Stock Prices, Trade Policy, and Welfare
An Analysis of the US-China Trade War*

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Abstract

We show that the specific factors model implies a rigorous link between movements in stock prices to effective rates of protection (ERP), productivity, wages, real variables, and welfare. We then apply this framework to understanding the implications of the U.S.-China trade war. We show that one can invert Jones's (1975) specific factors model and write changes in nominal variables (wages and ERP) as a function of stock-price changes. We then prove that ERP equals the dual measure of revenue TFP, providing a theoretical foundation for why many studies have found that trade liberalization "causes" productivity growth. We show that tariffs affect ERP through movements in macro variables (e.g., exchange rates) and by moving the relative prices of imports. Both of these channels mattered significantly in the trade war resulting in large declines in the TFP of listed firms and drops in expected U.S. wages and welfare over a ten-year horizon. The lower U.S. nominal wages and productivity may help also explain significant drops in expected CPI inflation on trade-war announcement dates.

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1 Introduction

Since the seminal work of Grossman and Levinsohn (1989), trade economists have known that movements in stock prices can be used as measures of the rate of returns to firm-specific factors. This insight has produced a large event-study literature in which researchers have shown that trade policy announcements systematically move the abnormal returns of firms in ways suggested by theory.[1] In important new work, Greenland et al. (2019) also show that firm abnormal returns in response to trade announcements can also explain real variables, such as changes in firm employment and sales. However, one of the difficulties of interpreting the results from prior research is that their estimating equations are not rigorously linked to a trade model, and so they do not provide guidance about how a policy change is likely to affect wages and welfare in general equilibrium. This paper's contribution is to show that one can derive a theory-based equations that link movements in stock prices to trade policy, productivity, wages, real variables, and welfare. We then apply this framework to understanding the implications of the U.S.-China trade war.

Our framework is based on the canonical specific factors model of Jones (1975) that we rewrite as a model of firm specific factors by using an approach akin to Bernard, Eaton, Jensen, and Kortum (2003). Jones's original paper focused on industries, not firms, and provided a theoretical relationship between the effective rate of protection (ERP), wages, and the returns to a specific factor that formed the intellectual underpinning for the idea that movements in output prices due to tariffs should also move returns to the specific factor (i.e., stock prices). One of the implementation challenges of the Jones framework is that ERPs defy measurement except under the "extremely severe" assumption that firms use no intermediate inputs (c.f. Ethier 1977).[2] This assumption is commonly made in recent tests of the specific factors model such as Topalova (2010) and Kovak (2013).

However, how do we measure ERPs in the general case? Our key insight is that if we start with what is observable—stock price movements—we can invert Jones's model and write changes in nominal variables (wages and ERP) as a function of stock-price changes. Indeed, stock price movements can be used as sufficient statistics for computing changes in wages and the ERP. Similar to Melitz (2003), where utility can be written as a function of the average operating profits of firms, we show that in the specific factors model, nominal wages equal the labor-share weighted average of stock returns. Since we can compute wage changes and observe the returns to capital, we can write movements in employment as proportional to another sufficient statistic based on stock returns that tells us the movement in relative wages. As in Jones (1975), the constant of proportionality is simply the elasticity between capital and labor, which can be readily obtained from other studies.[3] Finally, if we couple these movements in labor with the fact that the amount

[1] See, for example, Hartigan et al (1986), Breinlich (2014), Moser and Rose (2014), Breinlich et al (2018), Crowley and Song (2019), and Huang et al. (2019)

[2] In a very influential piece on efforts to derive a rigorous measure of the ERP, Ethier writes, "One prominent impression, one that also pervades the recent literature, concerns the extremely severe nature of the technological restrictions necessary for a simple measure to be correct.... On balance the case for using any specific array of effective rates rather than nominal rates or some other definition of effective rates as measures of the resource-allocation effects of a tariff structure is quite weak."

[3] Knoblach and Stockl 2020) conduct a meta-analysis of 49 studies and find that the value of σtypically

of each specific factor is unchanging, we can also compute the implied change in output. This approach yields a rigorous foundation for the results reported in Greenland et al. (2019) linking stock price movements to employment and sales movements.

In order to compute welfare in the model, we need to be able to compute two additional variables: the change in tariff revenue induced by the policy and the policies impact on the consumer price index (CPI). The first variable can be computed by well-established methodologies such as Fajgelbaum et al (2020). Estimating how trade affects aggregate consumer prices, however, is difficult in standard trade models because they lack a theory of the price level in the absence of a numeraire. Fortunately, assessing the impact of a trade policy announcement on the price level can also be easily determined by backing out 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). With these estimates in hand, we obtain our estimates of the impact of trade announcements on real wages and welfare.

Given that stock price movements provide us with a sufficient statistic for the effective rate of protection, we also provide a theoretical foundation for the ERP and its link to productivity. Our starting point is the definition of ERP in Jones (1975) and Ethier (1977): "the change in effective protection for an industry is the actual proportional change in value added per unit." [Ethier (1977) p. 238] This definition implies that if tariffs raise the firm's output price ERP will rise, and if tariffs raise its input prices ERP will fall. This intuition notwithstanding, economists have struggled to understand what theoretical concept is captured by ERP (c.f, Ethier 1977 and Anderson 1998).[4] We prove a simple relationship: ERP equals revenue total factor productivity (TFPR). The intuition is that greater TFPR implies more sales holding fixed the firm's inputs, but this can only happen if value added per unit output rises. In other words, TFPR is the primal definition of TFP and ERP is the dual. The fact that ERP equals TFPR also provides a theoretical foundation for the findings of Amiti and Konings (2007) and Topalova and Khandelwal (2011) showing that regressing TFP on tariff variables that should systematically move the ERP (i.e., the dual of TFPR) yield significant coefficients. This result will obtain as long as there is strong association between TFPQ and TFPR and tariffs matter for ERP. A corollary of this result is that the link between trade openness and TFP growth is a feature of specific factors models.

We also shed light on how to link ERP to trade policy measures. To do this, we build off the original idea of Corden (1966) who argued that the trade policy impact on the ERP could be should be divided into two components: protection's impact on macro variables that move due to changes in policy and its direct effect. In the words of Corden, "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] In order to capture the

falls between 0.4 and 0.7.

[4]For example, Anderson (1998) summarizes the prevailing view as "the usual definition [of ERP] corresponds to no economically interesting magnitude."

impact of total protection as suggested by Corden, we use a factor model coupled with an event study to separately estimate how an announcement moved the ERP by shifting macro variables during an event window and also how it affected ERP through the more conventional channel of shifting the relative prices of tradables.

[Very Preliminary Results]

[We are still working on the implementation, so the results are incomplete and subject to change. In particular, we are still working on adjusting for the non-randomness of the sample. We present some baseline numbers to show proof of concept and give a flavor of the type of analysis that will be in the final draft.]

We apply this methodology to the 2018-2019 U.S. China trade war. We find that the U.S.-China trade-war announcements are associated with large stock-price declines regardless of whether we look at impacts over 1-day, 3-day, or one week event windows. We find that during a 3-day window around each of the trade war announcements stock prices fell 12.2 percent in total: a $3.4 trillion loss in market value. We also show that while the trade war depressed equity values by lowering the returns of firms exposed to China, it had even larger negative effects by lowering the returns of firms more broadly. Under the assumption that labor is mobile among listed firms but not outside of this set of firms, this implies that the revenue TFP and wages of listed firms fell by a similar magnitude.

Our analysis of the impact of the tariff announcements on inflationary expectations indicates that they also caused a 1.9 percentage point drop in the price level over a 10-year horizon. The 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. In our setup, the large drop in TFP caused by the trade war depresses wages and may help explain why our estimate implied consumer price changes based on TIPS premia fell as well.

