Trade Protection, Stock-Market Returns, and Welfare[*]

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December 18, 2024

Abstract

Tariff announcements made during the U.S.-China trade war had broad effects on financial variables. Announcements systematically decreased stock prices and raised nominal and real bond prices. We use a specific factors model to show that the welfare impact of the tariff can be identified from the policy-induced movement in the present value of firm cash flows: a variable that can be estimated from financial data. Using this framework, we find that the U.S.-China trade war lowered U.S. welfare by three percent. We show that these cash flow movements can be further decomposed into market expectations about how tariffs affect current and future prices and productivity. Seen through the lens of our model, the market reactions to tariff announcements can be explained by expectations that tariffs lead to large, negative future price and TFP shocks that play an important role in dynamic, but not static, models.

JEL CLASSIFICATION: F13 F14 G10 F16
KEYWORDS: Event Study, Specific Factors Model, Trade War, Policy Uncertainty

1 Introduction

Trade models differ sharply in their predictions about the gains from trade. Canonical static models typically generate small effects of trade protection on welfare.[1] By contrast, dynamic models often stress the existence of productivity spillovers across firms that are not internalized, which implies that protection can have large future effects on productivity and welfare (c.f., Atkeson and Burstein (2010); Buera and Oberfield (2020); Perla et al. (2021); Sampson (2016)). Testing which approach is more realistic is difficult because dynamic effects may take years to materialize, and it is hard 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. More generally, trade policies can lead to a wide range of direct and indirect effects on an economy, making it difficult to capture all relevant factors in a single model.

To overcome these issues, we develop a method that quantifies the expected impact of a trade policy on welfare using the reaction of financial markets on policy announcement days. Financial data is particularly well suited to quantify the impact of a policy change because financial markets are forward-looking and react quickly to new information. However, trade economists have largely ignored financial market data when studying the welfare impact of trade policies because of the lack of a rigorous mapping from asset prices into welfare. Our analysis fills this gap. The use of financial data enables us to relax many common assumptions used in modeling policy analysis. Relative to canonical trade models, we make no assumptions about how and when prices and wages adjust to tariffs or whether tariffs cause productivity or macro variables like exchange rates to change. Instead, we show that knowing a policy's impact on the present discounted value of firms' cash flows—a variable that can be estimated from financial data—encapsulates the first-order welfare effect of the policy.

We apply this framework to understanding the implications of the U.S.-China trade war on U.S. welfare. We focus on the first announcements of tariffs that were actually implemented as opposed to other types of announcements (e.g., tweets) that were not clearly linked to a concrete action. In order to identify the tariff-announcement dates, we search for the first mention in the media of each tariff wave implemented by the U.S. or China during the 2018-2019 trade war. We document three stylized facts about the trade war that we use to motivate our theory and empirical analysis.

First, we find that tariff announcements produced large, broad, and persistent stock-price declines. The cumulative drop in the market on the eleven event dates was 11.5 percent, which amounts to a 4.1 trillion dollar loss in firm equity value. The data show these drops were broad, with the full distribution of firm returns shifting downward. Moreover, the drop in market value happened consistently with each new tariff announcement, which implies that markets were not just reacting to a sudden realization that U.S. policies were changing at the onset of the trade war. Indeed, the two biggest drops in the market occurred in 2019—over a year after the trade war began. Furthermore, we find markets hardly responded to non-tariff executive actions and orders, which suggests that

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[1]In small open-economy models, this happens because free-trade equilibrium is efficient, so trade protections only have second-order effects on welfare. In large-country economy models, this happens because imports only constitute a small fraction of GDP, so terms of trade effects hardly matter for national income.

mere "saber rattling" did not affect equity valuations.

Second, we turn to the cross-section. We show that firms that were *directly* exposed to China through sales or imports had *relatively* worse stock returns. This result is consistent with Huang et al. (2023) who examine abnormal returns on two of the eleven tariff-announcement days. According to modern financial theory, a policy can only have a large impact on stock returns if it has a large and persistent effect on firm cash flows or on firm discount rates. We document that both of these channels were active. We show that firms with worse stock returns on tariff-announcement days had worse future *real* outcomes, with significantly lower future profits (i.e., cash flow), employment, sales, and labor productivity.

Third, we examine the effect of tariff announcements on discount rates. We find these policies created a "flight to safety" on announcement days: nominal and real yields dropped while proxies for the equity premium (constructed from the option market) spiked. These novel empirical findings motivate us to develop a theory that allows tariff announcements to jointly impact firm discount rates and firm cash flows.

We then develop a model that maps these financial market reactions and the effect of the tariff announcements into aggregate welfare. We first specify a general-equilibrium production structure that can be integrated into an asset-pricing model. We show how to adapt Jones (1975)'s *industry* specific factors model into a *firm-level* specific factors model to describe the production side of the economy. In this setup, payments to firm-specific factors equal firm cash flows (i.e., revenues less variable costs). A key difference is that the Jones model maps price changes into output, employment, and factor prices, whereas we invert this logic to show how knowledge of returns to the specific factor can be used to identify the other variables Jones considers. This difference is important because it avoids having to model how tariffs affect *all* prices and firm productivity in the economy and instead only requires knowledge of how the tariffs affect the returns to the specific factor. The insight enables us to derive analytical solutions for how movements in expected firm cash flows map into movements in the expected firm-level effective rate of protection (ERP), productivity, wages, and employment.

We then integrate the production structure of the specific factors model into a model of the dynamic welfare impacts of the policy. We do this by embedding our inverted specific factors model into an infinite-horizon economy that grows at a constant rate. We refer to this balanced growth path as the "baseline" equilibrium and treat a policy shock as shifts to input and output prices and productivity in each future period away from the baseline. Since we can express wages in each period as a function of firm cash flows, we can also write consumption in each period as a function of firm cash flows and tariff revenues. We then show that the changes in the present discounted value (PDV) of consumption, i.e., welfare changes, can be written as the PDV of expected cash flow and tariff revenue changes.

The final step in identifying the impact of the trade war on welfare is to use stock market data to obtain an estimate of the impact of tariffs on the PDV of cash flows for the whole economy. Following Campbell and Shiller (1988), we show that we can write the present discounted value of cash flows as the difference between the policy-induced change in firm valuations and the change in expected discount rates. The change in firm valuations can be estimated from stock-price movements arising from a tariff an-

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nouncement, and the movement in discount rates can be measured using the vector-autoregression (VAR) methodology of Campbell and Vuolteenaho (2004). With our estimates of firm cash flows in hand, we use the structure of the specific factors model to identify the welfare impact. We estimate that the impact of the tariffs on cash flows drove welfare down by 3.6 percent. After adjusting for the upper bound of revenues generated by the tariffs, we estimate a welfare loss of 3.0 percent.

We use the structure of our model to understand why market participants reacted as if they believed the tariffs would have much larger effects on the economy than conventional static economic models suggest. We explain this phenomenon by decomposing the cash-flow effect of tariff announcements on welfare into the sum of three terms: a static price effect, a dynamic price effect, and a productivity effect. The static price effect captures what is typically used in static trade models to estimate the impact of tariffs on welfare, i.e., tariffs lead to a one-time (permanent) change in prices that will persist in all future periods. The dynamic price effect captures how the tariff will affect welfare by altering expected growth in future prices either through the propagation of tariffs through the economy or by inducing future tariff policy changes. Finally, the productivity effect captures how markets expect tariffs to affect productivity — this effect is typically absent in conventional trade models but central in dynamic models. In our setup, the price and productivity effects can arise either because tariffs lead to lower effective rates of protection, lower productivity, or increased volatility in these variables.

Turning to measurement, the static price effect is estimated by first mapping changes in tariffs into changes in the effective rate of protection using standard procedures, and then using the specific factors model to map these price changes into welfare changes. We find that this effect is small and quite similar in magnitude to those found in existing papers, which establishes that our particular modeling choices do not qualitatively affect our results. In other words, if one assumes no dynamic effects of tariffs on prices and productivity, our framework delivers similar results to those in existing frameworks. This suggests that the large effects we find must arise because markets believe that tariffs have important effects on the expected future realizations of prices and productivity. We argue that one can identify a lower bound of the dynamic price effects by assuming that markets expect tariffs to jump to a worst-case scenario (60 percent tariffs on China and 20 percent tariffs on other countries). We find this very negative potential outcome still cannot fully explain the -3.6 percent cash-flow effect, which implies that markets expected tariffs to lower U.S. productivity by at least 1.1 percentage points. Hence, our results suggest that a major reason markets think tariffs matter is that they are expected to affect future firm productivity as dynamic models assume.

Related Literature   Our work is closely linked to the literature on stock-market event studies related to trade policy announcements (Hartigan et al. (1986), Grossman and Levinsohn (1989), Breinlich (2014), Fisman et al. (2014), Moser and Rose (2014), Breinlich et al. (2018), Crowley et al. (2019), Huang et al. (2023), and Greenland et al. (2024)). We differ in the use of a general equilibrium model to interpret the data.

The specific factors model, which forms the basis of our approach, has also been used extensively in empirical estimation (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 or more 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. In particular, most papers in this literature only look at the impact of output tariffs, so tariffs are assumed to always raise the effective rate of protection. However, in our setup, tariffs can affect input prices as well, so the imposition of tariffs can either raise the effective rate of protection by increasing firm output prices or lower it by raising the cost of the firm's imported intermediate inputs.

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 import competition more generally.[2] We also identify large impacts of trade policy on TFP, but our identification is based on using stock-price data filtered through a general equilibrium model. Our work is also related to the macro literature evaluating the impact of trade on income that has found evidence of large impacts of trade on productivity, income, and growth (c.f., Frankel and Romer (1999); Alcalá and Ciccone (2004); Feyrer (2019); Wacziarg and Welch (2008); Waugh (2019)). Although our work also finds large impacts of trade on productivity and welfare, an important difference between our work and the macro literature is that we build these estimates up from firm-level data on stock prices and use a general equilibrium setup to obtain our estimates. 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. (2024)) as increased uncertainty is one potential explanation for our larger welfare effect, through either the dynamic price effect or the productivity effect.

We also build off the literature documenting the impact of the trade war on firm 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 import prices was close to complete, consistent with our finding that higher U.S. tariffs negatively affected importers.

Finally, our paper is related to the financial literature on decomposing asset prices into cash-flow and discount-rate effects (e.g., Campbell and Shiller (1988); Campbell and Vuolteenaho (2004); Greenwald et al. (2023); Atkeson et al. (2024)). Relative to this literature, our methodological contribution is twofold. First, we demonstrate how to integrate the high-frequency reaction of asset prices to announcements with a VAR approach to derive the implied effect of a policy to cash flows and discount rates. Second, we use a specific factor model to go from stock-market cash flows to welfare.

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[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.

2 Stylized Facts

This section documents three stylized facts about the tariff announcements that motivate our theory and welfare analysis. First, we examine the impact of the announcements on stock prices to demonstrate that the tariff announcements consistently produced large, broad, and persistent stock-price declines. Second, we show that firms directly exposed to China through importing, exporting, or multinational sales had more negative returns on tariff-announcement days and worse real outcomes going forward. These results establish that firm cash flows were likely affected by the trade war. Third, we show that tariff announcements affected discount rates by driving down nominal and real treasury yields while raising proxies for the equity premium obtained from option prices.

2.1 The Tariff Announcements

Over the course of the trade war, the U.S. implemented tariffs in waves. 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 found the earliest announcement date in the media using Factiva and Google search. In addition, we also used the same method to identify the earliest announcement dates for each time that China imposed retaliatory tariffs on U.S. exports. Events were chosen based on the announcement of new waves of tariffs that were implemented, not just threats or revisions to existing waves. Our approach to choosing event dates has the advantage of being comprehensive and objective in the sense that we do not use events based on actions or statements that do not correspond to observable changes in tariffs.

2.2 Stylized Fact 1: Tariff Announcements Produced Large, Broad, and Persistent Stock-Price Declines

Table 1 presents the eleven tariff-announcement dates, comprising six U.S. tariff and five Chinese tariff-retaliation events. The first column reports the first day markets could trade on new tariff information, which may be after the announcement if it was made after markets closed. Our first event (January 23, 2018) corresponds to the 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 (March 1, 2018) is the announcement of steel and aluminum tariffs, also more broadly applied, which were imposed on March 23, 2018. All of the subsequent U.S. tariff events only apply to China. At the start of the trade war, the U.S. announced new tariffs on China so rapidly that China sometimes did not have time to retaliate before the next round of tariffs was announced. On March 22, 2018, the U.S. announced tariffs on $60 billion of Chinese imports (later reduced to $50 billion). The U.S. implemented the steel and aluminum tariffs on March 23, 2018, prompting China to announce retaliatory tariffs that day. China then retaliated on June 15, 2018, by hitting $50 billion of U.S. exports to China. After these initial announcements, a pattern developed in which the U.S. would announce new tariffs and China would then retaliate. All eleven events are listed in Table 1 in date order, with more details and links to the announcement of each event provided in Appendix C.1.

