new technology. Protection exacerbates this inefficiency by protecting small, inefficient firms and reducing their incentive to innovate. The reduction in (future) technological spillovers reduces firms' incentives to innovate, and productivity slows due to a "macro" effect common to all firms. An attractive feature of the Perla et al. (2021) model is that it has the property that the impact of trade on the economy can be summarized by examining movements in the ratio of the average profitability of firms relative to the minimum profits of firms ($\overline{\pi}_{rat}$). Thus, a researcher who knew how a trade shock moved relative profits could use their model to assess the growth implications. We therefore use our estimates of the impact of the trade war on the stock prices of firms to infer changes in firms' expected profits and calibrate their model to estimate the effects of the trade war on growth and welfare. These estimates imply that the trade-war announcements reduced the average expected firm profit by about 6.2%, which lowers the profit ratio from 1.861 to 1.746 (i.e., $d\overline{\pi}_{rat} = -0.115$). Using the same parameter values as in Perla et al. (2021), these numbers imply a reduction in the economic growth rate of 0.3 percentage points and a welfare decline of 9.0%, which is close to our -7.8 percentage point decline.

6 Conclusion

This paper presents a methodology for using stock market data in order to compute the impacts of a trade policy change on expected welfare, wages, TFP, employment and output. Our method differs from standard methods of assessing a policy's impact on welfare in that it does not use a model to assess how a policy will affect firm profitability, but rather it is based on market expectations about how a policy change will affect future profitability. To the extent that market participants can accurately assess the effects of a policy on the future path of expected profits, an advantage of our method is that it does not require a researcher to explicitly model how a trade policy affects the ERP and TFP.

When we apply this methodology to understanding the impact of the U.S.-China trade war on the U.S. economy, we identify large effects in comparison to those commonly identified in static models. Stock markets lost $3.3 trillion dollars in value on the days close to the announcements, which could only happen in a specific factors model if there were substantial movements in productivity. When we filter these losses through the specific factors model, they imply losses of expected welfare of 7.8 percent, which is difficult to understand through the lens of a canonical static model. Interestingly, these losses are very similar in magnitude to those we obtain from calibrating the dynamic model of Perla et al. (2021) to the observed movements in expected firm profits. This result establishes that the large welfare effects we estimate are not a unique feature of the specific factors model but also appear in dynamic models that can be calibrated using stock-price data. The similarity in the estimates may arise from the fact that both approaches allow for firm productivity to be affected by trade policy. Identifying the channels underlying these large welfare effects is a subject of future research.

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

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September 29, 2021

Table of Contents

A.1 Introduction

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

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

A.2 Proofs of Propositions

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

A.2.1 Proposition 1

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

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

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

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

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

and

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

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

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

or

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

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

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

or

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

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

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

we have

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

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

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

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

which establishes that

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

□

A.2.2 Proposition 2

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

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

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

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

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

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

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

Substituting this into equation (A.5) yields

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

Substituting into equation (A.1) gives us

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

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

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

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

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

Making use of our wage result from Proposition 1 gives us

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

□

A.2.3 Proof of Proposition 3

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

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

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

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

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

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

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

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

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

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

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

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

$$p_f y_f - \sum_i m_{if} q_i = L_f w + V_f r_f, \tag{A.25}$$

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

$$p_f y_f - p_f y_f \sum_i \omega_{if} = L_f w + V_f r_f, \tag{A.26}$$

or

$$p_f y_f \left(1 - \sum_i \omega_{if}\right) = L_f w + V_f r_f, \tag{A.27}$$

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

$$(dp_f y_f + p_f dy_f) \left(1 - \sum_i \omega_{if}\right) = L_f dw + V_f dr_f + w dL_f + r_f dV_f. \tag{A.28}$$

Dividing through by $p_f y_f$ produces

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

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

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

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

A.3 Economic Surprise Variables

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

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

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

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

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

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

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

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

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

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

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

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

A.5 Sample Statistics

Table A.2: Descriptive Statistics

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

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

A.6 Event Dates

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

Table A.3: Event Dates

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

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

A.7 Construction of Figure 2

A.7.1 Stock-Price Plot

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

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

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

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

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

A.7.2 Price Change Plot

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

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

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

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

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

A.8 Correlation Between Macro Variables and Latent Factors

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

Table A.5: Correlation Matrix

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

A.9 FactSet Data Quality Issues

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

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

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

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

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

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

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

A.10 Disaggregated Industry Protected Specification

Table A.8: Robustness Tests (Industry Protected)

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

A.11 Robustness to Using Five-Day Window

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

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

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

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

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

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

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

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

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

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

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

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

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

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

where

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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