Interestingly, we estimate that both U.S. tariffs and Chinese retaliatory tariffs had statistically significant impacts on firm-level ERP (and therefore TFP). We follow Huang et al. (2019) in our selection of the observable exposure variables that matter when doing a stock-market event study of the U.S.-China trade war: whether the firm exports to or imports from China as well as the fraction of its revenues that it obtains from the Chinese market. This sales channel also turns out to be an important reason why the trade war hurt U.S. firms, perhaps reflecting the fact that U.S. tariffs not only likely provoked Chinese tariff and non-tariff retaliation, but also hurt U.S. multinationals by slowing their sales growth in China.[5] U.S. announcements seem to have worked through largely conventional effects—firms exposed to China experienced sharp declines in ERP while unexposed firms were largely spared. These results arise from two channels: first, firms importing from China saw their ERP fall in response to US tariffs (but not Chinese tariffs)

[5]While the U.S. only exported $130 billion to China in 2017, sales by U.S. multinationals amounted to $376 billion. Indeed, although the large bilateral deficit in 2017 was driven by the fact U.S. exports to China were only a quarter as large as Chinese exports to the U.S, total sales (exports plus multinational sales) by U.S. firms in China were only 11 percent lower than total sales by Chinese firms in the U.S. market. Sales in China by U.S. firms were $505 billion and sales in the U.S. by Chinese firms were $570 billion. Source: Bureau of Economic Analysis, U.S. Census.

because the former raised the price of their intermediate inputs; second, firms selling in China experienced drops in ERP because they now faced Chinese restrictions. The lower returns for firms selling in China following U.S. tariff announcements may reflect market anticipation of retaliation (which invariably came). Chinese retaliation also depressed the ERPs of firms selling in China but but had no impact on firms importing from China. This result is consistent with our intuition about how Chinese protection should affect the ERP of U.S. firms.

1.1 Related Literature (To be Added)

2 Theory

e develop a theory of how a policy announcement will affect wages, prices, real variables, and welfare using only information about stock prices and the standard event-study variables (i.e., firm accounting variables and policy variables that matter at the firm level). We develop the theory in three steps. The first involves developing a non-parametric mapping between movements in stock returns and wages, welfare, and implied effective rates of protection (ERP). We then use the fact that we can measure each firm's ERP to show how one can extract the impact of a policy announcement on prices in the economy. We then can apply Jones (1975) to estimate the impact of the policy change on all the variables of interest.

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

We begin by invoking a standard specific factors model in which labor is mobile and each firm f hires L_f workers at a wage w and uses V_f units of a firm-specific factor in order to produce y_f units of output. We assume that firms produce using heterogenous constant-returns-to-scale production functions. The unit-cost function for firm f can be written as $c_f(w, r_f, q_1, ..., q_n)$, where the arguments correspond to the wage, returns to firm f's specific factor, and a set of intermediate inputs, each produced at a price q_i. Some of these intermediates may be imported or produced by domestic firms, in which case $q_i = p_j$ for some firm j producing intermediate input i. Let the unit input requirements for labor and capital be given by a_f^L and a_f^V. As in Jones (1975), we impose the following full-employment conditions:

$$\sum_f a_f^L y_f = L, \text{ and} \tag{1}$$

$$a_f^V y_f = V_f, \tag{2}$$

where $L \equiv \sum_f L_f$. Finally, we follow Jones (1975) and assume that the the factor intensity of production (a_f^V / a_f^L) is governed by relative factor prices and the elasticity of substitution between capital and labor (σ):

$$\hat{a}_f^V - \hat{a}_f^L = \sigma(\hat{w} - \hat{r}_f), \tag{3}$$

where hats over variables indicate log changes. We are now ready to prove our first proposition linking stock prices to wages.

Proposition 1. *In any specific factors model featuring an identical elasticity of substitution between labor and capital for all firms, the log change in wages equals the employment-share weighted average of firm stock returns, i.e.,*

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

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

Proof. See Appendix A.2.1 □

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 goods prices into factor prices. Here, we invert the logic in Jones to show that if we can identify the movements in the specific factor prices, we can pin down wages. Second, and more substantively, we show that by assuming that there is one elasticity of substitution between labor and capital, we simplify the expressions in his canonical model and are able to construct a sufficient statistic for computing the impact of the movements in stock prices on wages without doing any estimation. Wages move one for one with the employment-weighted average of share prices.[6] By contrast, implementation of the Jones approach would require us knowing the full set of firm-level elasticities. While the assumption of a single elasticity of substitution is more restrictive, other studies have often adopted even more restrictive assumptions, e.g., assuming that $\sigma = 1$ (c.f., Kovak 2013).[7] Third, our method suggests that there is a much simpler way of estimating the wage impacts of a policy change than the one proposed by Jones. His approach (in the general case) requires knowing ERP's, which requires a researcher to observe all price changes in the economy as well as the full input-output structure, whereas our approach only requires observing stock-price changes. Finally, we obtain a simple expression of how each firm's employment shifts conditional only on observing its stock prices, which indicates that the movement in employment is proportional to the firm's share price less the employment weighted average of all share prices. Again, we have a sufficient statistic for understanding the employment movements.

In order to determine the implied movements in output and prices, we develop the theory further by adding a model of pricing behavior. The classical specific factors model is based on perfectly competitive atomistic firms, which cannot be applied directly to a world in which each firm has a different specific factor. Following Bernard, Eaton, Jensen, and Kortum (2003), we assume that each firm is a Bertrand competitor in its market. It is useful to temporarily change notation slightly so that f now denotes a product and f' indexes the set of potential entrants into that sector. In other words, we assume that for any product f, the marginal cost of any firm f' potentially producing this product is given

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

[7] Knoblach and Stockl (2020) conduct a meta-analysis of 49 studies and find that the value of σ typically falls between 0.4 and 0.7.

by $c_f^{f'}(w, r_f, q_1, ..., q_n)$. A potential entrant will enter only if it can make a strictly positive return on its specific factor, i.e., $p_f > c_f^{f'}(w, 0, q_1, ..., q_n)$. If this condition is satisfied and the firm enters, the return to its specific factor will be $r_{f'} = \frac{1}{a_f^V}\left(p_f - c_f^{f'}(w, 0, q_1, ..., q_n)\right)$. Since the entry condition only depends on the common market price for the good (p_f) and $c_f^{f'}(w, 0, q_1, ..., q_n)$, it is useful to rank the potential entrants by their cost of production so that

$$f'' > f' \iff c_f^{f''}(w, 0, q_1, ..., q_n) > c_f^{f'}(w, 0, q_1, ..., q_n) \tag{4}$$

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 firm 1 is the only producer of good f, we can now go back to our original notation and refer to its price as p_f and its marginal cost as c_f.

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_{fi} the expenditures of firm f on labor, the specific factor, and input i expressed as share of total revenue. We now can obtain an expression for a mapping between relative stock-price movements and output changes.

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

$$\hat{y}_f = \frac{\omega_f^L \sigma}{\omega_f^L + \omega_f^V}\left(\hat{r}_f - \sum_{f'} \frac{L_{f'}}{L}\hat{r}_{f'}\right)$$

where ω_f^L and ω_f^V denote the payments to labor and specific factors as a share of revenue.

Proof. See Appendix A.2.2 □

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

Propositions 1 and 2 indicate that knowledge of stock returns, the labor and capital input shares, and the elasticity of substitution between capital and labor,is sufficient to identify nominal wage movements, as well as employment and output movements. The elasticity of substitution between capital and labor has been estimated in a large number of studies, and Knoblach and Stockl (2020) conducted an exhaustive meta-analysis of close to 50 studies that estimated this parameter and found that its value typically falls

between 0.4 and 0.7. Thus, there is not a lot of uncertainty about how to move from stock prices to implied movements in real variables.

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 equation (6) yields

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

combining this with the result in Proposition (1) yields

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

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

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

2.2 Assessing the Role of Policy

The analysis presented thus far is predicated on a researcher being able to identify a set of stock price movements or abnormal returns that can be ascribed to a policy change. One strategy for identification is to use what Greenland et al (2020) term the "all-in" approach. In this approach, the researcher identifies a narrow window around a policy announcement and ascribes the stock price changes in that narrow window as capturing all of the relevant information associated with the announcement. A major advantage of this approach is that it does not require the researcher to be able to model all the ways in which a policy might affect a firm. However, this approach does not lend itself to exploring particular channels through which a policy affects factor prices. For example, a tariff announcement might affect stock prices by both moving macro variables (e.g., growth or exchange rates) and by moving micro variables (e.g., differentially affecting the importer productivity or input prices), and researcher might be interested in separating these two effects. Moreover, since firm stock prices might move for idiosyncratic reasons on a day (perhaps due to the release of some non-policy related information), a researcher may want filter out stock price movements that are orthogonal to the policy announcement. Therefore, as an alternative to the all-in approach, we develop a structural approach to firm stock price movements in which we identify movements in stock prices that arise from a policy's impact on a firm's input and output prices.