Table 1: Stock Market Return on Days with Tariff Announcements

Event Date	$\ln R_{M,t}$ (x100)	Country	Description
23jan2018	0.3	US	U.S. imposes tariffs on solar panels and washing machines
01mar2018	-1.1	US	U.S. imposes steel and aluminum tariffs
22mar2018	-2.4	US	U.S. imposes $60B in annual tariffs on China
23mar2018	-1.9	CHN	China retaliates and announces tariffs on 128 U.S. exports
15jun2018	-0.2	CHN	China announces retaliation against U.S. tariffs on $50B of imports
19jun2018	-0.4	US	U.S. announces imposition of tariffs on $200B of Chinese goods
02aug2018	0.5	CHN	China unveils retaliatory tariffs on $60B of US Goods
06may2019	-0.4	US	U.S. to raise tariffs on $200B of Chinese goods up to 25%
13may2019	-2.5	CHN	China to raise tariffs on $60B of U.S. goods starting June 1
01aug2019	-0.9	US	U.S. imposes a 10% tariff on another $300B of Chinese goods
23aug2019	-2.5	CHN	China retaliates with higher tariffs on soy and autos
Cumulative	-11.5		

Note: $R_{M,t}$ is the return that an investor would receive from holding the market portfolio (i.e., the net return) plus one. The first and last columns report the date and description of each tariff announcement. The second column reports the (log) stock-market return on each announcement day. The third column lists the country that imposed the tariffs associated with each event. The stock-market return is the value-weighted market portfolio return from CRSP.

Stock markets reacted consistently to these tariff announcements. Table 1 reports the value-weighted stock-market return from CRSP on each of the tariff-announcement dates. We see that the stock market fell on all of the event dates except one U.S. event date and one Chinese event date, with a total drop of 11.5 percent over all of the events.[3] These consistent declines suggest that markets did not fully anticipate future tariff announcements at the outset.

Figure 1 plots the cumulative stock-market return over a-ten-day window around the tariff-announcements so that we can better understand the dynamics of the stock market surrounding these announcements. The data reveal that in the four trading days before the events, stock-price movements were quite small on average—there is little evidence of anything out of the ordinary happening in the market before the announcements. However, as Table 1 showed, there were large declines of over 10 percent on the announcement days. These falls were persistent, as the market did not recover in the following five trading days.

One potential concern is that trade war announcements might be systematically correlated to other announcements happening on the same day. While no monetary policy announcement occurs on our event days, we also report the cumulative stock-market returns around tariff-announcements after controlling for the set of macroeconomic release

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[3]We chose a one-day window because tariffs are sometimes announced and then their scope and details are explained later in the day, which makes it difficult to identify the precise time of the announcement. Our choice of a one-day window to analyze stock-market responses is also consistent with the existing work on high-frequency identification in the monetary policy literature. For instance, while Nakamura and Steinsson (2018) use the intra-day response of the yield curve to identify the surprise component of monetary policy shocks, they revert to a one-day window to measure their effects on stock-market returns (see their Table V) because the stock market may under or overreact to announcements in the very short term.

Figure 1: The Dynamics of Stock-Market Returns around Tariff Announcements
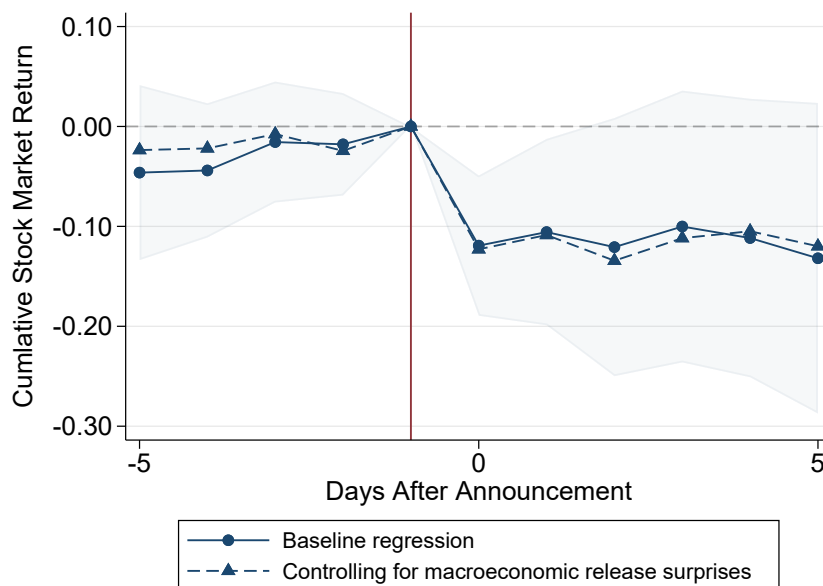
Note: This figure plots the cumulative log stock-market return starting the day before the announcement. Formally, we estimate the following regression on all trading days between 2017 and 2019: $\ln R_{M,t} = \alpha + \sum_{s=-4}^{5} \beta_s D_{s,t} + \epsilon_t$, where $D_{s,t} = 1$ if day t is s days after an announcement; $D_{s,t} = 0$ otherwise. We then plot the cumulative return of the stock market from the eve of the announcement as $11 \sum_{k=s+1}^{-1} \hat{\beta}_k$ if $s < -1$ and $11 \sum_{k=0}^{s} \hat{\beta}_k$ if $s > -1$. The dashed line reports the results of the same procedure controlling for economic surprises, i.e. $\ln R_{M,t} = \alpha + \sum_{s=-4}^{5} \beta_s D_{s,t} + \sum_{d=1}^{D} \gamma_d \times ES_{d,t} + \epsilon_t$ where $ES_{d,t}$ denotes the difference between the release value for a data series d and the Bloomberg median of economists' forecast on the previous day between 2017 and 2019 created by Lewis (2020). Shaded areas correspond to the 95 percent confidence interval computed using robust standard errors. The stock-market return is the value-weighted market portfolio return from CRSP.

surprises compiled by Lewis (2020). As shown in Figure 1, we find that controlling for these contemporaneous economic releases does not change our estimates, implying that there is no systematic correlation between surprises from economic data releases and tariff announcements.

Tariff Announcements Caused Large Declines in Stock Returns   The stock-market movements on tariff-announcement days were not only consistently negative and persistent but also large in magnitude. We show this by comparing the average stock-price movement on tariff-announcement days with the distribution of stock-market changes we would obtain if we had just randomly picked 11 days between 2017 and 2019. In order to estimate this, we compute the distribution of log returns obtained by aggregating the daily log returns over 11 placebo event days, repeating this procedure one thousand times. Figure 2 plots the actual change in returns on our tariff-announcement days as a vertical line in red, compared to the density of changes in log return in blue on placebo days. Out of all our draws, only 0.04 percent of them produced a change in log returns lower than our estimate. Thus, we can strongly reject the hypothesis that the negative stock returns on the tariff-announcement dates arose by chance.

Figure 2: Cumulative Stock-Market Returns on Days with Tariff Announcements versus Random Days
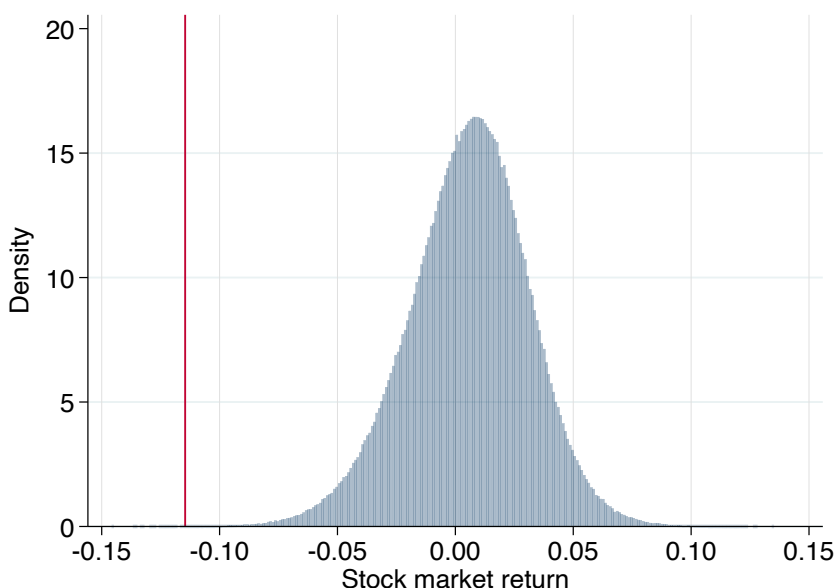
Note: The figure compares the cumulated log stock-market return over our 11 announcement days (in red) with the density of cumulated log stock-market returns obtained over 11 random days between 2017 and 2019 (in blue), drawn 1,000 times. The stock-market return is the value-weighted market-portfolio return from CRSP.

Non-Tariff Actions and Orders Against China Did Not Move Markets Much   Our approach to choosing event dates is objective in the sense that we only identify events that resulted in substantial increases in tariff as opposed to signaling of potentially worsening relations between the U.S. and China. The difference between levying tariffs on China

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and mere "saber-rattling" is clearly visible when we examine stock-price movements on days in 2017-2019 in which the U.S. announced executive orders and actions targeting China that were unrelated to tariffs.[4] We report the stock returns for each of these dates in Table 2. We find that non-tariff actions did not have much of an impact on stock markets. Instead, the negative stock-market returns we observe on tariff-announcement days seem to be specifically related to the expected economic impacts of the *tariff announcements*. The obvious explanation is that executive orders and actions have little more than symbolic impacts on the U.S. economy as a whole and markets largely shrugged them off.

Table 2: Stock-Market Returns on Announcement Days of Executive Orders and Actions Targeting China

Event Date	$\ln R_{M,t}$ (x100)	Description
17jul2017	0.0	Treasury sanctions Chinese companies for proliferation activities in support of a key designated Iranian defense entity
20dec2017	-0.0	U.S. sanctions human rights abusers and corrupt actors
27apr2018	0.1	Treasury identifies Chinese trafficker as a Significant Foreign Narcotics Trafficker
18sep2018	0.5	Department of Justice orders Xinhua and China Global Television Network to register as foreign agents
25sep2019	0.6	Treasury sanctions six Chinese entities and five individuals for Iran sanctions violations
07oct2019	-0.4	Commerce Department adds 28 organizations to its Entity List for human rights violations in Xinjiang
08oct2019	-1.5	State Department issues visa restrictions on Chinese officials responsible for human rights abuses in Xinjiang
Cumulative	-0.7	

Note: The first and last columns report the date and description of each event day. The second column reports the log stock-market return on each announcement day. $\ln R_{M,t}$ is the log of one plus the proportional change of the stock-market return, defined as the value-weighted market portfolio return from CRSP.

Tariff Announcements Caused Broad Declines in Stock Returns Interestingly, we find that these aggregate stock-market declines were the result of broad-based declines in the market. Figure 3 compares the density of firm-level returns during announcement days with all the other days during our sample period. We focus on the set of firms in the Compustat-CRSP linked dataset and incorporated in the U.S. The data reveal that the distribution of stock returns is shifted to the left on tariff-announcement days and that there is a left tail of firms that were disproportionately hurt by the announcements.

2.3 Stylized Fact 2: Tariff Announcements Differentially Affected "Exposed" Firms

We now turn to the cross-sectional effect of tariff announcements. More precisely, we investigate whether firms with significant direct China exposure experienced more pronounced negative stock-market returns than firms that were not exposed. We consider three ways in which firms were exposed to China: importing, exporting, and foreign sales

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[4]See https://www.uscc.gov/research/timeline-executive-actions-china-2017-2021

Figure 3: Effect of Tariff Announcements on the Cross-Section of Firm-level Returns
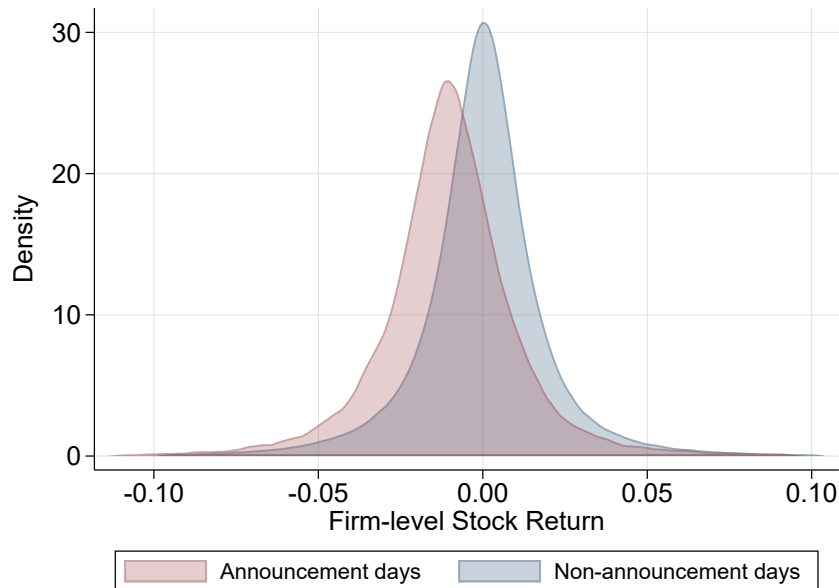
Note: The figure compares the average density of firm-level returns on announcement days (in red) and non-announcement days (in blue). We first residualize firm-level returns with respect to a set of day fixed effects (while still leaving a dummy corresponding to announcement days). We then plot the density of residuals on announcement days and non-announcement days.

(either through exporting or subsidiaries). As Table 3 shows, 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. These data show that the supply-chain information is critical in understanding firms' exposure to international trade. From Table 3, we see that only 10 percent of the firms in our sample import directly from China, and only 2 percent export directly to China. However, if we take subsidiaries into account, these numbers rise to 25 and 4 percent, respectively. When we add imports by all firms in the supply chain, we find 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). Our results show that 52 percent of all firms were exposed to China through one or more of these channels.

In Figure 4, we plot the kernel densities of the cumulative returns of the firms directly exposed to China "exposed" vs those firms that were not directly exposed "unexposed." There are three important takeaways from this figure. First, exposed and unexposed firm returns were on average negative on event days. Thus, the overall negative shift in the return distribution that we saw in Figure 3 was not just driven by exposed firms having lower returns—the distribution of returns for unexposed firms also shifted to the left. Second, the distribution of stock-market returns for exposed firms during the U.S. tariff-announcement events is to the left of the unexposed firms. Third, both Chinese and U.S.