2.2.1 Policy and the Effective Rate of Protection

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 sproved that the movement in the returns to each factor can be written as

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

where

$$\varphi_f \equiv \frac{L_f}{\theta_f^V} / \sum_{f'}\frac{L_{f'}}{\theta_{f'}^V}, \tag{9}$$

θ_f^L and θ_f^V are the wage bill and payments to the specific factor expressed as a share of value added:

$$\theta_f^L \equiv \frac{wL_f}{p_f y_f\left(1-\sum_i \omega_{fi}\right)}, \text{ and } \theta_f^V \equiv \frac{r_f V_f}{p_f y_f\left(1-\sum_i \omega_{fi}\right)}, \tag{10}$$

and $\hat{p}_f^e$ is the firm's "effective rate of protection" (ERP), which is defined as

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

Thus, if we know how a policy affects the ERP, we can infer the implied movement in the return to wages and the specific factor.[8]

The first term in equation (8) captures the direct link between a firm's return and its ERP. Higher spreads between output and intermediate input prices, reflected in the ERP equation (11), raise rates of return by the amount in parenthesis. Since wage changes will be less than price changes if only one firm's ERP is increasing, a firm's return on its specific factor will tend to be higher when φ_f is large, which will happen when it employs a lot of labor relative to amount of specific factor used. In this case, proportionally more of the gap between output and input prices will be used to raise the return to the specific factor. Similarly, it will tend to be large when other firms tend to use labor intensive production techniques because higher demand demand for labor by firm f can be met by increasing the wage by less. The second term captures the indirect link that arises from how shifts in the ERPs of other firms affect the return to the specific factor of the firm by moving the demand for labor. The second summation term will be large when the average ERPs of all other firms rise. A firm whose competitors have higher ERPs will have a lower stock market return because its competitors will be able to pay higher wages, which will force the firm to raise its wage too. The fall in the return to the specific factor will be greater if the firm uses a more labor intensive production technology (i.e., θ_f^L/θ_f^V is large).

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

[8]The ERP is the key variable in the specific factors model because it is essentially the amount of value added generated by the firm per unit of output. In other words, it will equal the firm's output price change ($\hat{p}_f$) if the firm does not use any intermediate inputs ($\omega_{fi} = 0\ \forall\ i$), but more generally it will rise by less than the output price change if a policy increases the price of imports or other intermediate inputs (i.e., $\hat{q}_{fi} > 0$).

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_{fi}). Fortunately, there is an easy workaround to the problem of not having the data necessary to compute the ERP directly. As we prove in the following proposition stock price movements provide a sufficient statistic for the ERP.

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

$$\hat{p}_f^e = \theta_f^V \hat{r}_f + \theta_f^L \sum_{f'} \frac{L_{f'}}{L} \hat{r}_{f'}$$

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

$$\hat{p}_f^e = TFPR_f$$

,
where $TFPR_f$ is the change in the firm's revenue total factor productivity.

Proof. See Appendix A.2.2 □

From Proposition (3), stock price movements provide a sufficient statistic for calculating changes in the ERP, which turns out to be equivalent to the market's expectation for the change in firm's revenue TFPR.[9] The intuition for this result stems from the zero profit condition, which implies that $\hat{p}_f^e = \theta_f^V \hat{r}_f + \theta_f^L \hat{w}$. This expression can only be positive if aggregate payments to factors rise, which can only happen if firm sales are growing faster than firm inputs, i.e., TFPR is rising. Importantly, we do not need to take a stand on whether the TFPR of the firm moved because the policy moved output prices, input prices, or changed some other structural factor in the firm that raised TFPR—we have obtained a summary measure of the sum total of these channels.

The fact that we can measure TFPR at the firm level means that if we could estimate a policy's impact on firm TFPR, we could use equation (8) to assess how much the policy variables moved share prices and then apply our earlier propositions to understand the wage and welfare impacts. One way to obtain a mapping from policy into effective rates of protection is to assume the existence of a policy pricing function $p_f(\tau)$ that provides a mapping from a vector of policy variables ($\boldsymbol{\tau} = (\tau_1, ..., \tau_N)$) into the ERP (TFPR) of the firm:

$$p_f^e = p_f(\boldsymbol{\tau})\, \nu_{ft}, \tag{12}$$

where ν_{ft} is an error term that captures movements in the ERP that are not due to the policy change.

Proposition (3) also provides us with a method of specifying event-study regressions in the context of the specific factors setup. In particular, suppose that changes in the ERP are related changes in home protection of the output of the firm (τ_f), foreign protection

[9] Following Hsieh and Klenow (2009), TFPR equals the change in value added net of changes in labor and capital inputs.

(τ_f^*), and protection that affects intermediate inputs (τ_f^I) in a linear fashion, so that we can write

$$\hat{p}_f^e = \alpha + \beta_0 \tau_f + \beta_1 \tau_f^* + \beta_2 \tau_f^I + \epsilon_f^e \tag{13}$$

where α and the β_i are parameters to be estimated and ϵ_f^e is an iid error term.

Propositions 1 and 2 provide the theoretical foundation for the reduced form regressions linking abnormal returns and firm-level variation in employment, labor productivity, and sales. This expression is closely related to the standard event study regression used to assess the impact of protection on stock prices, but it differs in important ways. In event studies, researchers typically regress abnormal returns on these measures of protection. Abnormal returns, AR_f, are typically based on the capital asset pricing model:

$$AR_f \equiv \hat{r}_f - \beta_f^{CAPM} \sum_{f'} \frac{MV_{f'}}{MV} \hat{r}_{f'} = \alpha' + \beta_0' \tau_f + \beta_1' \tau_f^* + \beta_2' \tau_f^I + \epsilon_f', \tag{14}$$

where MV_f is the firm's market value in the stock index, β_f^{CAPM} is the beta for the firm derived from the capital asset pricing model and α' and the β_i' are a vector of parameters to be estimated. We now summarize the relationship between reduced form event study estimates and structural estimates in the following proposition:

Proposition 4. *If the assumptions underlying the specific factors model hold and the firm's ERP is determined according to equation (13), then ordinary-least squares estimation of equation (14) will yield biased and inconsistent estimates of the β_i.*

Proof. See Appendix A.2.4 □

Proposition 4 is useful because it highlights a problem of inference that arises from using CAPM-based event-study methods to estimate the effect of trade policy on firm pricing behavior. The fact that $E\left[\hat{\beta}_i'\right] \neq E\left[\hat{\beta}_i\right]$ means that a policy that matters for the output or input prices faced by firms, i.e., its ERP, will not necessarily be identified as such by an event study (i.e., $E\left[\hat{\beta}'_i\right] \neq 0$ does not imply that $E\left[\hat{\beta}_i\right] \neq 0$). By the same token, a policy that *does not matte*r for the output or input prices faced by firms, will not necessarily be identified as such by an event study (i.e., $E\left[\hat{\beta}_i\right] = 0$ does not imply that $E\left[\hat{\beta}_i\right] = 0$). This makes nterpretation of these coefficients from standard event study methods difficult. .

One can obtain some intuition for what is missing in standard event studies by contemplating the specific factors model equation (8), which provides the mapping between firm stock returns ($\hat{r}_f$) and ERP/TFPR ($\hat{p}_f^e$). The relationship varies by firm and depends on the TFPRs of all of the other firms because the ERPs of other firms affect the stock returns of any given firm f through movements in the wage. Thus, even if one knew exactly how a policy affected the ERP of a given firm f, one could not identify the impact on the firm's stock return without knowing the full vector of impacts on the ERPs of all firms. In the next section, we therefore solve the problem of how to move from having a model of how a policy change affects ERPs to understanding what impact this policy will have on welfare.

3 Estimation

3.1 Tariffs and the ERP

Since we now have a method of using asset prices to measure the change in the expected ERP for a firm, we can impute the movement in this variable if we specify the policy pricing function that maps policy changes into ERP's ($p_f(\boldsymbol{\tau})$). Starting with Corden (1966), the literature has argued that policy announcements are likely to affect firms through two potential channels: the policy's impact on macro variables (e.g., exchange rates) and its impact on the relative prices of tradables subject to tariffs. For example, one might believe that a tariff announcement affected a firm's expected ERP because it moved exchange rates and because tariffs move relative prices of goods in ways not captured by the exchange rate and other macro variables (e.g., if some imports from China are hit with tariffs and others are spared).

In order to operationalize this idea and estimate the policy function ($p_f(\boldsymbol{\tau})$) that is separable into macro and relative price terms, we change notation slightly by adding time subscripts to all variables that vary over time and assume that the policy function is additively log separable in macro and relative price variables:

$$p_f(\boldsymbol{\tau}_t) = p_f^M\left(\boldsymbol{\delta}\left(\boldsymbol{\Phi_t}, \boldsymbol{\tau_t}\right)\right) p_f^R\left(\boldsymbol{\tau_t}\right), \tag{15}$$

where $\boldsymbol{\delta}\left(\boldsymbol{\Phi_t}, \boldsymbol{\tau_t}\right) = (\delta_{1t}, ..., \delta_{Kt})$ is a $K \times 1$ vector of macro latent variables (exchange rates, policy uncertainty, etc.) that may be affected by a vector of variables unrelated to the event ($\boldsymbol{\Phi_t}$) as well as policy announcements ($\boldsymbol{\tau_t}$). $p_f^R\left(\boldsymbol{\tau_t}\right)$ then captures the movements in the ERP due only to the relative price movements induced by the tariffs. If there is no tariff announcement on day t, we have $\boldsymbol{\tau_t} = \mathbf{0}$ and $p_f^R(\mathbf{0}) = 1$. If there is an announcement on day j we have $\boldsymbol{\tau_j} \neq \mathbf{0}$, and the tariffs will move the pricing function by shifting macro and/or relative price variables. Substituting equation (15) into equation (12) and log differentiating gives us

$$\hat{p}_{ft}^e = \sum_{k=1}^{K}\sum_{i=1}^{N} \frac{\partial \hat{p}_f^M}{\partial \delta_k}\frac{\partial \delta_k}{\partial \tau_{it}} d\tau_{it} + \sum_{i=1}^{N} \frac{\partial \hat{p}_f^R}{\partial \tau_{it}} d\tau_{it}. \tag{16}$$

The first term in this expression captures the policy's impact on ERP's that arises from its effect on macro variables and the second term captures its impact by affecting the relative prices. Thus, returning to our example, if a tariff moved exchange rates, the first term would tell us how much of the tariff's effect occurred through the exchange rate and the second term would tell us the price affects of the tariffs that are not captured by exchange rates. Since we do not know the set of macro variables that matter for understanding movements in ERP's in equation (15), we assume that these movements can be described a set of latent variables:[10]

$$\hat{p}_f^M\left(\boldsymbol{\delta}\left(\boldsymbol{\Phi_t}, \boldsymbol{\tau_t}\right)\right) = \alpha_f + \sum_{k=1}^{K} \beta_{kf}\delta_{kt} \tag{17}$$

[10] 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."

where α_f is a firm fixed effect, β_{kf} is our estimate of $\frac{\partial \hat{p}_f^M}{\partial \delta_k}$ in equation (16) and tells us the firm's sensitivity to latent variable k (its "loading").

In order to specify the functional form for the relative price effects, $\hat{p}_f^R$, 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 let the length of the event window be denoted by w. We define D_{jt}^w to be an indicator variable that is one if day t falls within the event window for event j and zero otherwise. During the event window, we assume that there is a set of treatment variables Z_{if} ($i \in \{1, ..., N\}$) that identify 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 effect of relative price movements on the ERP can be written as

$$\hat{p}_{ft}^R = \sum_{j \in \Omega^{UC}} \theta_j D_{jt}^w + \sum_{j \in \Omega^{UC}} \sum_{i=1}^{N} \gamma_{ij} Z_{if} D_{jt}^w \tag{18}$$

where θ_t is a parameter that captures how the event affected ERP's for all firms differently from how the factor model would have predicted; γ_{ij} is our estimate of $\frac{\partial \hat{p}_f^R}{\partial \tau_{it}}$ during event window j (and if we want to assume that a policy variable has the same effect on all events we can impose the restriction that $\gamma_{ij} = \gamma_i$).

A key feature of equation (18) is that it has an isomorphic structure as equation (17). In particular, we can think of the D_t and D_{jt}^w as latent variables that only matter during an event window, and θ_t 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 log differentiate equation (12) and substitute equations (15) and (17) into it, we obtain

$$\hat{p}_{ft}^e = \alpha_f + \sum_{k=1}^{K} \beta_{kf} \delta_{kt} + \epsilon_{ft}, \tag{19}$$

where

$$\epsilon_{ft} \equiv \left(\sum_{j \in \Omega^{UC}} \theta_j D_{jt}^w + \sum_{j \in \Omega^{UC}} \sum_{i=1}^{N} \gamma_{ij} Z_{if} D_{jt}^w \right) + \nu_{ft}. \tag{20}$$

We make the identifying assumption that latent variables (δ_{kt}) matter for 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.,

$$\lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} (\delta_{kt} - \delta_k)^2 > 0, \tag{21}$$

where $\delta_k \equiv \frac{1}{T} \sum_t \delta_{kt}$. Since D_t and D_{jt}^w are only non-zero during the event window and the number of events is finite, we also know that $\lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} (D_t - D)^2 = 0$ and

$\lim_{T\to\infty} \frac{1}{T}\sum_{t=1}^{T}\left(D_{jt}^{w} - D_{j}^{w}\right)^{2} = 0$, where $D \equiv \frac{1}{T}\sum_t D_t$ and $D_j^w \equiv \frac{1}{T}\sum_t D_{jt}^w$. In other words, D_t and D_{jt}^w will not be identified as latent variables, which means that we will correctly identify the number and values of latent variables as well as the values of all of their parameters in equation (19), and the terms on the right-hand side of equation (20) will appear in the error term of equation (19). This enables us to use the residuals from this equation ($\hat{\epsilon}_{ft}$) as the dependent variable in an event study to identify the remaining parameters.

3.1.1 Correcting for Economic Surprises

One potential concern with our estimates of $\hat{\delta}_{kt}$ is that they might contain not only information about the trade war but possibly other information released on the same day. For example, an exchange rate might move because of some other announcement unrelated to the trade war. In order to address this problem, we will incorporate into the analysis a vector of economic surprise variables $(ES_{1t,}ES_{2t}, ..., ES_{\overline{N}t})$. In order to filter out the effects of economic surprises that matter for stock prices, we run the following regression

$$\hat{\delta}_{kt} = \alpha_k' + \sum_{i=1}^{\overline{N}} \phi_{ik} ES_{it} + \delta'_{kt}, \tag{22}$$

where α_k' and ϕ_{ik} are parameters to be estimated, $\overline{N}$ is the number of economic surprises, and δ_{kt}' is the error term. We then set our estimate of the impact of the trade announcement on the common factors to be $\hat{\delta}'_{kt}$ based on this regression because it captures the impact of the tariff announcement on macro factors that cannot be explained by other economic surprises.

3.2 Measurement of $\hat{P}$

The estimation procedures described thus far enable us to measure all of the nominal variables in the equilibrium as well as the movements in real variables, so we now address how to identify movements in consumer prices and therefore real wages and welfare. We use estimates of the 5- and 10-year expected inflation rates from Abrahams et al. (2016), which were calculated based on the differences in yields between nominal bonds and inflation indexed bonds after making appropriate adjustments for liquidity, inflation risk, and real interest risk. . We denote their Y-year estimate of annual expected inflation on day t as $\hat{\pi}_t^Y$. The implied change in the *price level* over Y years is therefore Y times the change in average annual inflation rates or $Y\hat{\pi}_t^Y$. Similarly, $\left(\hat{\pi}_t^Y - \hat{\pi}_{t-1}^Y\right)$ is the change in expected annual inflation on day t based on the prices of B-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 day before) is

$$\hat{P} = \sum_j \sum_t \left[Y\left(\hat{\pi}_t^Y - \hat{\pi}_{t-1}^Y\right)\right] D_{jt}^w. \tag{23}$$

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

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

$$Y\left(\hat{\pi}_t^Y - \hat{\pi}_{t-1}^Y\right) = \alpha^Y + \sum_{i=1}^{\overline{N}} \beta_i^Y ES_{it} + \epsilon_t^\pi, \tag{24}$$

and then run the following regression:

$$\hat{\epsilon}_t^\pi = \alpha^\pi + \sum_{j \in \Omega^{UC}} \gamma_j^\pi D_{jt}^w + \epsilon_t', \tag{25}$$

where α^π and γ_j^π are parameters to be estimated. Our estimate of the impact of the tariff announcement on day j on prices is then given by

$$\hat{P}_j = w \sum_j \hat{\gamma}_j, \tag{26}$$

and the aggregate impact of all the trade war events on expected inflation is

$$\hat{P} = \sum_j \hat{P}_j. \tag{27}$$

3.3 Computing the Impact of Tariffs on the Economy

We now can estimate the impact of the events on wages and welfare. We assume that the movements of the latent variables estimated in equation (19) during the event windows captures the impact of trade announcements on macro variables. We can also filter out the impact of other economic surprises that may have confounded our estimates by using the procedure described in Section 3.1.1. This procedure enables us to estimate the macro impact of the tariff announcements ($\hat{p}_{ft}^M$) on ERP by using equation (17) and replacing δ_{kt} with δ_{kt}'. In order to compute the impact of announcements on the expected rate of protection through macro variables ($\hat{p}_{f\tau}^M$), we simply setting $\hat{p}_f^M = \sum_j \sum_t D_{jt}^w \hat{p}_{ft}^M$. Similarly, if we estimate equation (20), we can to compute the change in ERP due to the tariff's expected impact on relative prices by using equation (18) to compute ($\hat{p}_{ft}^R$). As before we can then compute the aggregate impact of the tariffs on the ERP arising only from relative price effects by setting $\hat{p}_f^R = \sum_j \sum_t D_{jt}^w \hat{p}_{ft}^R$. In this case we have, $\hat{p}_f^\tau = \hat{p}_f^M + \hat{p}_f^R$, where $\hat{p}_f^\tau$ is the full impact of the tariffs on the firm's effective rate of protection.