Table 3: China Trade Exposure of Listed U.S. Firms

	Mean
Firm imports from China	0.10
Firm or subsidiary imports from China	0.25
Firm, subsidiary, or supplier imports from China	0.31
Firm exports to China	0.02
Firm or subsidiary exports to China	0.04
Firm sells in China via exports or affiliates	0.42
Average share of revenue from Chinese exports or affiliate sales	0.03
Firm exposed to China through imports, exports, or affiliate sales	0.52
Number of Firms: 2,437	

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. See Appendix C.3 for the construction of these variables. This sample of firms excludes the finance sector.

tariff announcements produced lower returns overall and even lower returns for exposed firms. This result, which is also present if one does a traditional stock-market event study (see, for example, Huang et al. (2023)), establishes that tariff announcements not only drove down the full distribution of firm returns, but they differentially lowered the returns of exposed firms.

Figure 4: Dispersion in Returns (One-Day Windows)
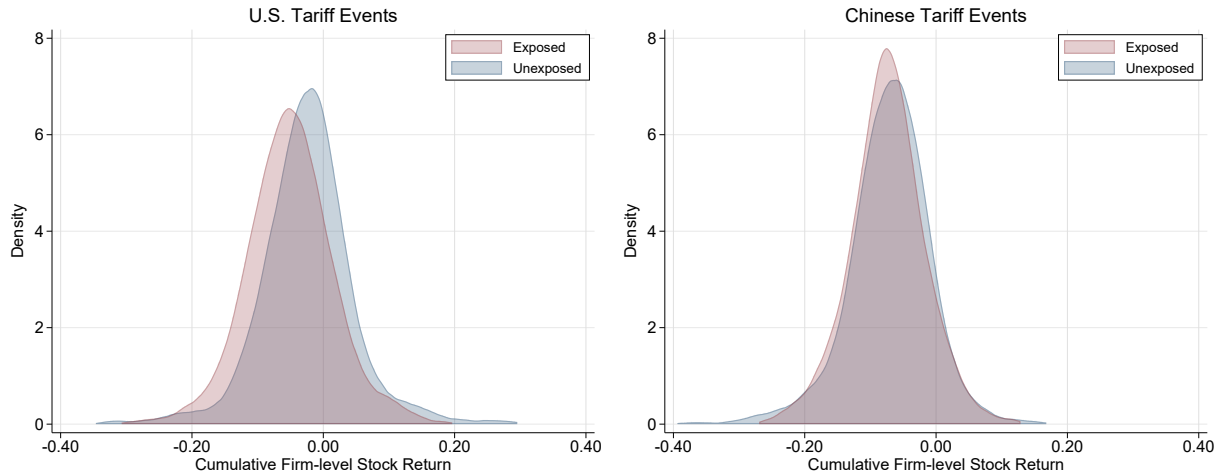
Note: This figure plots the kernel densities of cumulative abnormal returns of firms exposed to China (light red) and unexposed (light blue) during one-day windows around tariff announcements. Exposed firms are firms that export to, import from, or have positive revenues in China.

Firms with Worse Stock-Market Returns Had Worse Future Real Outcomes We follow the approach of Greenland et al. (2024) to see if firms that experienced worse stock-market returns on tariff-announcement dates also experienced worse future real outcomes. Greenland et al. (2024)'s pioneering work on the granting of permanent normal trade relations to China in 2000 demonstrates an important link between stock-price

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movements and *future* movements in cash flow. Using data for the period 2013 to 2021, we regress firm employment, sales, profits, and labor productivity on the average of firm returns around tariff-announcement dates, interacted with a post dummy that takes a value of one for the years 2019, 2020, and 2021.

Table 4 reports the results for the U.S.-China trade war. The data reveal that firms that had particularly poor returns around tariff-announcement days had significantly lower future profits, employment, sales, and labor productivity. Moreover, the magnitudes are quite substantial. A firm whose average return around tariff-announcement days was one standard deviation lower (-0.56 percent) had average profits, employment, sales, and labor productivity that were 12.9, 3.9, 6.7, and 2.2 percent lower, respectively, between 2019 and 2021 than before the trade war began. Moreover, the fall in labor productivity in addition to the fall in firm sales and profitability echoes micro studies that find a strong link between tariffs and within-firm productivity. The empirical link between stock returns and future movements in economic variables motivates our building of a mapping between stock return and cash flow, which forms the basis of our identification strategy.

Table 4: Relationship between Changes in Returns and Future Observables

	(1) $\ln(\text{Profit}_{ft})$	(2) $\ln(\text{L}_{ft})$	(3) $\ln(\text{Sales}_{ft})$	(4) $\ln(\text{Sales/L})_{ft}$
Post $\times \ln \text{R}_f$	0.23***	0.07***	0.12***	0.04**
	(0.04)	(0.01)	(0.02)	(0.02)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
R^2	0.915	0.976	0.962	0.873
Observations	11940	17032	16760	16736

Note: Data is at the firm-annual level for the period 2013 to 2021, from Compustat and CRSP. Profit is defined as operating income after depreciation less interest and related expenses. $\ln R_f$ is the log of one plus the average return on 5 days surrounding the tariff-announcement dates across all event dates in 2017-2019. In this table, $\ln R_f$ is then multiplied by 100. The Post dummy takes a value of one in 2019, 2020, and 2021. All columns include the following control variables at the start of the sample (i.e. 2013) interacted with the Post dummy as covariates: Property, Plant, and Equipment (PPE) per worker, market capitalization, cash-flow-to-asset ratio, book leverage, and Tobin's Q. Appendix Table F.2 reports the coefficients on the control variables and Appendix C.2 provides details on variable construction. Standard errors are in parenthesis. ***$p < 0.01$,** $p < 0.05$,* $p < 0.1$.

2.4 Stylized Fact 3: Tariff Announcements Moved Interest Rates and Equity Premia

As we discuss later in Section 4, separating discount-rate movements from stock returns is necessary to identify the impact of a policy on expected cash flows. While we will formally model the determinants of firm-level discount rates in Section 4.3, in this section, we document that two aggregate determinants of firm-level discount rates—risk-free interest rates and equity premia—moved systematically with tariff announcements.

We first estimate the effect of announcements on the nominal yield curve. We measure the daily (annualized) yield to maturity on 3-month, 6-month, and 12-month T-bills from

the Federal Reserve Economic Data (FRED) and the yield to maturity of 1- to 20-year treasuries from Gürkaynak et al. (2007). Figure 5 shows the cumulative daily changes in these yields across all trade-war announcements. As in the previous section, all of these specifications control for surprises in contemporaneous macroeconomic releases. We find that tariff announcements are associated with decreased nominal rates at all maturities. The effect is U-shaped with respect to maturity: interest rates declined by approximately 20 basis points (bps) for 3-month maturities, 60bps for 4-year maturities, and 40bps for 20-year maturities. The finding that announcements affect yields at very long maturities is reminiscent of Hanson and Stein (2015), who find that monetary policy shocks impact the yield-to-maturity of long-term bonds.

Figure 5: Cumulative Effect of Tariff Announcements on Discount Rates
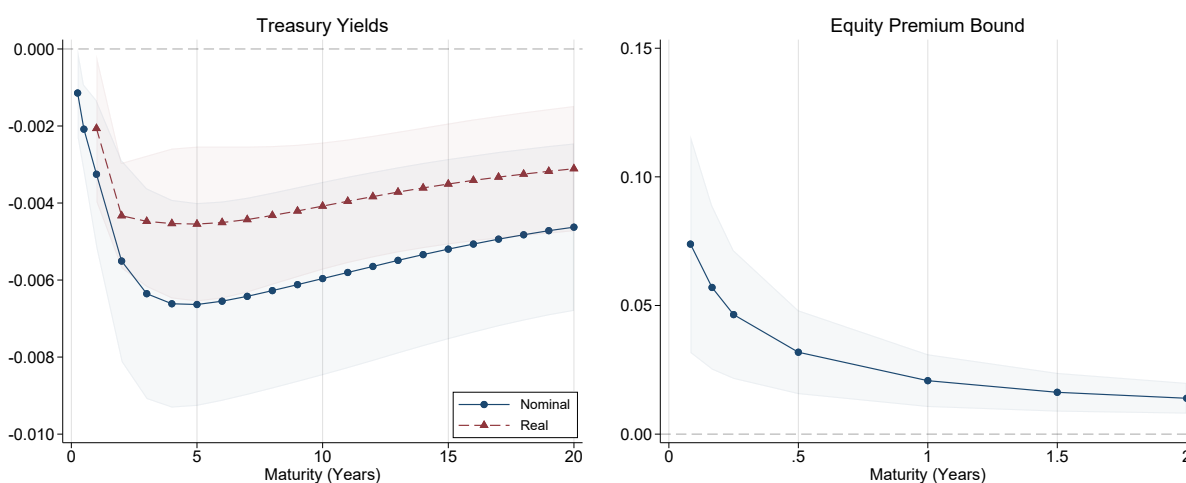
Note: Each figure reports the cumulated daily change of variables over all days with a tariff announcement, after controlling for surprises in macroeconomic releases. The first subfigure reports the change in the nominal and real yield curves, using data from FRED (for nominal yields at the 3-month, 6-month, and 12-month maturity) and Gürkaynak et al. (2007) (for nominal and real yields at longer maturity). The second subfigure reports the change in the equity-premium bound, constructed using the methodology of Martin (2017) on data from OptionMetrics. Shaded areas correspond to the 95% confidence interval computed using robust standard errors.

Changes in nominal yields could reflect a change in real yields or a change in expected inflation (or the inflation-risk premium). To isolate the first component, we also plot in the left panel of Figure 5 (in red) the effect of tariff announcements on the real yield curve, that is, the yield to maturity of Treasury Inflation-Protected Securities (TIPS), as reported in Gürkaynak et al. (2007). We find that tariff announcements decreased real rates for all maturities, although less so than for nominal rates. The difference suggests that the tariff announcements had a negative effect on expected inflation (or on the inflation-risk premium).

Finally, we examine the effect of announcements on (proxies for) the equity-risk premium, which is the extra return investors require in order to hold equities rather than risk-free bonds. We follow the procedure developed in Martin (2017) to estimate a lower

bound for the equity premium from the one-month horizon to the three-year horizon using data from OptionMetrics. We refer to it as the Equity-Premium Bound (EPB) in the rest of the paper. Similar to the VIX, this proxy is constructed from the price of out-of-the money call and put options on the S&P500 index. Martin (2017) argues that it produces a tight lower bound on the equity premium—i.e., that it closely tracks the actual equity premium.

Figure 5 shows that tariff announcements also had a large and significant positive effect on the annualized EPB. Interestingly, the effect of announcements on the EPB declines rapidly with maturity: while announcements increase the EPB at the 1-month horizon by 6 percentage points, they only increase the EPB at the 3-year horizon by 1 percentage point. Empirically, this reflects the fact that trade announcements dramatically increase the price of out-of-the-money call or put options with short maturity, but they have more muted effects on long maturity ones.

We examine the robustness of these findings in the Appendix. Appendix Table E.1 reports the change in nominal yields, real yields, and in the equity-premium bound event by event. It shows that our results are not driven by outlier events: almost all announcements tend to decrease real yields and increase the equity-premium bound. We explore the robustness of Figure 5 in Appendix Figure E.1, which reports the dynamic effect of announcements on these variables over a ten-day window. The appendix figure shows that the change in these variables is concentrated on the days of the announcements, which indicates that the market did not under or overreact during these days.

3   Theory

We present the theory in two steps. First, in Section 3.1, we develop a dynamic infinite-horizon, firm-level, specific factors model of production and derive how a change in the effective rate of protection maps into firm cash-flow movements and wage movements. We invert this model to show that movements in firm cash flow (which are identical to the returns to the specific factor in this setup) are sufficient statistics that pin down the movements in wages, employment, effective rates of protection (ERP), and productivity. Second, in Section 3.2, we embed these policy-induced movements in cash flows into a dynamic model of consumer behavior to express the consumption-equivalent welfare effect of the policy in terms of the PDV of these cash-flow movements.

3.1   Production

The production structure is based on the Jones (1975) specific factors model, extended along two dimensions. First, we assume that fixed factors are firm-specific instead of industry-specific. Second, we extend it from a static one-period model into a dynamic infinite-horizon model. In our model, time is discrete and indexed by t; and there is a set of firms in the economy indexed by f. At each time t, firm f produces according to a constant-returns-to-scale technology, which combines three types of inputs: a firm-specific fixed factor V_f, a quantity of labor L_{ft} hired in a competitive labor market, and a set of N differentiated intermediate inputs (m_{ift}), where $i \in \{1, ...N\}$. Firms maximize

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profits taking the output price, wages, and input prices as given.[5] There are no adjustment costs between periods. Hence, profit maximization over all periods is equivalent to profit maximization in each period (and the same is true for cost minimization).