Since we know how the tariffs affected each firm's effective rate of protection, we now can assess the impact of the tariffs on nominal variables and welfare. If we replace $\hat{p}_f^e$ in equation (8) with $\hat{p}_f^\tau$, we can compute the movement in each firm's stock return due only to the tariff announcements ($\hat{r}_f^\tau$). We then can replace $\hat{r}_f$ with $\hat{r}_f^\tau$ in formula derived in proposition 1 to compute the change in wages due to the tariffs ($\hat{w}^\tau$). In order to compute the change in welfare (equation 7), we also need estimates of the announcements on tariff revenues and the CPI ($\hat{P}$). The method for computing the latter was described in the previous section.

We compute the change in tariff revenue ($TR \times \widehat{TR}$) due to the trade war announcements by using the import demand elasticities estimated in Fajgelbaum et al. (2020) to

estimate import quantities (based on Census data) after the levying of the tariffs and multiplied the implied import levels by the amount of the tariff increase. We set TR equal to the total tariff revenues collected in 2017, and I equal to total U.S. value added generated by the private sector as reported in the input-output tables for same year. In order to compute the implied tariff revenue generated by the tariffs, we need to construct the counterfactual change in imports that would arise if the only change were the tariffs against China:

$$\widehat{\text{Imports}}_h = \text{Imports}_{h,17} - \sigma \Delta\tau_h \text{Imports}_{h,17}, \tag{28}$$

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

A nice feature of this approach is that it also allows us to understand how much of the movements in stock prices and wages was due to macro and relative price effects. If we simply use $\hat{p}_f^M$ instead of $\hat{p}_f^\tau$ as our measure of the tariff's impact on firm ERP, we obtain the estimate of the trade war's impact on ERP (and hence wages and stock returns) that only arises through its impact on macro variables. Similarly, by using $\hat{p}_f^R$ instead of $\hat{p}_f^\tau$ as our measure of firm ERP, we can identify the impact of the trade war on nominal variables through the relative price effects caused by the tariffs.

4 Data

Our analysis requires data on stock returns, inflationary expectations, balance sheet items, exposure to China, 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. The balance sheet data (e.g., investment, cash flows, MTB, etc.), covering the same period but at the quarterly frequency, are from the CRSP/Compustat Merged (CCM) data also provided by WRDS. When we merge the Compustat data with the CRSP data for a balanced panel of firms that report stock returns on every day, we obtain a sample of 2,605 firms that cover all sectors. We set $\hat{r}_{ft}$ to be the log change in the firm's stock price.

For each firm in our sample, we collect the dates of its individual announcements that relate to buybacks (announcements, cancellations), dividends (affirmations, increases, decreases), earnings calls, stock splits, mergers and acquisitions (announcements, cancellations), and follow-on equity offerings. These data are from the Capital IQ Key Developments, which keeps track of material news and events that can impact the market value of securities. We view the returns of a firm on the day before, the day, and the day after an individual announcement as being contaminated. Therefore, we adopt the following procedure to avoid misattributing the abnormal returns due to concurrent individual firm events to the trade war events. For each event date, we exclude the abnormal returns of firms that have made an individual announcement within a window that extends a day before and a day after the event window we consider when we estimate equation (18). For example with our baseline window of three days, we exclude the abnormal returns of a firm that made an individual announcement up to two days before and after the event date from the estimation.

The construction of the input share variables came from matching each firm's NAICS 6=digit industry to the 2012 450×450 Bureau of Economic Analysis Input-Output table. We set $r_f V_f$ equal to the firm's sales less its cost of goods sold as reported in Compustat in 2017.[11] We set wL_f equal to the compensation to the ratio of compensation of employees to the value of total industry output from the IO table multiplied by the firm's sales. Similarly, we set $\sum_i \omega_{if}$ equal to the ratio of intermediate expenses in the firm's industry divided by industry output in the IO table. We then set $p_f y_f = wL_f + r_f V_f + \text{Sales}_{f,2017} \sum_i \omega_{fi}$, where $\text{Sales}_{f,2017}$ equals the firms sales from Compustat. This procedure guarantees that the cost shares sum to one.

We obtained estimates of inflationary expectations from Richard Crump who updated the estimates generated in Abrahams et al. (2016).[12] A commonly used measure of inflation expectations is the difference in yields on a Treasury and a Treasury Inflation-Protected security, however in addition to inflation expectation this could contain inflation and liquidity risk. The methodology in Abrahams et al. (2016) isolates the inflation expectations component. Our 65 economic surprise variables encompass all major price, monetary policy, and macroeconomic data releases used in economic forecasting and were provided by Daniel Lewis (see appendix for details). These variables equal the difference between a data release and the Bloomberg median of economists' forecast on the day before (see Lewis et al. (2019) for methodology).

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 iPhone's from the U.S. subsidiary of Foxconn. In order to identify the supply chains, we use D-U-N-S numbers from Dun & Bradstreet to merge importers from Datamyne to a list of firms and their subsidiaries from Capital IQ. We use a firm-name match to link firms, subsidiaries, and their suppliers that are reported in Datamyne, Compustat, Bloomberg, and FactSet and identify which firms are trading with China directly or indirectly through their network or suppliers. After matching firms with identical names in two or more datasets, we manually compared firms with similar names to identify whether they are matches. We define "China Revenue Share" to be the share of a firm's revenues in 2018 (either obtained through sales of subsidiaries or exports) that arise from sales in China as reported in FactSet.

The Datamyne data has a number of limitations. First, while some of the Datamyne data is at the Harmonized System (HS) 6-digit level, much of it is at the HS2-digit level. Since U.S. tariffs are set at the Harmonized Tariff System 8-digit level, it is not possible to know what share of a firm's trade was affected by tariffs. We therefore opt to use a binary exposure measure. Our "China Import" dummy is one if the firm or its supply network

[11] If this was negative, we set it equal to the average over 2016-2017. If this still was negative, we dropped the firm.

[12] Inflation expectations are missing on the February 28, 2018 event day, but they were available the day before the event and the day after, so we estimated γ_j^π for this event by dropping the observation for February 28 and setting the value for the dependent variable March 1 in equation (24) equal to $Y\left(\hat{\pi}_t^Y - \hat{\pi}_{t-2}^Y\right)$.

imported from China in 2017 and zero otherwise. We also construct a "China Export" dummy analogously for exports. Second, the Datamyne data only covers seaborne trade. The U.S. Census data reveals that in 2017, 62 percent of all imports from China and 58 percent of exports to China are conducted by sea, so although we capture over half of the value of U.S. China trade, the China import and export dummies are likely to miss some US 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 try to capture missing importers, we also include in a large firm dummy equal to one for all firms with more than 1000 employees, from Compustat.