As in Jones (1975), it is easiest to solve this model by focusing on the unit-cost function. Denote firm f's unit cost of production at time t by $c_f(w_t, r_{ft}, q_{1t}, ..., q_{nt}, A_{ft})$, where the arguments correspond to the wage (w_t), the shadow price of the firm's fixed factor (r_{ft}), the prices of a set of intermediate inputs ($q_{1t}, ..., q_{nt}$), and a Hicks-neutral productivity parameter A_{ft}.[6] Shephard's Lemma tells us that the unit-input requirements are given by the derivative of the cost function; that is, $a_{Lft} = \frac{\partial c_f}{\partial w_t}$, $a_{Vft} = \frac{\partial c_f}{\partial r_{ft}}$, and $a_{ift} = \frac{\partial c_f}{\partial q_{it}}$, where $a_{Lft}, a_{Vft}, a_{ift}$ denote the unit-input requirements for labor, fixed factor, and intermediate input i, respectively. In equilibrium, a firm's marginal cost is equal to its output price,

$$a_{Lft}w_t + a_{Vft}r_{ft} + \sum_i a_{ift}q_{it} = p_{ft}. \tag{1}$$

We impose the full-employment conditions on labor and each firm's specific factor in each period:

$$\sum_f a_{Lft}y_{ft} = L, \text{ and} \tag{2}$$

$$a_{Vft}y_{ft} = V_f, \tag{3}$$

where L denotes the total supply of labor, which is fixed at the aggregate level. Since $a_{Lft}y_{ft} = L_{ft}$, the first full-employment condition (2) requires that firm-level employment adjusts with firm-level production. In contrast, the second full-employment condition (3) stipulates that the unit-input requirement of the specific factor (a_{Vft}) is inversely proportional to firm output (y_{ft}) because the amount of the firm-specific factor (V_f) is fixed. Note that this second full-employment condition implies that the total compensation received by firm f's fixed factor equals firm f's cash flow (its revenue net of labor and input expenses), i.e., $r_{ft}V_f = (p_{ft} - a_{Lft}w_t - \sum_i a_{ift}q_{it})y_{ft}$.

In order to model the impact of a policy change, we start with a "baseline" equilibrium in which all product prices, input prices, and firm productivity are constant over time. We treat a policy shock as a policy that shifts prices and productivity away from the baseline equilibrium in each period. Since, in the baseline equilibrium, aggregate employment (L), each firm's specific factor (V_f), prices, and productivity are fixed over time, we know that the wage and firm-level employment are also fixed over time; that is, $w_t = w$ and $L_{ft} = L_f$. Accordingly, we simplify notation going forward by dropping the t subscript whenever we are discussing variables that do not change over time in the baseline equilibrium. While we assume that the baseline equilibrium does not have growth, we show

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[5] One could motivate this by assuming Bertrand competition in which each domestic firm faces foreign exporters selling at a price $p_f^* + \tau_f$, where p_f^* is the international price of the good and τ_f is the output tariff facing firm f's foreign competitors.

[6] The shadow price of the firm's fixed factor r_{ft} is given by the price that would exhaust firm rents; that is, it corresponds to the solution of $p_{ft} = c_f(w_t, r_{ft}, q_{1t}, ..., q_{nt}, A_{ft})$. This equation has a unique solution as long as the cost function increases with r_{ft}, approaches zero as r_{ft} approaches zero, and approaches infinity as r_{ft} approaches infinity. Firm output, y_{ft}, is determined by the exogenous quantity of fixed factor (see equation 3). Firm owners own the specific factor, so they are paid $r_{ft}V_f$ in each period.

in Appendix B that we can easily modify the setup to allow for baseline productivity growth without changing any of our propositions.

We model a tariff change as causing a set of log-change deviations in output prices, input prices, and, potentially, TFP ($\hat{p}_{ft}, \hat{q}_{it}, \hat{A}_{ft}$) in the period t relative to the baseline values ($p_{ft} = p_{f0}, q_{it} = q_{i0}$, and $A_{ft} = A_{f0}$). Because the amount of each firm's specific asset is fixed ($\hat{V}_f = 0$), log changes in the shadow price of the specific factor equal the log change in firm cash flow (i.e., $\hat{r}_{ft} = \widehat{r_{ft}V_f}$), where hats over variables indicate log changes in these variables from their baseline values in period t. Thus, we will henceforth refer to $\hat{r}_{ft}$ as the log change in the firm's cash flow in period t due to the policy change.

Following Jones (1975), we assume that the production function is separable in its factors of production. Assuming a constant elasticity of substitution between the specific factor and labor (σ) enables us to write the factor intensity of production (a_{Vft}/a_{Lft}) as:

$$\hat{a}_{Vft} - \hat{a}_{Lft} = \sigma \left(\hat{w}_t - \hat{r}_{ft} \right). \tag{4}$$

We are now ready to prove our first proposition linking changes in cash flows to wages.

Proposition 1. *If the elasticity of substitution between labor and the specific factor for all firms is constant, then the log change in wages equals the employment-share weighted average of the log changes in cash flow, i.e.,*

$$\hat{w}_t = \sum_f \frac{L_f}{L} \hat{r}_{ft},$$

and the log change in employment in each firm equals $\hat{L}_{ft} = \sigma \left(\hat{r}_{ft} - \sum_{f'} \frac{L_{f'}}{L} \hat{r}_{f't} \right).$

Proof. See Appendix A.1 □

The intuition behind the first equation in Proposition 1 is that the full-employment condition implies that changes in factor prices cannot increase the aggregate demand for labor. However, the aggregate demand for labor will only remain constant if the changes in relative wages ($\hat{w}_t - \hat{r}_{ft}$) are zero "on average," i.e., log changes in wages ($\hat{w}_t$) in period t from their baseline value of w equal a firm-size weighted average of log changes in cash flow ($\sum_f \frac{L_{ft}}{L} \hat{r}_{ft}$). The second equation 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 $-\hat{L}_{ft}$.[7]

Proposition 1 is based on the structure of Jones (1975) but differs in several respects. First, Jones was concerned about a mapping from tariff-induced changes in product prices into factor prices. Here, we invert the logic in Jones to show that knowing the log changes in cash flow pins down changes in wages and employment. Second, by assuming that there is one elasticity of substitution between labor and the specific factor, 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 cash

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[7]We relax the assumption of a vertical labor supply curve in Appendix A.1.1. Allowing aggregate employment to move with changes in cash flow does not undermine the basic result that we can express equilibrium wage changes as a linear function of changes in cash flow.

flow.[8] Wages move one-for-one with the employment-weighted average of log changes in cash flow.[9]

We can also use the structure of our model to obtain mappings from cash-flow movements into many other variables of interest. Our starting point is the firm-level definition of the effective rate of protection (ERP):

$$\hat{p}_{ft}^e \equiv \frac{\hat{p}_{ft} - \sum_i \omega_{ift} \hat{q}_{it}}{1 - \sum_i \omega_{ift}}, \tag{5}$$

where ω_{ift} denotes the expenditure shares of firm f on input i as a share of total revenue (similarly, we will denote ω_{Lft} and ω_{Vft} the expenditure shares on labor and the fixed factor). The numerator in this definition is the change in the firm's output price less a weighted average of all of the input prices, while the denominator is the share of value added in sales. A standard approach to compute the effective rate of protection is to write $\hat{p}_{ft}$ and $\hat{q}_{it}$ as functions of the tariffs (i.e., $\hat{p}_{ft} = \hat{p}_{ft}(\boldsymbol{\tau_t})$ and $\hat{q}_{it} = \hat{q}_{it}(\boldsymbol{\tau_t})$), where $\boldsymbol{\tau_t}$ denotes the tariff vector.[10] We introduce a generalization of this approach in which we allow tariffs to also affect productivity and relate the effective rate of protection to factor prices in the following proposition:

Proposition 2. *The sum of log changes in the effective rates of protection ($\hat{p}_{ft}^e$) and adjusted productivity $\left(\frac{\hat{A}_{ft}}{1-\sum_i \omega_{ift}}\right)$ for a firm can be expressed as a linear function of the log changes in cash flows ($\hat{r}_{ft}$):*

$$\hat{p}_{ft}^e + \frac{\hat{A}_{ft}}{1 - \sum_i \omega_{ift}} = \left(\frac{\omega_{Vft}}{1 - \sum_i \omega_{ift}}\right) \hat{r}_{ft} + \left(\frac{\omega_{Lft}}{1 - \sum_i \omega_{ift}}\right) \sum_{f'} \frac{L_{f't}}{L} \hat{r}_{f't}. \tag{6}$$

Moreover, the log changes in firm cash flows ($\hat{r}_{ft}$) and wages ($\hat{w}_t$) can be expressed as linear functions of the log changes in effective rates of protection ($\hat{p}_{ft}^e$) and productivity ($\hat{A}_{ft}$):

$$\hat{w}_t = \sum_f \varphi_{ft} \left(\hat{p}_{ft}^e + \frac{\hat{A}_{ft}}{1 - \sum_i \omega_{ift}}\right) \text{ and} \tag{7}$$

$$\hat{r}_{ft} = \left(\frac{1 - \sum_i \omega_{ift}}{\omega_{Vft}}\right) \left(\hat{p}_{ft}^e + \frac{\hat{A}_{ft}}{1 - \sum_i \omega_{ift}}\right) - \left(\frac{\omega_{Lft}}{\omega_{Vft}}\right) \sum_f \varphi_{ft} \left(\hat{p}_{ft}^e + \frac{\hat{A}_{ft}}{1 - \sum_i \omega_{ift}}\right), \tag{8}$$

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[8]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.

[9]At first, it may seem surprising that wages rise one for one with average log changes in cash flow, however, this result is present in other models in which firms have positive operating profits. For example, in Melitz (2003), both per-worker real wages and average firm profits are monotonically rising in average productivity.

[10]For example, Corden (1966)'s classic paper assumes perfect passthrough of tariffs, so $\hat{p}_{ft} = \Delta \ln\left[1 + \tau_{ft}^O\right]$ and $\hat{q}_{it} = \Delta \ln\left[1 + \tau_{it}\right]$, where τ_{ft}^O is the tariff on the firm's output and τ_{it} is the tariff on input i. More recently, Kovak (2013) uses industry data and sets the industry price $\hat{p}_t = \Delta \ln\left[1 + \tau_t^O\right]$ and $\hat{q}_{it} = 0$.

where $\varphi_{ft} = L_{ft} \left(\frac{1 - \sum_i \omega_{ift}}{\omega_{Vft}} \right) / \sum_{f'} L_{f't} \left(\frac{1 - \sum_i \omega_{if't}}{\omega_{Vf't}} \right).$

Proof. See Appendix A.2   □

    The proposition clarifies an important difference between our approach and past work on the specific factors model. The standard approach in the literature is to assume that productivity is unaffected by tariff policy ($\hat{A}_{ft} = 0$). In this case, if one knows how deviations in tariffs pass through into output and input prices (i.e., one can write $\hat{p}_{ft}$ and $\hat{q}_{it}$ as functions of tariffs), equations (5), (7), and (8) provide a mapping from effective rates of protection into factor prices. However, in the more general case in which tariffs affect productivity, this mapping no longer holds.

    In comparison, our approach is to estimate the impact of the tariffs on cash flows ($\hat{r}_{ft}$) using financial data, which captures the combined movement in effective rates of protection and productivity according to equation (6). In other words, given the structure of our model, estimating a tariff policy's impact on firm cash flows bypasses the need to estimate its impact on the effective rates of protection and productivity of firms. If we are further able to obtain estimates for the impact of the tariffs on prices (i.e., effective rates of protection), then this proposition shows that we can also identify the impact of the tariffs on productivity as a residual using equation (6): something we will do in the last section of the paper.

3.2   Welfare

In order to understand the welfare implications of a policy change, we assume there is a representative agent supplying the quantity of labor L and owning all firms. The agent's nominal income in period t, I_t, is the sum of labor income, firm cash flows, and tariff revenues TR_t:

$$I_t = w_t L + \sum_f r_{ft} V_f + TR_t.$$

The agent's real consumption, C_t, equals nominal income divided by the consumption price index. To simplify notation, and without loss of generality, we normalize this price index to equal one. Hence, the consumption of the representative agent is equal to its aggregate income, i.e., $C_t = I_t$. The last two equalities imply that the log deviation in consumption can be written as a weighted average of the log deviation in wages, cash flows, and tariff revenues:

$$\hat{C}_t = \frac{wL}{C}\hat{w}_t + \sum_f \frac{r_f V_f}{C}\hat{r}_{ft} + \frac{TR}{C}\hat{TR}_t. \tag{9}$$

    The policy change can be thought of as affecting an infinite sequence of changes in wage, cash flow, and tariff revenue: $\hat{w}_t$, $\hat{r}_{ft}$, and $\hat{TR}_t$ for t ranging between 0 and infinity. Because the policy affects prices at different time horizons and in different states of the world, $(\hat{C}_t)_{t=0}^{\infty}$ is a sequence of random variables.

    We define the "consumption-equivalent welfare effect" of this deviation, denoted $\mathcal{C}$, as the (fixed and deterministic) deviation in log consumption that would generate the

same change in welfare as the (time-varying and stochastic) deviation in log consumption $(\hat{C}_t)_{t=0}^{\infty}$. In other words, the consumption-equivalent welfare effect is the percentage change in consumption (in every state and every period) that would compensate the agent for the effect of the policy change.

We now characterize this consumption-equivalent welfare effect for a representative agent with log utility over consumption—we discuss the more general case of an agent with Epstein-Zin preferences below.

Proposition 3. *For an agent with log utility, the consumption-equivalent welfare effect of the deviation path $(\hat{C}_t)_{t=0}^{\infty}$ is*

$$\mathcal{C} = (1 - \rho) \sum_{t=0}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{C}_t \right], \tag{10}$$

where $\rho \equiv 1 - C_t/W_t$ denotes the consumption-to-wealth ratio.

Proof. See Appendix A.3 ☐

This proposition expresses the consumption-equivalent welfare effect $\mathcal{C}$ as a weighted average of the expected log deviation in consumption at all horizons. The parameter ρ, which in equilibrium equals the agent's subjective discount factor, governs how future consumption is weighted relative to today consumption. This expression captures two important channels through which tariffs can impact welfare. First, and most obviously, tariffs may decrease or increase the average level of consumption, which would move welfare proportionally. Second, even if average consumption is fixed, tariffs may increase the variance of consumption, which would decrease welfare by decreasing the average of log consumption. In the formula, this second channel is captured by the fact that the summand reflects the average deviation in log consumption at each horizon, rather than the deviation in the log of average consumption.

In Appendix B.3, we derive a more general expression for the consumption-equivalent welfare effect $\mathcal{C}$ for an agent with Epstein-Zin preferences, with arbitrary relative risk aversion and elasticity of intertemporal substitution. Relative to the log utility case, the consumption-equivalent welfare effect gains an additional term that depends on the product between (i) the impact of tariffs on the higher-order cumulants of log consumption growth and (ii) the distance between the agent's relative risk aversion and one. In particular, if agents are more risk averse than log utility (i.e., $\gamma > 1$), and if tariffs increase the even cumulants of log consumption (like variance) or decrease odd cumulants (like skewness), then our baseline welfare effect (the one given in Proposition 3) will underestimate the full welfare loss.

4 Estimating Consumption-Equivalent Welfare

The previous section provided an expression for the aggregate welfare effect in terms of expected movements in future wages, firm cash flows, and tariff changes. In order to empirically implement this, we need to express these unobservable infinite sequences in terms of variables that we can estimate: the reaction of asset prices to policy announcements. We do this in three steps. Section 4.1, shows how to express the impact of tariffs

on consumption-equivalent welfare ($\mathcal{C}$) in terms of the PDV of deviations in firm values and discount rates. Sections 4.2 and 4.3 then show how to use asset-price movements to estimate the impact of tariff announcements on firm values and discount rates, respectively.

4.1   Linking Cash Flows, Firm Values, and Discount Rates

We begin by decomposing the welfare effect into how much is due to each source of household income. Substituting equation (9) into equation (10), we obtain an expression for the welfare effect in terms of the discounted value of policy-induced changes in wages, cash-flows, and tariff revenues:

$$\mathcal{C} = (1 - \rho) \sum_{t=0}^{\infty} \rho^t \mathrm{E}_0 \left[\frac{wL}{C} \hat{w}_t + \sum_f \frac{r_f V_f}{C} \hat{r}_{ft} + \frac{TR}{C} \widehat{TR}_t \right].$$

We now can use Proposition 1 to solve for the change in wages in terms of the change in firm cash flows. Substituting $\hat{w}_t = \sum_f \frac{L_f}{L} \hat{r}_{ft}$ into the previous equation and rearranging gives:

$$\mathcal{C} = \underbrace{\sum_f \frac{wL_f + r_f V_f}{C} \left((1 - \rho) \sum_{t=0}^{\infty} \rho^t \mathrm{E}_0[\hat{r}_{ft}] \right)}_{\text{Deviation in cash-flow: } \mathcal{C}_{\hat{r}}} + \underbrace{\frac{TR}{C} \left((1 - \rho) \sum_{t=0}^{\infty} \rho^t \mathrm{E}_0 \left[\widehat{TR}_t \right] \right)}_{\text{Deviation in tariff revenue}}. \tag{11}$$

This equation expresses the welfare effect as the sum of two terms: the PDV of the deviation in (expected) firm cash flows and the PDV of the deviation in tariff revenues. Importantly, welfare is determined by the expected deviation in log (or relative) cash flows. This captures the idea that, from the perspective of a risk averse representative consumer, a dollar reduction in cash flows has a greater negative impact on welfare during bad states of the world—when cash flows are already low—than during good states of the world

The first term in equation (11) cannot be computed directly from cash flows because it requires us to know an infinite sequence of their movements, but we can show that it can be computed from movements in firm values and discount rates. Let Π_{ft} be the total valuation of firm f at time t (i.e., the market value of its equity plus its debt). The return of owning firm f between t and $t+1$ is defined as:

$$R_{f,t+1} \equiv \frac{\Pi_{f,t+1}}{\Pi_{f,t} - r_{f,t} V_f}.$$

Assuming the no-bubble condition $\lim_{t \to \infty} R_{ft}^{-1} \Pi_{ft} = 0$, we can express a firm's value as the discounted value of its future cash-flows:[11]

$$\Pi_{f0} = \mathrm{E}_0 \left[\sum_{t=0}^{\infty} \frac{r_{ft} V_f}{R_{f1} \dots R_{ft}} \right]. \tag{12}$$

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[11]The definition of returns means $\Pi_{f0} = r_{f0} V_f + \frac{\Pi_{f1}}{R_{f1}} = r_{f0} V_f + \frac{r_{f1} V_f}{R_{f1}} + \frac{\Pi_{f2}}{R_{f1} R_{f2}}$. Iterating forward gives the result.

We can log-linearize this formula to express the deviation in firm value due to a policy announcement as the sum of two terms: a deviation in the PDV of firm cash-flows and a deviation in the PDV of firm discount rates:

Proposition 4. *Around a baseline path in which the ratio of cash flow to firm value, $r_{ft}V_f/\Pi_{ft}$, is equal to the constant consumption-to-wealth ratio, C_t/W_t, we have:*

$$\hat{\Pi}_{f0} = (1-\rho)\sum_{t=0}^{\infty}\rho^t \mathrm{E}_0\left[\hat{r}_{ft}\right] - \sum_{t=1}^{\infty}\rho^t \mathrm{E}_0\left[\hat{R}_{ft}\right].$$

Proof. See Appendix A.4. □

This proposition, which is an application of the Campbell and Shiller (1988) decomposition to our economy, says that an increase in the value of a firm can reflect an increase in the expected future cash flows earned by firm owners or a decrease in the rate at which these future cash flows are discounted.[12] We can solve for the PDV of the deviation in firm cash flows—the first term on the right—in terms of the deviation in firm value ($\hat{\Pi}_{f0}$) plus the PDV of the deviation in firm discount rates ($\sum_{t=1}^{\infty}\rho^t \mathrm{E}_0\left[\hat{R}_{ft}\right]$). Combining this result with equation (11) allows us to write the aggregate welfare effect as a sum of three components:

$$\mathcal{C} = \underbrace{\sum_f \frac{wL_f + r_f V_f}{C}\hat{\Pi}_{f0}}_{\text{Deviation in firm values}} + \underbrace{\sum_f \frac{wL_f + r_f V_f}{C}\left(\sum_{t=0}^{\infty}\rho^t \mathrm{E}_0\left[\hat{R}_{ft}\right]\right)}_{\text{Deviation in firm discount rates}} + \underbrace{\frac{TR}{C}(1-\rho)\sum_{t=0}^{\infty}\rho^t \mathrm{E}_0\left[\widehat{TR}_t\right]}_{\text{Deviation in tariff revenues}}.$$

(13)

The first term is a weighted average of the log change in firm value due to the policy announcement. The second term is a weighted average of the change in firm discount rates at the time of the announcement, which accounts for the fact that only deviations in firm values due to deviations in cash flows (as opposed to deviations in discount rates) matter for welfare. The third term accounts for deviations in tariff revenues. We now provide details on how we estimate each term.

4.2 Measuring the Deviation in Firm Values

The deviation in firm values is a weighted average of the change in each firm's value ($\hat{\Pi}_{f0}$), where the weights correspond to the value added generated by the firm ($wL_f + r_f V_f$) divided by baseline consumption (C). We estimate the change in each firm's value due to announcement j as its log return on the first day the markets could trade the new information ("high-frequency identification"). There is a bias tradeoff in choosing the length of the window. On the one hand, a shorter window may lead to biased estimates if there is over- or under-reaction in the short run, if the tariff announcement leaks before its formal announcement, or if relevant information is released later. On the other hand, a longer window will lead to noisier estimates, as unrelated news is released over time.

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[12]Since we normalized the price index to be one, both cash flows and discount rates should be understood in real terms. For example, suppose tariff announcements only affected inflation, it would increase nominal cash flows and discount rates by the same amount yielding no change in asset prices.

Formally, we identify the effect of tariff announcement j on the market value of equity of a firm f as the coefficient $\beta_{f,j}$ in the following regression:

$$\ln R_{f,t} = \alpha_f + \sum_{j=1}^{J} \beta_{f,j} D_t^j + \sum_{d=1}^{D} \gamma_{f,d} ES_{d,t} + \epsilon_{f,t}. \tag{14}$$

where D_t^j is an indicator variable equal to one if day t is in the window of announcement j, and $ES_{d,t}$ corresponds to the surprise in the economic series d. We estimate this regression using all trading days between 2017 and 2019, separately for each firm f. We then construct the effect of announcement j on the overall market value of firm f as

$$\hat{\Pi}_{f0} \equiv \sum_{j=1}^{J} \kappa_f \beta_{f,j} \tag{15}$$

where κ_f denotes the ratio of firm f's market value of equity to its market value of assets. This leverage adjustment reflects the fact that the overall market value of a firm is the sum of the value of its debt and the value of its equity. Under the assumption that firm debt is risk-free and has zero maturity, its value does not react to the announcement, and so we obtain the formula above.

Aggregation We compute the aggregate deviation in firm values (the first term in equation (13)) by taking a weighted average of the $\hat{\Pi}_{f0}$ in which the weights are $(wL_f + r_f V_f)/C$. One problem in constructing these weights is that our Compustat-CRSP sample is only composed of public firms, which is not representative of the overall economy. In particular, our sample tends to underweight small firms and service-sector firms, so we need to weight firms in our sample to approximate the distribution of employment size and sectors in the U.S. economy.

Unfortunately, we only observe value added as a share of consumption (the weight for the first two terms in equation (13)) at the sector level, so we can only weight returns by employment after we have aggregated all the firms into industries. We, therefore, weight the data in four steps. First, we divide the set of firms in Compustat into 18 sectors (that are indexed by s and defined by their 2-digit NAICS codes) and four employment bins (indexed by b and defined by three employment thresholds: 500 and below, 501-5,000, 5,001-20,000, and over 20,000). We then form a weighted average using firm employment as weights to compute the average deviation in firm values ($\hat{\Pi}_{f0}^j$) for all firms in an employment bin-sector-event, i.e., a $\{b, s, j\}$-tuple. Second, we sum across events (j) to obtain the cumulative effect of tariff announcements within each "cell," which we define to be bin-sector, i.e., a $\{b, s\}$-tuple. Third, we construct the weighted average of these deviations across all employment bins (b) using the share of U.S. employment in each bin-sector cell as weights to compute aggregate returns at the sector level (s). Fourth, we aggregate across sectors using U.S. value added produced by the sector in 2017 (using data from the Census Bureau and the BEA, respectively) divided by C, which we define to be total U.S. value added plus tariff revenue. We describe this methodology in more detail in Appendix D.

The left panel in Figure 6 compares our constructed weights with the relative employment share of cells within the CRSP-Compustat sample. Our weighting procedure

weights small firms and services more than the CRSP-Compustat sample. The right panel of Figure 6 plots the average deviation in firm values within these cells. One can see that the drops in asset values tend to be smaller for smaller and service firms relative to other firms, which is consistent with the fact that these firms tend to be less exposed to trade. Combining these two figures implies that our weighting procedure will tend to decrease the magnitude of the aggregate deviation in firm values relative to the value-weighted CRSP-Compustat return.

Figure 6: Weights and changes in firm value by sector and employment bins
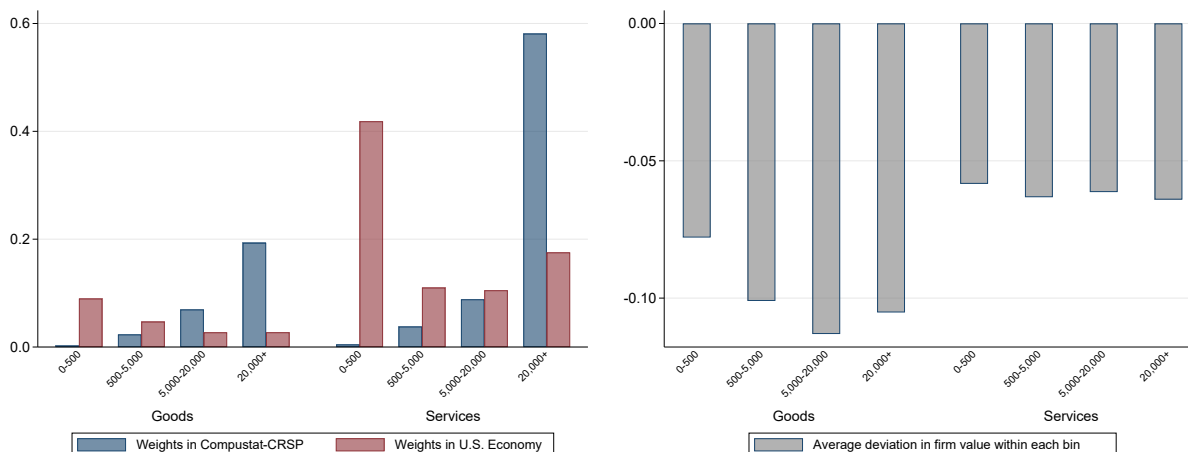
Note: For goods (2-digit NAICS: 11, 21, and 31-33) and services (remaining 2-digit NAICS) sectors in 2017.

We find that tariff announcements caused aggregate firm values to fall 6.7 percent (see Table 8). This drop is just over half the decline in the aggregate stock-market return reported in Table 1. The difference in the two numbers is due to the combination of two effects: first, as we can see from equation (15), the drop in firm values is smaller than the drop in firm equity prices (in percentage terms) because firms are levered. Second, smaller and service-sector firms tend to have lower drops in asset values in magnitude, and so our weighting procedure tends to dampen the overall effect of announcements on asset values (Figure 6). We explore the robustness of our results to changes in the event window and in the weighting methodology in Section 5.