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

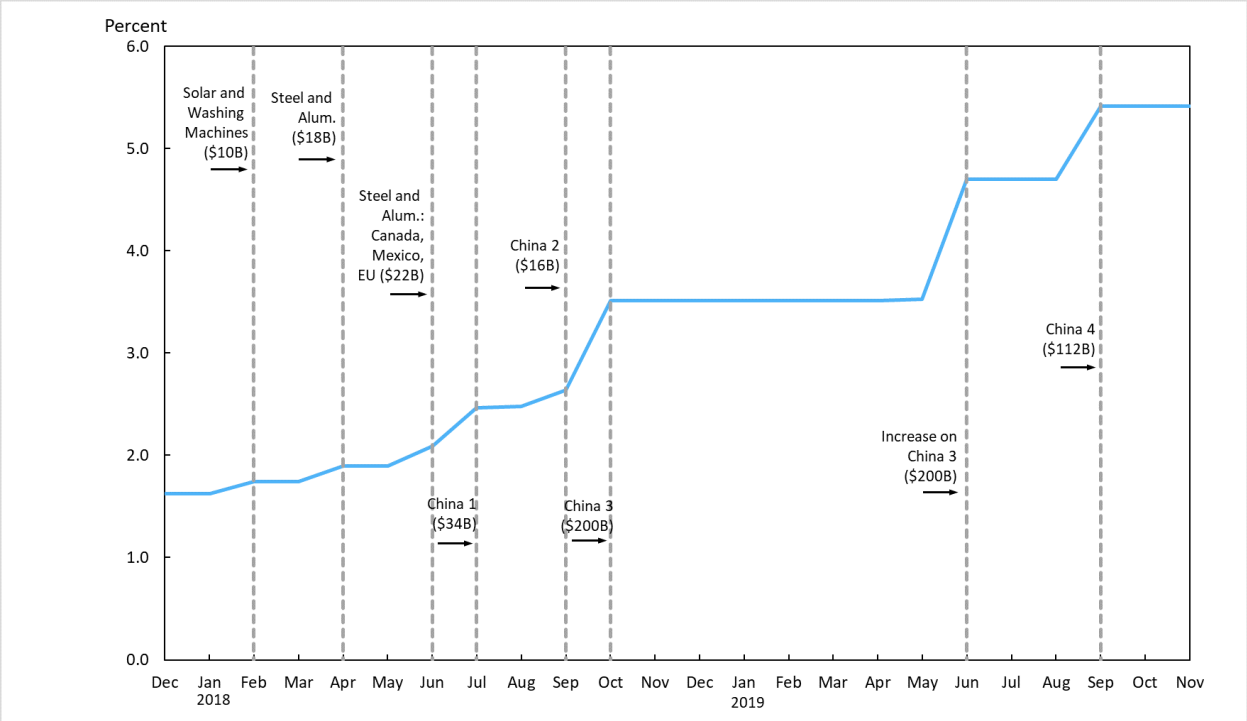
	Mean
Firm imports from China	0.11
Firm or subsidiary imports from China	0.26
Firm, subsidiary, or supplier imports from China	0.31
Firm exports to China	0.02
Firm or subsidiary exports to China	0.05
Firm sells in China via exports or affiliates	0.41
Average share of revenue from Chinese exports or affiliate sales	0.03
Firm exposed to China through imports, exports, or affiliate sales	0.51
Firm with more than 1,000 employees	0.61
Firm is large or is exposed to China through imports, exports, or affiliate sales	0.72
Number of Firms: 2,605	

Note: This table reports the means of indicator variables that are one if a firm satisfies the listed criterion.

These data show that the supply chain information is critical in understanding firms' exposure to international trade. From Table 1, we see that only 11 percent of the firms in our sample import directly from China, and only 2 percent export directly to China. However, if we take into account subsidiaries, these numbers rise to 26 and 5 percent, respectively. When we add in imports by all firms in the supply chain, we see that 31 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 51 percent of all firms were exposed to China through one of these channels. If we also take account of large firms, the share of treated firm increases to 72 percent.

Figure (1) shows the new U.S. tariffs levied on China by the U.S. during 2018 and 2019. For each of these tariff events we located the earliest announcement in the media using Factiva and Google search. In addition, we also used the same method to identify the

Figure 1: Average U.S. Tariffs by Wave of the 2018-2019 Trade War



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

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 US 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 US announced a 25 percent tariff on $50 billion of Chinese imports. Although this was implemented in two tranches on two separate dates ($34 billion on July 7, 2018 and $16 billion on August 23, 2018), we include this as only one event as what is important for our purposes is the first time it was announced. All of the 11 events are listed in Table 2 in date order, with more details and links to the announcement of each event provided in the Appendix. Our approach to choosing event dates has the advantage of being comprehensive and objective.

Table 2 presents the stock market return on each of these event dates. We see that the stock market fell on all of the event dates except one U.S. event date and one China event date, with a total drop of 10.1 percent over all of the events, and 12.2 percent over a three

Table 2: Stock Returns on Event Dates

Event Group	Event Date	R_t (%)	$\sum_{t-1}^{t+1} R_t$ (%)	Description
US	22Jan18	0.78	1.61	Trump imposes tariffs on solar panels and washing machines
US	28Feb18	-1.06	-3.50	Trump says US will impose steel and aluminum tariffs
CHN	22Mar18	-2.49	-4.68	Trade war escalates as China says it will impose tariffs on 128 U.S. exports
US	29May18	-0.98	0.16	White House to impose 25% tariff on $50 bn worth of Chinese goods
CHN	15Jun18	-0.10	0.11	China announces retaliation against US tariffs on $50 bn of imports
US	19Jun18	-0.38	-0.22	Trump announces imposition of tariffs on $200 bn of Chinese goods
CHN	02Aug18	0.63	0.92	China announces tariffs on $60 bn of U.S. goods
US	06May19	-0.39	-0.95	US to raise tariffs on $200 bn of Chinese goods up to 25%
CHN	13May19	-2.51	-1.26	China to raise tariffs on $60 bn of US goods starting June 1
US	01Aug19	-0.99	-2.85	Trump said he will impose a fresh 10% tariff on another $300 bn of Chinese goods
CHN	23Aug19	-2.61	-1.59	China hits back at Trump with higher tariffs on soy, autos
US+CHN	all	-10.10	-12.24	

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

day window. These drops in the market imply substantial losses for U.S. firms—a factor that Proposition 1 suggests will tend to drive real wage decreases.

5 Preliminary 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, welfare, and investment.

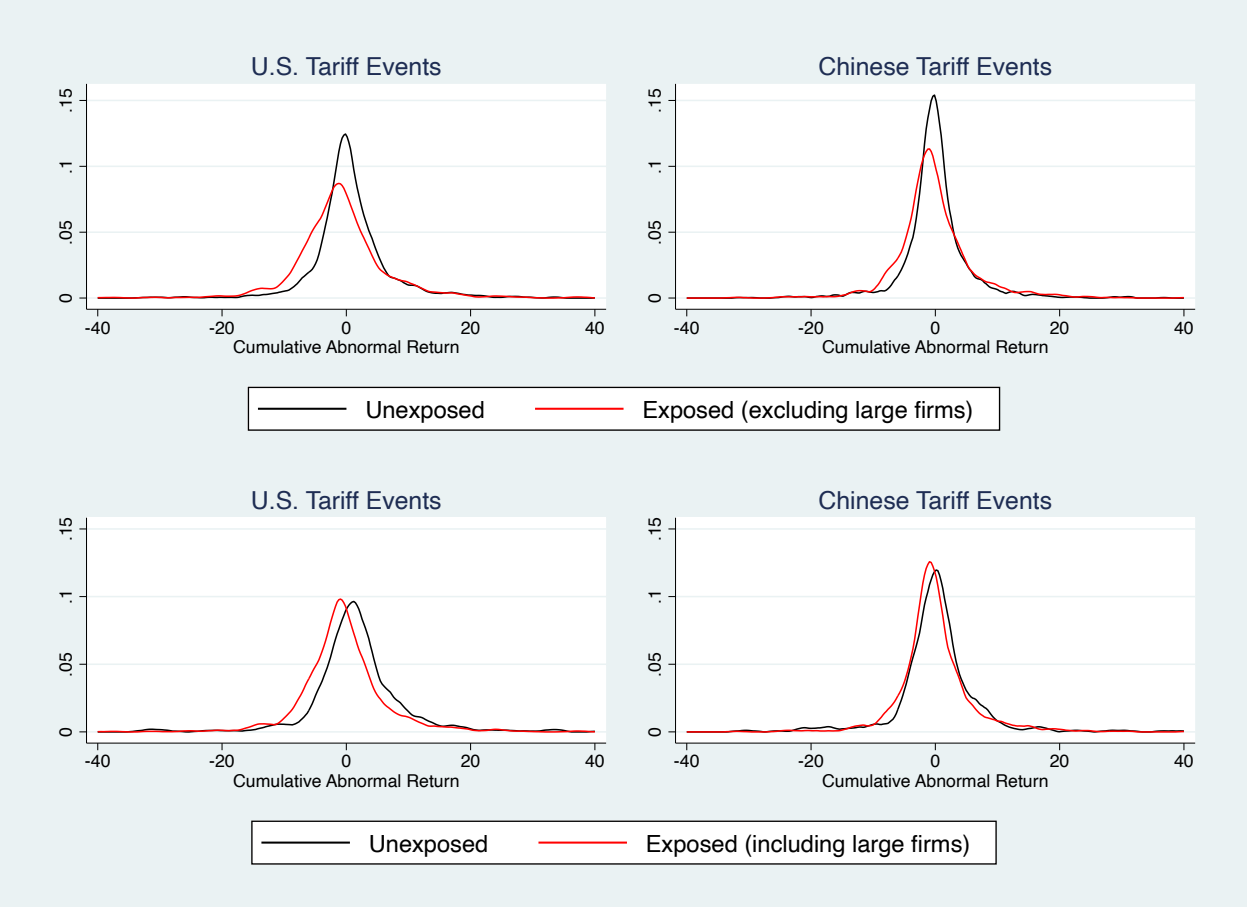
5.1 Event Study Results

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 (17) following the approach of Bai and Ng (2002) and Bai and Ng (2013). We follow Bai and Ng (2002), who recommend choosing the number of latent variables to minimize the following loss function when errors may be cross-sectionally correlated:

$$IC(K) = \ln(\mathcal{L}(K)) + K\left([F + T - K]\frac{\ln(FT)}{FT}\right),$$

where F is the number of firms; $\mathcal{L}(K)$ is the log likelihood function based on the estimation of equation (17); N is the number of firms; and T is the number of days. Each additional factor adds 2,373 β_{kf} parameters (one for each firm). The first factor is similar to what would be obtained in a classic CAPM setup. Based on the Bai and Ng (2002) loss function, we use five factors in our baseline. The first factor accounts for 24.2 percent of the variance, but additional factors account for much less, with the next four factors accounting for 2.62, 2.46, 1.89, 1.57 percent of the variance, respectively. Thus, macro variables explain 32.7 percent of the variation in firm ERP.

Figure 2: Dispersion in Returns (3-Day Windows)



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

In order to visualize how the tariff announcements affected the relative price component of each firm's ERP depending on whether they were exposed and unexposed firms (as defined in Table 1), we plot the kernel densities of the error terms in equation (19) using a 3-day window around each event j ($\epsilon_{fj} \equiv 100 \times \sum_{t=j-1}^{j+1} \hat{\epsilon}_{ft}$) for both sets of firms in Figure 2. In the top row, we define the set of exposed firms to include firms that import from, export to, or have some positive revenues in China. In the second row, we additionally include the large firms in the exposed category. On the two left panels, we see that the distribution of errors for firms exposed to China during U.S. tariff announcement events is shifted to the left relative to firms that were not exposed. Similarly, we see that announcements of Chinese tariff retaliation produce a similar pattern, with the distribution of abnormal returns for exposed firms lying to the left of the distribution for unexposed firms, but not as pronounced as with the U.S. tariff events. Comparing the top and bottom panels, we see that this effect is not driven solely by large firms, but instead is due to firms trading with China. These results indicate that tariff announcements tended to reduce the ERP of exposed firms by raising their input costs relative to their output prices.

We identify the relative price effects of tariffs on ERP by estimating equation (18). As is standard in the literature, we set $w = 3$ as our baseline. Table 3 presents the results from regressing the ERP on the China exposure variables for each of the six U.S. tariff events. The estimated coefficients under each event date correspond to the $\hat{\gamma}_{ij}$ in equation (18), and we report the average value of these estimated coefficients across all events in the first column. Thus, columns 2-7 all 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 -0.127 on the China importer dummy in column 3 implies that during the 3-day event window around the February 28, 2018 steel and aluminum announcement, firms that imported from China declines in their ERP that were on average 0.127 percentage points lower than other firms *every day* within this 3-day period. Thus, their *cumulative* decline in their ERP was -0.381 ($= 3 \times 0.127$) percent. Similarly, since the average estimates in column 1 tell us about six events each composed of three days, the differential impact of being an importer from China on ERP cumulated over all six events is 18 times larger: -1.2 percentage points ($= -0.064 \times 6 \times 3$).

Table 3: Impact of U.S. Tariffs Announcements on ERP (3-Day Windows)

	(1) Average	(2) 22Jan18	(3) 28Feb18	(4) 29May18	(5) 19Jun18	(6) 06May19	(7) 01Aug19
China Importer	-0.064***	-0.027	-0.127***	0.028	-0.042	-0.102*	-0.111
	(0.023)	(0.045)	(0.048)	(0.039)	(0.048)	(0.053)	(0.076)
Large Company	-0.097***	-0.046	-0.127**	-0.154***	-0.017	-0.214***	-0.027
	(0.026)	(0.052)	(0.056)	(0.041)	(0.060)	(0.056)	(0.098)
China Exporter	-0.142***	-0.092	0.045	-0.197***	-0.413***	-0.091	-0.105
	(0.040)	(0.061)	(0.085)	(0.053)	(0.082)	(0.083)	(0.123)
China Revenue Share	-0.457***	-1.231***	-0.029	0.311	-1.079***	-1.172***	0.458
	(0.167)	(0.349)	(0.270)	(0.269)	(0.325)	(0.341)	(0.469)

Note: This table presents the results from estimating equation (18) for all U.S. tariff events. The dependent variable ($\hat{\epsilon}_{ft}$) is the abnormal return obtained from estimating equation 17 with five factors. China Importer is a dummy that equals one if the firm or any of its subsidiaries or suppliers imports from China. Large Company dummy equals 1 if a firm has more than 1000 employees in 2017. China Exporter is a dummy that equals one if the firm or its subsidiaries export to China. China Revenue Share is the share of the firm's revenue that comes from sales in China. Column 1 presents the the average of the coefficients on each of the event days. Standard errors are in parentheses.

Table3 suggests that U.S. tariff announcements had on average negative and significant impacts on the ERPs of importers, and large companies (another proxy for importers). Although the effects are not always significant for every event, we obtain a negative coefficient on both of these variables for all but one event. We also see negative and significant coefficients for the China exporter variables in all but two of twelve cases. These negative coefficients on the exporter variables are likely due to three (not mutually exclusive) reasons. The first is that exporters may have anticipated that U.S. tariffs would provoke Chinese retaliatory tariffs, thereby lowering the ERP of exporters. Second, market participants may have anticipated that U.S. tariffs would also provoke Chinese retaliatory non-tariff barriers that could lower revenues obtained either by exporting or multinational sales. Third, it is also possible that U.S. tariffs weakened the Chinese economy, which could lower profits for U.S. firms selling there. The average estimated effect is also economically significant. The coefficient on China revenue share in

the first column of Table 3 implies that firms selling in China had an average decline in the ERP of -0.17 percent ($= -0.457 \times 0.025 \times 15$) over the course of the 15 days in the event windows of the U.S. tariff events.

Although all four variables have negative and significant coefficients on average, Table 3 also reveals the important heterogeneity of effects across different event dates based on estimation of equation (18). This heterogeneity reflects the potential pitfall of assuming that all tariff announcements should have similar effects. From columns 2 to 7, we see that the size of the coefficients on the variables that are likely to capture direct exposure to tariffs—the China importer and large company dummies—vary from close to zero to -0.21.

Table 4: Impact of Chinese Tariff Announcements on ERP (3-Day Windows)

	(1) Average	(2) 22Mar18	(3) 15Jun18	(4) 02Aug18	(5) 13May19	(6) 23Aug19
China Importer	-0.031	0.065*	0.001	-0.087	-0.086*	-0.049
	(0.021)	(0.038)	(0.039)	(0.058)	(0.050)	(0.046)
Large Company	-0.053**	-0.240***	-0.084*	0.047	0.065	-0.054
	(0.025)	(0.047)	(0.047)	(0.066)	(0.064)	(0.052)
China Exporter	-0.084**	-0.047	-0.052	-0.134	-0.099	-0.087
	(0.034)	(0.071)	(0.051)	(0.097)	(0.063)	(0.054)
China Revenue Share	-0.491***	-0.331	-0.704**	0.126	-0.876***	-0.671***
	(0.133)	(0.229)	(0.312)	(0.404)	(0.335)	(0.225)

Note: This table presents the results from estimating equation (18) for all U.S. tariff events. The dependent variable ($\hat{\epsilon}_{ft}$) is the abnormal return obtained from estimating equation 17 with five factors. China Importer is a dummy that equals one if the firm or any of its subsidiaries or suppliers imports from China. Large Company dummy equals 1 if a firm has more than 1000 employees in 2017. China Exporter is a dummy that equals one if the firm or its subsidiaries export to China. China Revenue Share is the share of the firm's revenue that comes from sales in China. Column 1 presents the the average of the coefficients on each of the event days. Standard errors are in parentheses. In the lower panel of the table, we report the cumulative market effects as well as the differential and common effects as defined in equation (**??**), and the total event effect as the sum of the common and differential effects. In this lower panel, the first column is the total (not the average) for all the events.