4.3   Measuring the Deviation in Firm Discount Rates

We now turn to the estimation of the deviation in firm discount rates, which corresponds to the second term in the deviation in aggregate welfare in equation (13). The challenge in computing this term is in obtaining an expression for the change in discount rates induced by the policy $\left(\sum_{t=0}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{ft} \right] \right)$. Intuitively, adjusting the change in firm values by the change in their discount rates will allow us to infer the change in their expected cash flows. By definition, the deviation in the discount rate of firm f in period t ($\hat{R}_{ft}$) corresponds to a weighted average of the deviation of the interest rate on its debt ($\hat{R}_{ft}^D$) and the deviation in the expected return of its equity ($\hat{R}_{ft}^E$):

$$\mathrm{E}_0\left[\hat{R}_{ft}\right] = (1-\kappa_f)\mathrm{E}_0\left[\hat{R}_{f,t}^D\right] + \kappa_f\mathrm{E}_0\left[\hat{R}_{f,t}^E\right], \tag{16}$$

where κ_f denotes the ratio of the market value of equity to the market value of assets for firm f (assumed to be constant over time). To make progress, we make the simplifying assumptions that (i) the log deviation in the interest rate on a firm's debt is equal to the log deviation in the risk-free rate and that (ii) the deviation in the expected return on its equity is equal to the risk-free rate plus an adjustment for the firm equity exposure to the stock market (beta) multiplied by the deviation in the expected return of the aggregate stock-market return, following the Capital Asset Pricing Model (CAPM):

$$\mathrm{E}_0\left[\hat{R}_{f,t}^D\right] = \hat{R}_{\text{risk-free},t}, \tag{17}$$
$$\mathrm{E}_0\left[\hat{R}_{f,t}^E\right] = \hat{R}_{\text{risk-free},t} + \beta_{f,M}\left(\hat{R}_{M,t} - \hat{R}_{\text{risk-free},t}\right),$$

where $\beta_{f,M}$, which is assumed to be constant over time, can be estimated as the slope coefficient in a regression of excess firm-level returns on the excess stock-market returns. We will relax these assumptions to account for credit spreads and additional equity factors below. Substituting these two equations into (16) and aggregating over time gives the following expression for the deviation in firm f discount rate:

$$\underbrace{\sum_{t=1}^{\infty}\rho^t\mathrm{E}_0\left[\hat{R}_{ft}\right]}_{\substack{\text{Deviation in firm } f \\ \text{discount rates}}} = \underbrace{\sum_{t=1}^{\infty}\rho^t\mathrm{E}_0\left[\hat{R}_{\text{risk-free},t}\right]}_{\substack{\text{Deviation in future} \\ \text{risk-free rates}}} + \kappa_f\beta_{f,M}\underbrace{\sum_{t=1}^{\infty}\rho^t\mathrm{E}_0\left[\hat{R}_{M,t} - \hat{R}_{\text{risk-free},t}\right]}_{\substack{\text{Deviation in future} \\ \text{excess stock-market returns}}}. \tag{18}$$

This equation expresses the deviation in firm f discount rates as the sum of the deviation in future risk-free rates and the deviation in future excess stock-market returns multiplied by two firm-specific quantities: its equity-to-asset ratio (κ_f) and its equity-market beta ($\beta_{f,M}$), which jointly capture the firm's overall exposure to changes in equity premia. Overall, this equation reduces the problem of estimating firm-specific deviations in discount rates to the estimation of two aggregate quantities: the deviation in future risk-free rates and the deviation in future excess stock-market returns.

We adapt the vector-autoregression (VAR) methodology of Campbell and Vuolteenaho (2004) and Bernanke and Kuttner (2005) to measure these two quantities. More precisely, we assume that a vector of asset prices x_t, which includes the log risk-free rate and the log excess stock-market return as its first two elements, evolves according to a VAR process:

$$x_{t+1} = a + Bx_t + u_{t+1}. \tag{19}$$

This VAR structure allows us to express the expected effect of a policy announcement on x_t in terms of its effect on x_0: $\mathrm{E}_0[dx_t] = B^t dx_0$. Hence, the VAR structure implies the following equation for the deviation in future risk-free rates and excess returns defined

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in equation (18):[13]

$$\underbrace{\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{\text{risk-free},t} \right]}_{\text{Deviation in future risk-free rates}} = \boldsymbol{e}_1' \rho \boldsymbol{B} (\boldsymbol{I} - \rho \boldsymbol{B})^{-1} d\boldsymbol{x}_0, \qquad (20)$$

$$\underbrace{\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{M,t} - \hat{R}_{\text{risk-free},t} \right]}_{\text{Deviation in future excess returns}} = \boldsymbol{e}_2' \rho \boldsymbol{B} (\boldsymbol{I} - \rho \boldsymbol{B})^{-1} d\boldsymbol{x}_0, \qquad (21)$$

where $\boldsymbol{e}_i$ denotes a vector whose i-th element equals one, and zero otherwise. Hence, the problem of estimating the deviation in firm discount rates (the left-hand-side in equation (18)) is reduced to the problem of estimating two aggregate quantities: the matrix $\boldsymbol{B}$, which governs the law of motion of variables in the VAR, and the vector $d\boldsymbol{x}_0$, which measures the effect of the announcement on the variables in the VAR. We now turn to the estimation of these two quantities.

VAR Estimation We now briefly discuss our VAR estimation (see Appendix E.2 for more details). For our baseline results, we consider the VAR system in equation (19) at the quarterly frequency where the vector $\boldsymbol{x}_t$ contains seven variables:

$$x_t = \Big(\ln R_{\text{risk-free},t}, \ln R_{M,t} - \ln R_{\text{risk-free},t}, \text{TS}_t, \text{EPB}_t, \text{VS}_t, \text{CS}_t, \ln PD_t \Big).$$

Our choice of frequency and variables is similar to Campbell and Vuolteenaho (2004). We opt for a quarterly frequency (even though our data is available at the daily frequency) as we are interested in measuring the long-term impacts of changes in the vector $\boldsymbol{x}_0$ on future risk-free rates and excess stock-market returns. The first variable in the VAR is the log real risk-free rate in the quarter (annualized yield of 3-month T-Bills minus smoothed average of inflation in the previous twelve months, divided by four). The second variable is the log excess stock-market return in the quarter (the log value-weighted stock-market return minus the annualized yield of 3-month T-Bill). The remaining variables are the term spread TS_t (the difference in the yield-to-maturity of ten-year treasuries and the annualized yield of 3-month T-Bills), the equity-premium bound EPB_t (discussed in the previous section), the value spread VS_t (i.e., measured as the difference between the log book-to-market ratios of small value and small growth stocks), the credit spread CS (the difference in the yield of BAA and 3-month T-bill), and the log price-dividend ratio $\ln PD_t$ (the ratio between the value of the stock market and the dividends distributed in the previous year). One key difference, relative to Campbell and Vuolteenaho (2004), is that we augment the VAR with the equity-premium bound defined by Martin (2017), which is

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[13]Indeed, the deviation in future risk-free rates is

$$\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{\text{risk-free},t} \right] = \sum_{t=1}^{\infty} \rho^t \left(\boldsymbol{e}_1' \mathrm{E}_0 \left[d\boldsymbol{x}_t \right] \right) = \sum_{t=1}^{\infty} \rho^t \left(\boldsymbol{e}_1' \boldsymbol{B}^t d\boldsymbol{x}_0 \right) = \boldsymbol{e}_1' \left(\sum_{t=1}^{\infty} (\rho \boldsymbol{B})^t \right) d\boldsymbol{x}_0 = \boldsymbol{e}_1' \rho \boldsymbol{B} (\boldsymbol{I} - \rho \boldsymbol{B})^{-1} d\boldsymbol{x}_0.$$

A similar derivation holds for the deviation in future excess stock-market returns .

available starting from 1996. We will examine the robustness of our results with respect to changing the set of variables in the VAR below.

We first estimate the VAR matrix $\boldsymbol{B}$ by regressing each variable in the VAR on a constant term as well as the quarterly lagged variables in the VAR. To get more power, we estimate our VAR on all trading days instead of only the days at the end of every quarter.[14] Table 5 reports the result of this estimation. Consistent with the literature, we find that the log price-dividend ratio and the equity-premium bound are two important predictors of log excess returns. The R^2 of this regression is approximately 12 percent (at a quarterly horizon), which is high relative to the existing literature, suggesting that our VAR captures a large amount of excess return predictability. We then estimate the un-

Table 5: VAR Matrix $\boldsymbol{B}$

	(1) F.log $R_{\text{risk-free}}$	(2) F.log R_{EM}	(3) F.TS	(4) F.EPB	(5) F.VS	(6) F.CS	(7) F.log PD
log $R_{\text{risk-free}}$	0.917***	-0.526	0.075	-0.114	-2.517	-0.022	1.773
	(0.05)	(1.71)	(0.10)	(0.56)	(2.36)	(0.03)	(1.80)
log R_{EM}	-0.004	0.176**	0.007	-0.022	-0.177	-0.001	0.180**
	(0.00)	(0.08)	(0.01)	(0.03)	(0.13)	(0.00)	(0.08)
TS	0.038	2.554*	0.485***	0.218	0.675	-0.068**	4.744***
	(0.05)	(1.54)	(0.12)	(0.34)	(2.69)	(0.03)	(1.55)
EPB	0.003	0.794***	0.012	0.574***	0.095	0.000	1.117***
	(0.01)	(0.30)	(0.02)	(0.07)	(0.41)	(0.00)	(0.29)
VS	-0.001	0.036	-0.003	0.001	0.930***	-0.001	0.092***
	(0.00)	(0.03)	(0.00)	(0.01)	(0.05)	(0.00)	(0.03)
CS	-0.194	-12.704**	1.419***	-0.059	-9.455	1.124***	-19.043***
	(0.15)	(5.64)	(0.44)	(1.35)	(9.25)	(0.11)	(5.71)
log PD	-0.003**	-0.163***	0.005	0.015	0.002	0.001*	0.795***
	(0.00)	(0.05)	(0.00)	(0.01)	(0.07)	(0.00)	(0.05)
R^2	0.83	0.12	0.84	0.37	0.89	0.87	0.84
N	6,545	6,545	6,545	6,545	6,482	6,545	6,545

Note: The table reports the result of estimating the regression in equation (19), using daily variables to get more identification. That is, we estimate the VAR specification: $\boldsymbol{x}_{t+63} = \boldsymbol{a} + \boldsymbol{B}\boldsymbol{x}_t + \boldsymbol{u}_{t+63}$ where t denotes a day (note that 63 corresponds to the average number of trading days in a quarter). The sample is all trading days between 1996 and 2022. Standard errors are estimated using Newey-West robust standard errors with a bandwidth of 63 to account for overlapping observations.

expected change in the VAR variables due to tariff announcements, $d\boldsymbol{x}_0$. Similar to the procedure used to estimate the deviation in firm values, we estimate $d\boldsymbol{x}_0$ as the sum of daily changes in the vector $\boldsymbol{x}_t$ over all announcement days after controlling for the release of macroeconomic surprises; that is, as the sum of $\boldsymbol{\beta}_j$ in the regression

$$\Delta \boldsymbol{x}_t = \boldsymbol{\alpha} + \sum_{j=1}^{J} \boldsymbol{\beta}_j D_t^j + \sum_{d=1}^{D} \boldsymbol{\gamma}_d ES_{d,t} + \boldsymbol{\epsilon}_t, \tag{22}$$

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[14]This is similar to what Martin (2017) does to assess the predictability power of the equity-premium bound on quarterly excess returns.

where D_t^j is an indicator variable equal to one if day t is in the window of announcement j, and $ES_{d,t}$ corresponds to the surprise in the economic series d. Table 6 reports the results of the estimation. As discussed in Section 2, the stock-market drops around the announcement days, the risk-free rate decreases, slightly at the 3-month horizon and more strongly at the 10-year horizon, while the equity premium increases. Moreover, the value spread also increases; that is, the value of the equity of growth firms (i.e., firms with low book-to-market ratio) drops more than the value of equity of value firms (i.e., firms with high book-to-market ratio). This is consistent with the idea that growth firms tend to have cash flows with a longer maturity than value firms, and, therefore, are more sensitive to changes in discount rates.

Table 6: Cumulative Effect of Tariff Announcements on the VAR Components $d\boldsymbol{x}_0$

	(1) $\log R_{\text{risk-free}}$	(2) $\log R_{EM}$	(3) TS	(4) EPB	(5) VS	(6) CS	(7) $\log PD$
Event	-0.000**	-0.125***	-0.005***	0.046***	0.092***	-0.001***	-0.127***
	(0.000)	(0.040)	(0.001)	(0.013)	(0.030)	(0.000)	(0.039)
N	753	754	753	753	753	753	753

Note: The table reports the sum of β_j in the regression (22). The sample includes all trading days from 2017 to 2019. Robust standard errors are in parentheses.

Table 7 combines the estimates for $\boldsymbol{B}$ (Table 5) and the estimate for $d\boldsymbol{x}_0$ (Table 6) to compute the deviation in future risk-free rates and future excess stock-market returns following equations (20) and (21). We find that the deviation in future risk-free rates due to tariff announcements is approximately -2.1 percentage points while the deviation in future excess stock returns is approximately 8.9 percentage points. These estimates imply that the overall drop in the aggregate stock-market return due to changes in the required return on equity is 6.8 percentage points ($= -2.1 + 8.9$).[15] Given that the overall drop in the (value-weighted) stock-market return is approximately -11.5 percentage points, this implies that changes in discount rates account for approximately half of the decline in the aggregate stock-market value around tariff announcements. Note that the relative importance of discount-rate shocks on announcement days is consistent with existing results on their relative importance for the unconditional variance of returns (see, for instance, Campbell (2003)).

We check the plausibility of the estimates coming from the VAR by comparing the VAR's estimates for movements in the real risk-free rate and equity premium with the observed changes in the term structure of real yields and the equity-premium bounds measured in Section 2. The left panel of Figure 7 plots the change in the average (real) risk-free rate and the excess stock-market return predicted by the VAR as a function of time. The right panel of Figure 7 reproduces the change in the term structure of real Treasury yields and in the equity-premium bound around announcement days obtained in the last section. These two figures give similar results regarding the evolution of discount rates following tariff announcements: the real risk-free rate decreases, especially at longer

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[15]This calculation can be seen as an application of equation (18) for a firm with $\kappa_f = 1$ and $\beta_f = 1$.

Table 7: Estimated Changes in Future Discount Rates

	Deviation in Future Risk-free Rates	Deviation in Future Excess Returns
	$\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{\text{risk-free},t} \right]$	$\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{M,t} - \hat{R}_{\text{risk-free},t} \right]$
Baseline	-0.021	0.089

Note: The table reports the deviation in risk-free rate, $e_1' \rho B (I - \rho B)^{-1} dx_0$, and the deviation in the equity premium, $e_2' \rho B (I - \rho B)^{-1} dx_0$. Note that the matrix B is reported in Table 5 while the vector dx_0 is reported in Table 6. We use $\rho = 0.975^{1/4}$ which corresponds to an annualized consumption-to-wealth ratio of $1 - 0.975 = 2.5\%$, to match the average dividend yield of the overall stock market between 2017 and 2019.

horizons, while the expected excess stock-market returns sharply increases, especially at short horizons. Thus, the VAR is consistent with the reduced-form evidence on the evolution of discount rates.[16]

Figure 7: Effect of Tariff Announcements on Discount Rates: VAR versus Reduced-Form
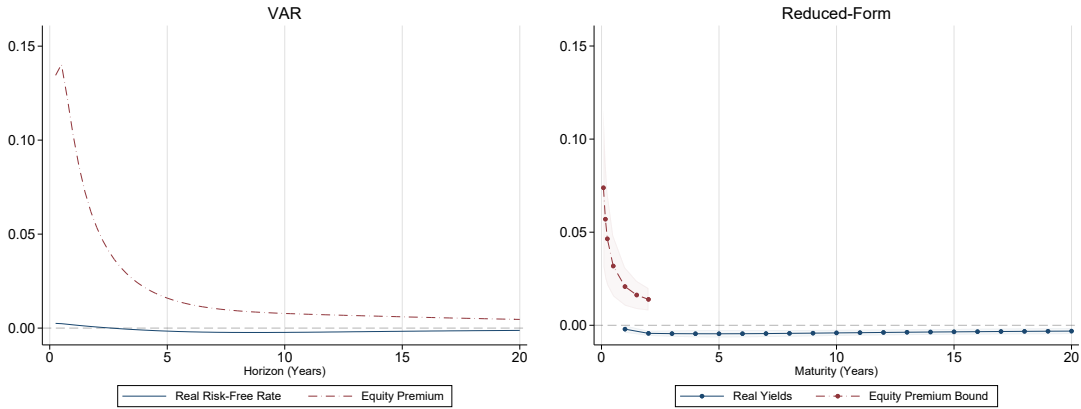
Note: The figure in the left panel plots the effect of tariff announcements on the annualized (real) risk-free rate and excess stock-market return between 0 and t; that is, $(4/T) \sum_{t=1}^{T} \mathrm{E}_0[\hat{R}_{\text{risk-free},t}] = (4/T) \sum_{t=1}^{T} e_1' B^t dx_0$ and $(4/T) \sum_{t=1}^{T} \mathrm{E}_0[\hat{R}_{M,t} - \hat{R}_{\text{risk-free},t}] = (4/T) \sum_{t=1}^{T} e_2' B^t dx_0$. The right panel plots the effect of tariff announcements on the yield to maturity of TIPS as well as on the equity-premium bounds across different maturities, as defined by Martin (2017) (the right panel was reported earlier in Figure 5).

Aggregation We then aggregate these firm-level deviations in discount rates using the same weighting scheme as the one used for the deviation in firm values; that is, we reweight firms based on their employment level and industry to approximate the composition of firms in the U.S. economy.

Overall our methodology indicates that changes in firm discount rates account for a 3.1 percent drop in the overall market value of firms. Note that this number is about half

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[16]Relatedly, Knox and Vissing-Jorgensen (2022) propose to only use the reduced-form changes in the yields of Treasuries and in the equity-premium bound to back out discount rates. The downsides of this methodology are that (i) the equity-premium bound is only a lower bound on the "true" equity premium and that (ii) it is only available up to a three-year maturity. Our VAR methodology solves these two issues at the cost of assuming more structure on the evolution of the economy.

of the 6.8 percent implied effect of discount rates on the aggregate market value of firm equity (as computed in the previous paragraph). As in the previous section, this reflects the dampening effect of leverage (see equation (16)): as firms issue a mix of debt and equity, the required return on their assets (a weighted average of the required returns on their debt and on their equity) rises less than the required return on their equity.

4.4 Measuring the Deviation in Tariff Revenues

The last term for the welfare effect of the policy is the deviation in tariff revenues. In order to avoid introducing additional estimates into the procedure, we opt to bound the impact of tariff revenues on our estimation. We have yearly U.S. tariff rates for each product h (HS10) and exporting country c. Let $\Omega_{h,2019}^{US}$ be the set of countries that export product h to the U.S. in 2019 and Ω_{2019}^{US} the set of products the U.S. imported in 2019. We can construct the upper bound for how much revenue will be generated by an increase in tariffs by assuming that higher tariffs have no impact on import values. In this case, we can set future import values equal to their 2017 values. The upper bound of the percent change in tariff revenue for 2019 relative to the baseline of 2017, $\widehat{TR}$, is the sum of the product of the total import value and the tariff rate:

$$\widehat{TR} = (TR_{2017})^{-1} \sum_{h \in \Omega_{2019}^{US}} \sum_{c \in \Omega_{h,2019}^{US}} \text{Tariff Rate}_{h,2019,c} \times \text{Import Value}_{h,2017,c} - 1.$$

Similarly, the lower bound for the amount of revenue raised by a tariff is zero if all tariff increases result in prohibitive tariffs that cause import values to fall to zero, so $\widehat{TR} = -1$. In order to be conservative and estimate the smallest possible decline in welfare, we focus on the the upper bound for the increase in tariff revenues but note that because TR/C in equation (13) is small, there is little scope for different assumptions about the movement in tariff revenues to affect the results.

5 Results on Aggregate Welfare

We now compute the aggregate welfare effect of the tariff announcements, which is the sum of the three components in equation (13), across all announcement days: the deviation in firm values, the deviation in firm discount rates, and the deviation in tariff revenues. We report the impact of the tariff announcements on welfare in Table 8. In our baseline specification, we find that the deviation in firm value is -6.7 percent while the deviation in firm future discount rates is approximately 3.1 percent; as a result, the implied deviation in firm future cash-flows is -3.6 percent ($= -6.7 + 3.1$). Combined with the fact that the maximum increase in welfare due to higher tariff revenues is 0.6 percent, we find that the overall welfare effect of tariff announcements is -3.0 percent. In the rest of the section, we examine the robustness of our results, we relate our estimates to conventional measures of welfare in trade, and we compare our estimates to a difference-in-difference framework.

Table 8: Welfare Effect

| | Components | | | Welfare |
	Firm Value	Firm Discount Rate	Tariff Revenues	$\mathcal{C}^{\text{first-order}}$
Baseline	-0.067	0.031	0.006	-0.030
Robustness w.r.t. firm sample				
Enforcing balanced panel	-0.072	0.038	0.006	-0.028
Removing firm specific announcements	-0.068	0.031	0.006	-0.031
Robustness w.r.t. firm weights				
Finer employment grid	-0.061	0.032	0.006	-0.023
No effect on financial firms	-0.063	0.030	0.006	-0.026
No effect on firms below 500 employees	-0.035	0.016	0.006	-0.013
Robustness w.r.t. tariff revenues				
Estimates from Fajgelbaum et al. (2020)	-0.067	0.031	0.002	-0.034
Robustness w.r.t. announcement window				
3-day window for firm value	-0.057	0.031	0.006	-0.021
3-day window for firm discount rate	-0.067	0.046	0.006	-0.015
Robustness w.r.t. VAR variables				
Without TS	-0.067	0.035	0.006	-0.025
Without EPB	-0.067	0.035	0.006	-0.025
Without VS	-0.067	0.047	0.006	-0.013
Without CS	-0.067	0.041	0.006	-0.020
Without $\log PD$	-0.067	0.004	0.006	-0.056
Robustness w.r.t. discount rate model				
3-FFM instead of CAPM	-0.067	0.042	0.006	-0.019
Corp yields instead of risk-free rate	-0.067	0.032	0.006	-0.028

Note: The table reports the welfare effect of trade announcements, $\mathcal{C}$, as well as its three components defined in equation (13): the aggregate deviation in firm values, the aggregate deviation in firm discount rates, and the effect on tariff revenues.

5.1 Robustness

We now assess the robustness of our baseline estimates along several dimensions. The results of these robustness checks are reported as additional rows in Table 8.

Firm Sample We first explore the robustness of our results with respect to the sample of firms. We first show that our estimates remain the same if we restrict ourselves to a balanced sample by removing all firms with missing returns between 2017 and 2019, which removes approximately 10 percent of the firms. We also show that our estimates remain the same if we remove firms with firm-specific announcements during the same window as one of our tariff announcements (as reported in Capital IQ).

Firm Weights As explained above, to compute the aggregate welfare effect of tariff announcements, it is essential to weight firms in the Compustat-CRSP sample to approximate the distribution of employment and sectors in the U.S. economy. We now explore the robustness of our results with respect to this weighting scheme by using three alternative procedures.

First, we use finer employment bins within each sector (defined by employment thresholds of 500, 750, 1000, 1500, 2000, 2500, 5000, 10000, and 20000). To deal with the

fact that this leads to sparsely populated cells, we regress deviations in firm values and discount rates on log employment and log employment squared within each sector and announcement. We then use the predicted values from these regressions to fill out deviations within each cell. This alternative methodology tends to find a slightly less negative drop in firm value and, therefore, on welfare. We describe this alternative methodology in more detail in Appendix D.

Second, we estimate the welfare effect assuming that firms in the financial sector are unaffected by tariffs. This robustness exercise is motivated by two reasons: first, it reflects the fact that our model more naturally applies to nonfinancial firms, and second, adding the deviation in financial firms may lead to a double counting, as these firms own claims on non-financial firms. Assuming tariffs have no impact on financial firms hardly affects the results.

Finally, we compute the welfare effect under the drastic assumption that there is no effect of tariff announcements on firms below 500 employees (that is, we assume that the deviation in firm values and discount rates is zero for all firms below this threshold). Despite this assumption, we still find a sizable welfare effect equal to -1.3 percent.

Tariff Revenues Our baseline choice of the maximum possible tariff revenue associated with the tariffs tends to understate the welfare losses associated with the tariffs. We correct for this bias by using Fajgelbaum et al. (2020)'s estimates of tariff revenues instead of our upper bound. This more realistic estimate causes the welfare effect to fall from -3.0 percent to -3.4 percent.

Event Window In the baseline results, we estimate the deviation in firm values and discount rates using the response of financial variables on the day of the tariff announcements. As a robustness check, we now explore using a longer three-day window. We first estimate the change in firm value measured using a three-day window. As reported in Table 8, we find that the implied welfare effect of tariff announcements is slightly smaller, reflecting the fact that the stock market declines only a little less using a three-day window rather than a one-day window.

Next, we estimate the change in firm discount rates using a three-day window. Appendix Table E.3 reports the change in the VAR variables obtained over a three-day window around announcement days. Compared to the estimates obtained using a one-day window reported in Table 6, the estimates become much noisier—in particular, all changes in the VAR variables that are unrelated to stock-market returns lose statistical significance. We use these estimates of $d\boldsymbol{x}_0$ in equations (20) and (21) as inputs into the VAR estimation to obtain an estimate of the discount rate using the three-day window. Appendix Table E.4 reports that these responses imply a smaller decrease in future risk-free rate, and, consequently, a larger increase in overall firm discount rates. As a result, these responses imply a smaller welfare effect (Table 8). These results should be interpreted with caution, however, as the responses of the variables used in the VAR to tariff announcements are not significant.

VAR Variables To estimate firm-level discount rates, we specify a VAR with a set of variables that is very similar to the existing literature. Still, it is useful to check that our results are qualitatively not dependent on the exact choice of variables in the VAR. Hence, as a ro-

bustness check, we re-estimate the VAR after removing successively each one of the components of the vector x_t. We report the results for the deviation in future risk-free rates and future excess stock-market returns in Appendix Table E.4 and the resulting numbers for the welfare effect in Table 8. Overall, we find similar changes in discount rates after successively removing each variable from the VAR. The only exception occurs when we run a VAR excluding the price-dividend ratio, in which case the predicted change in discount rates is significantly lower. This reflects the importance of the price-dividend ratio as a predictor of future discount rates (Cochrane (2008)).

Factor Model In the baseline results, we made the simplifying assumption that the log deviation in the interest rate paid on firm debt was the same as the log deviation in the risk-free rate and that the deviation in the required return on firm equity was given by its beta exposure to the stock market times the deviation in the expected excess return on the market (CAPM). As a robustness check, we now sequentially relax these two assumptions.