Table 4 presents analogous regressions estimated using data for the five Chinese tariff retaliation events. Column 1 shows that on average, both exporter indicators have negative significant coefficients while the importer indicators are insignificantly different from zero. As with the U.S. tariff events, we also find substantial heterogeneity in the effects of the events on the returns for firms. Not surprisingly, announcements of Chinese retaliation are generally not associated with any differential impact on the ERP of U.S. importers, but we do see consistent drops in the ERP of firms selling in China when China announces retaliation. The only event to indicate a positive coefficient on China revenue share is in column 3. This perhaps is due to the retaliation being seen as less severe than expected. These returns are significant and negative on average as one can see in the first column.

5.2 Tariffs and the Price Level

The results presented thus far concern the impact of the trade war on the nominal returns of specific factors. Changes in inflationary expectations could move these returns around without having any impact on real returns. For example, if all final goods prices rose on

a day, equation (A.22) implies that it would also be an equilibrium if all factor and import prices rose by the same amount. Thus, the absolute movement in real returns for firms need not tell us about real wage changes. In order to pin down the impact of the tariff announcements on real wages, we need to identify the impact of the announcements on aggregate prices. We do so by estimating equation (25) and then using equation (27) to estimate the impact of the announcements on price level.

Table 5: Regression of Cumulative Inflation Rates on the Sum of Event Window Dummies

	(1) 5-year	(2) 5-year	(3) 10-year	(4) 10-year
Event Dummy	-0.052**	-0.053*	-0.060***	-0.063**
	(0.021)	(0.028)	(0.023)	(0.032)
Event Dummy × China Event Dummy		0.002		0.006
		(0.041)		(0.046)
N	980	980	980	980

We report the results of our estimates of the trade war on the price level in Table 5. The estimates indicate that during each day in an announcement window trade-war announcements were associated with a 0.052 percentage drop in the expected price level five years later and a 0.063 percentage point drop ten years later. Given that we have eleven events spanning three days each, our results imply that the trade war lowered inflationary expectations so that prices were expected to be 1.6 percentage points lower five years later and 1.9 percentage points ten years later.

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5.3 Wage and Welfare Impacts [In progress]

6 ConclusionIncomplete

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

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A.1 Introduction
A.2 Proofs of Propositions
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A.1 Introduction

This online appendix contains supplementary theoretical and empirical results. Section A.2 presents the proofs of the various propositions in the theory section. Section A.3 lists our set of economic surprise variables. Section A.4 presents sample statistics.

A.2 Proofs of Propositions

A.2.1 Proposition 1

Proposition. *In any specific factors model featuring an identical elasticity of substitution between labor and capital for all firms, the log change in wages equals the employment-share weighted average of firm stock returns, i.e.,*

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

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

Proof. Totally differentiating equations (1) and (2) yields:Totally differentiating equations (1) and (2) 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 (3) 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 (3) 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 1

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

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

where ω_f^L and ω_f^V denote the payments to labor and specific factors as a share of revenue.

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

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

If we assume that the share of expenditures in intermediate inputs is unchanged as a result of a policy change, i.e., $\sum_i \omega_{fi}\hat{a}_{fi} = 0$, 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 in 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. *The percent change in the ERP for a firm ($\hat{p}_f^e$) in a specific factors model is given by*

$$\hat{p}_f^e = \theta_f^V \hat{r}_f + \theta_f^L \sum_{f'} \frac{L_{f'}}{L} \hat{r}_{f'}$$

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

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

$$\omega_f^L \hat{w} + \omega_f^V \hat{r}_f + \sum_i \omega_{if} \hat{q}_i = \hat{p}_f. \tag{A.22}$$

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

$$\theta_f^L \hat{w} + \theta_f^V \hat{r}_f = \frac{\hat{p}_f - \sum_i \omega_{if} \hat{q}_i}{1 - \sum_i \omega_{if}}, \tag{A.23}$$

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

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

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 $\sum_i \omega_{fi}$ 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 $(1 - \sum_i \omega_{fi})$ and rearranging produces

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

where θ_f^L and θ_f^V are the shares of labor and the specific factor in value added. Since the left-hand side of this equation is revenue TFP, we have proved the ERP is the same as TFP. □

A.2.4 Proof of Proposition 4

Proposition. *If the assumptions underlying the specific factors model hold and the firm's ERP is determined according to equation (13), then ordinary-least squares estimation of equation (14) will yield biased and inconsistent estimates of the* β_i.

Proof. We can rewrite equation (13) as :

$$\theta_f^L \sum_{f'} \frac{L_{f'}}{L}\hat{r}_{f'} + \theta_f^V \hat{r}_f = \alpha + \beta_0 \tau_f + \beta_1 \tau_f^* + \beta_2 \tau_f^I + \epsilon_f \tag{A.31}$$

where $\alpha$is the constant term in the regression. The left-hand side of this equation is the implied movement in the ERP for the firm based on the stock-price movements and the independent variables are the policy movements. It is easy to compare the estimates that one would obtain from estimating this pricing equation with those that would obtain from estimating the reduced form event study equation given in equation (14). We can rewrite equation (A.31) as

$$\hat{r}_f - \beta_f^{CAPM} \sum_{f'} \frac{MV_{f'}}{MV}\hat{r}_{f'} = \alpha + \beta_0 \tau_f + \beta_1 \tau_f^* + \beta_2 \tau_f^I + \epsilon'_f, \tag{A.32}$$

where

$$\begin{aligned}\epsilon'_f \equiv \frac{\epsilon_f}{\theta_f^V} + \alpha\frac{1-\theta_f^V}{\theta_f^V} + \beta_0\frac{1-\theta_f^V}{\theta_f^V}\tau_f + \beta_1\frac{1-\theta_f^V}{\theta_f^V}\tau_f^* + \beta_2\frac{1-\theta_f^V}{\theta_f^V}\tau_f^I \\ - \beta_f^{CAPM}\sum_{f'}\frac{MV_{f'}}{MV}\hat{r}_{f'} - \frac{\theta_f^L}{\theta_f^V}\sum_{f'}\frac{L_{f'}}{L}\hat{r}_{f'}.\end{aligned} \tag{A.33}$$

If one estimates equation (A.32) or equivalently equation (14), the estimated coefficients on the τ_f terms will be biased and inconsistent because the error term (ϵ'_f) will contain τ_f terms as well as other variables that vary with the firm's return. □

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 US manufacturing purchasing managers index, Case-Shiller home price index, and Markit US services purchasing managers index, federal funds shock, forward guidance shock, asset purchase shock, and the federal reserve information shock.

A.4 Sample Statistics

Table A.1: Descriptive Statistics

	N	Mean	Standard Deviation	25th Percentile	Median	75th Percentile
$\hat{\epsilon}_{ft}$	83,360	0.00	3.15	-1.03	-0.07	0.90
China Importer Dummy	73,410	0.31	0.46	0.00	0.00	1.00
Large Company Dummy	73,410	0.61	0.49	0.00	1.00	1.00
China Exporter Dummy	73,410	0.05	0.21	0.00	0.00	0.00
China Revenue Share	73,410	0.03	0.07	0.00	0.00	0.02
Industry Protected Dummy	83,360	0.03	0.17	0.00	0.00	0.00
$I_{fs}/K_{f,s-4}$	31,552	0.06	0.07	0.03	0.04	0.08
Cashflow$_{fs}/K_{f,s-4}$	30,784	0.45	1.26	0.07	0.22	0.53
MTB$_{f,s-4}$	29,863	1.83	1.23	1.08	1.41	2.08
I_{fs}	34,828	98.29	391.79	1.63	9.11	41.50

Note: Factor model using stock returns RET from CRSP, ϵ_{ft} is estimated from equation 17. Section 5.1 (daily) summary stats are in the first part of the table and section 5.2 (quarterly) in the lower part for the period 2016Q1 to 2019Q4. China Importer Dummy and China Exporter Dummy equal one for firms that import or export to China as recorded in Datamyne. China Revenue Share and Non-China Revenue Share are the shares of a firm's revenues that come from China and foreign countries other than China, respectively. The Large Company Dummy is one when a firm has at least 1,000 employees, sourced from FactSet. Industry Protected Dummy is defined when a firm's 6-digit NAICS code is affected by US tariff events.The respective variables in CCM are as follows: I_{fs} is quarterly capital expenditures (CAPXQ) in millions of dollars, K_{fs} capital stocks are measured by PPENTQ (Property Plant and Equipment), Cashflow$_{fs}$ is OIBDPQ (Operating Income Before Depreciation). MTB$_{fs}$ defined as (ATQ+PRCCQ*CSHOQ-SEQQ-TXDITCQ)/(ATQ), where ATQ is total assets, PRCCQ is the closing stock price in the quarter, CSHOQ is common shares outstanding, SEQQ is total shareholder's equity, and TXDITCQ is deferred taxes and investment tax credit. We used TXDBQ (deferred taxes) if TXDITCQ was missing.