First, we use the Fama-French 3-factor model instead of the CAPM to estimate the discount rate on firm equity. This effectively allows the discount rate of a firm equity to depend not only on its exposure to the stock market (as in the CAPM) but also on its size and book-to-market values. As reported in Appendix Table E.4, we find that tariff announcements slightly increase the expected return of the SMB portfolio; that is, tariff announcements have a larger effect on the discount rate of small firms relative to big firms. This implies that, relative to the CAPM, our Fama-French 3-factor model generates an estimate for firm-level discount rates that is higher for small firms (firms with $\beta_{f,SMB} > 0$) and lower for big firms (firms with $\beta_{f,SMB} < 0$). These changes would average out if we were doing a value-weighted average of firms in our sample. However, because we overweight smaller firms, this leads to a lower aggregate deviation in firm discount rates by 1.1 percentage points. As a result, the overall decline in welfare is mechanically reduced by 1.1 percentage points.

Second, we assume that the log deviation in the interest rate paid on firm debt is equal to the log deviation in the yields of BAA bonds rather than the risk-free rate on debt. As reported in Table 8, we find that our measure of welfare hardly changes; that is, our VAR estimates exhibit relatively little deviation in credit spread following announcement shocks. See Appendix E.3 for more details.

5.2 Interpreting the Results Through the Lens of Our Model

We now use our firm-specific factor model to relate our baseline estimates for the welfare effect of tariffs to the ones implied by static models of trade. Combining equation (11) with Proposition 2 allows us to express the welfare effect of asset prices due to changes in firm cash flows into the expected ERP and productivity movements (see Appendix B.2 for details):

$$ \mathcal{C}_{\hat{r}} = \sum_f \frac{wL_f + r_f V_f}{C} \left\{ \underbrace{\hat{p}^e_{f0}}_{\text{Static Price Effect}} + \underbrace{\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{p}^e_{ft} - \hat{p}^e_{ft-1} \right]}_{\text{Dynamic Price Effect}} + \underbrace{\sum_{t=0}^{\infty} \rho^t \mathrm{E}_0 \left[\frac{\hat{A}_{ft}}{1 - \sum_i \omega_{if}} \right]}_{\text{TFP Effect}} \right\}. \quad (23) $$

This equation decomposes the cash-flow effect of tariff announcements on welfare into three terms: a static price effect, a dynamic price effect, and a productivity effect. The static price effect of a tariff tells us how much a given vector of tariff changes would affect welfare if the initial tariffs caused the same percentage change in the ERP from the baseline level in each future period and had no impact on productivity. Weighting these ERP movements by the ratio of firm value added to consumption gives us the first component of the welfare impact. The dynamic price effect captures welfare losses due to future growth in the ERP deviations. For example, if tariffs affect the growth of ERP through some dynamic pricing process or through an escalation of the trade war, this would be captured in the dynamic price effect. Weighting these future ERP changes by firm value added and the appropriate discount factor provides a mapping from this expected growth in future prices into welfare. Finally, the TFP effect captures how a tariff announcement affects welfare by affecting TFP now and in the future.

Equation (23) makes clear the difference between measuring welfare using a comparative static exercise and our approach. In comparative statics exercises, $\hat{p}^e_{f0}$ is measured by estimating how tariffs change the ERP assuming that these tariffs do not affect expected future TFP and that all future changes in ERP equal the initial change ($\hat{p}^e_{ft} = \hat{p}^e_{f0}$). Our approach, which is based on estimating the cash-flow effect directly, allows us to relax the assumptions that the TFP and dynamic price effects are zero and capture the full effect of a tariff increase.

We now use equation (23) to decompose our baseline number for the welfare effects of asset prices through firm cash flows into a static price effect, a dynamic price effect, and a TFP effect. First, as we explain in detail in Appendix B.2, we can estimate the static price effect ($\hat{p}^e_{f0}$) by applying tariff pass-through estimates during the trade war from Fajgelbaum et al. (2020) and Amiti et al. (2019) to compute the static impact of the tariff on the effective rates of protection and aggregating these to understand what our estimate would have been if markets had just thought the applied tariffs would cause a permanent change in ERP and had no impact on TFP. Depending on how one models the way in which U.S. firms adjust their pricing in response to tariffs, we estimate that the static effect of the tariffs would have lowered U.S. welfare by 0.17 to 0.3 percent (see Appendix G for details). These estimates are remarkably similar to those obtained by Amiti et al. (2019) and Fajgelbaum et al. (2020) who estimate welfare losses of 0.20 and 0.27 percent, respectively.[17] The similarity of the results establishes that the specific factors model, which forms the basis of our setup, delivers standard results if one assumes that the start of a tariff war will not affect TFP or have any time varying impact on prices.

Turning to the dynamic price effect, its lower bound is likely to be what would happen if markets expected the U.S. to levy its maximal tariffs with probability 1. In the 2024 presidential campaign, President Trump discussed levying tariffs of 60 percent on China and 20 percent on all other countries—a larger average increase than that of the 1930 Smoot-Hawley tariff (c.f. Irwin (2017))—which we take as the likely maximum expected U.S. threat point. If markets were certain that these tariffs would be implemented shortly

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[17]The estimate of 0.20 comes from multiplying the monthly cost of the tariffs to importers in December of 2018 in Table 2 of Amiti et al. (2019) by twelve and dividing by U.S. GDP. Fajgelbaum et al. (2020) report an equivalent variation loss of 0.27 percent if tariffs are not passed through into export prices and 0.22 if they are (Table VII).

after the start of the trade war, we calculate the dynamic price effect would lower U.S. welfare by 1.0 to 2.2 percentage points depending on the assumptions made about tariff passthrough into domestic prices (see Appendix B.2 for details). Subtracting the largest possible losses due to the price effects still leaves a large welfare loss due to the change in expected TFP: $-1.1 (= -3.6 + 0.3 + 2.2)$. In other words, our baseline estimates imply that markets anticipated the tariffs would cause a welfare loss that was at least three times larger than standard estimates imply because of expected falls in TFP. At a minimum, our estimates imply that standard estimates depend crucially on optimistic assumptions about the probability that tariffs will beget future tariffs or cause lower productivity, and it is these assumptions that explain the difference between the small impact of tariffs found in static models and the ones we identify.

5.3 Treatment Effects

Another way to relate our results to the literature is to contrast the impact of tariff announcements on firms in general vs. the differential impact of tariffs on "exposed" vs. "unexposed" firms using a standard difference-in-difference approach.

Table 9: Impact of Tariff Announcements on Cash Flows

	(1) U.S.	(2) China
China Importer	-1.97***	-0.45**
	(0.26)	(0.20)
China Exporter	-1.17***	0.03
	(0.41)	(0.30)
China Revenue Share	-5.52***	-4.95***
	(1.77)	(1.49)

Note: The dependent variable is residualized cash flow (CF_{ft}) multiplied by 100, which is constructed by summing $\hat{\Pi}_{f0}$ (constructed using equation (15)) and the change in the discount rate (which is based on the change in the VAR variables on announcement days after controlling for economic surprises). This table uses a one-day window around each event and reports the sum of the coefficients across U.S. and China event days in the first and second columns, respectively. China Importer is a dummy that equals one if the firm or any of its subsidiaries or suppliers import from China. China Exporter is a dummy that equals one if the firm or subsidiaries export to China. China Revenue Share is the share of the firm's revenue from China. There are 26,807 observations. Standard errors are in parenthesis. Asterisks correspond to the following levels of significance: ***$p < 0.01$,** $p < 0.05$,* $p < 0.1$.

To this end, we use an event study, where we project firm-level deviations in cash flow on a set of our three firm-level characteristics $Z_{if} \in$ {Importer, Exporter, China Revenue Share} associated with China exposure, allowing for different coefficients for each announcement day and each exposure type.

$$\text{CF}_{ft} \equiv \sum_{t=0}^{\infty}(1 - \rho)\rho^t \text{E}_0 \left[\hat{r}_{ft}\right] = \alpha_t + \sum_j \sum_i \gamma_{ij} Z_{if} D_{jt} + \epsilon_{ft}, \tag{24}$$

where the left-hand side variable is the expected present discounted value of firm cash flow, which can be measured using Proposition 4, estimated using the method described

in Sections [4.2](#) and [4.3](#); α_t is a day fixed effect; D_{jt} is a dummy variable that is one if day t is the same as announcement day j; is a measure of firm f's exposure to China; γ_{ij} is parameter to be estimated; and ϵ_{ft} is an i.i.d. error term.

In Table [9](#), we present the cumulative effecst of the U.S. tariffs in column (1) and the cumulative effects of the China tariffs in column (2). Tables with individual coefficients for each day are presented in Appendix [H](#). The coefficients should be interpreted as the effect of the announcement on the expected cash flows of exposed firms relative to un-exposed firms. The cumulative impact of the U.S. events indicates that in general U.S. tariff announcements had large, negative, and significant impacts on the cash flows of importers, exporters, and firms selling in China: the expected cash flows of U.S. importers fell 1.97 percentage points more than firms that did not import from China; the relative fall in expected cash flows of exporters were 1.17 percentage points more than those of non-exporters, and firm's selling in China saw their expected cash flows fall by 0.06 percentage points for every percentage point of revenue share they obtained from China. The coefficient on China Revenue Share implies that a firm with the average sales exposure to China (three percent of revenue) experienced a fall in expected cash flow of 0.18 percentage points lower than a firm with no sales in China across all of the U.S. events. Similarly, Chinese announcements significantly lowered expected cash flows for firms selling in China (either by exporting or through multinationals).

To compare the magnitude of treatment effect relative to the aggregate effect, we then estimate an aggregate welfare effect using only the deviations in firm values and discount rates predicted by these firm-level characteristics (without taking into account the intercept). We find this welfare effect is -0.89 percentage points, which is approximately a quarter of our baseline welfare result (before taking into account tariff revenues). This reflects the fact that it is important to take into account the overall negative effect of tariffs announcements on all firms, not just the differential one with respect to Chinese exposure.

6 Conclusion

The main contribution of this paper is to assess the welfare effect of a trade war using the reaction of financial markets to policy announcements. Using an infinite-horizon specific factors model, we show that the change in firm cash flows is a sufficient statistic for identifying expected movements in wages, employment, and welfare.

Our estimates for the welfare effect of the trade war are large compared to conventional measures based on static models. Seen through the lens of our model, the difference arises because conventional analyses assume that tariffs have no effect on TFP and will not change the probability of future price changes (arising from dynamic price effects or future protection). Our baseline estimates indicate that the expected TFP effect, in particular, must be large. This result provides strong support for dynamic models that feature trade-related TFP spillovers as well as models that embed the political economy of future tariff escalations into the costs of starting a tariff war.

Our paper also opens new paths for future research. First, our research suggests that obtaining a better understanding of how trade affects TFP could lead to richer explanations of why comparative static models deliver small effects from protection while markets react much more negatively. Second, although our focus is on the impact of

the tariff announcements on welfare, the methodology could just as easily be applied to other unanticipated policy announcements. In addition, our theory develops predictions for how cash flows can be used to understand movements in employment, productivity, prices, etc. These links may help future researchers better understand the mechanisms driving our results.

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Appendix to "Trade Protection, Stock-Market Returns, and Welfare"

December 18, 2024

Contents

Introduction

This online appendix contains supplementary theoretical and empirical results. Section A presents the proofs of the propositions in the theory section and model extensions. Section B generalizes of our framework that allows for growth. Section C turns to data and measurement issues. We present the sources for each event in Section C.1. Section C.2 provides a list of all the variables and the data sources used. Sections C.3 and C.3 provide more details on the data sources and construction of the China-exposure variables. Section G.2 presents sample statistics.

Next, we provide additional details for the welfare calculations. Section D describes how we reweight our sample of publicly listed firms using the size distribution of U.S. firms. Section E provides details of the procedure to estimate the changes in discount rates, with additional robustness tables in Section F. Wee provide details of the calculations of the static and dynamic price effects in Section G. Finally, we provide more details of the estimation of treatment effects in Section H.

A Proofs

A.1 Proof of Proposition 1

Proposition. *1 If the elasticity of substitution between labor and the specific factor for all firms is constant, then the log change in wages equals the employment-share weighted average of the log changes in cash flow, i.e.,*

$$\hat{w}_t = \sum_f \frac{L_f}{L} \hat{r}_{ft},$$

and the log change in employment in each firm equals $\hat{L}_{ft} = \sigma \left(\hat{r}_{ft} - \sum_{f'} \frac{L_{f'}}{L} \hat{r}_{f't} \right).$

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

$$\hat{y}_{ft} = -\hat{a}_{Vft}, \tag{A1}$$

and

$$\sum_f \frac{L_f}{L} \left(\hat{a}_{Lft} - \hat{a}_{Vft} \right) = \hat{L}, \tag{A2}$$

where we have used the fact that in the baseline equilibrium $L_{ft} = L_f$. Substituting equation (4) into the previous equation yields

$$-\sum_f \frac{L_f}{L} \sigma \left(\hat{w}_t - \hat{r}_{ft} \right) = \hat{L}, \tag{A3}$$

or

$$\hat{w}_t = \sum_f \frac{L_f}{L} \hat{r}_{ft} - \frac{\hat{L}}{\sigma} \tag{A4}$$

If the supply of labor is fixed, we have $\hat{L} = 0$, which establishes that

$$\hat{w}_t = \sum_f \frac{L_f}{L} \hat{r}_{ft}. \tag{A5}$$

2

Substituting equation (A1) into equation (4) yields

$$-\hat{y}_{ft} - \hat{a}_{Lft} = \sigma(\hat{w}_t - \hat{r}_{ft}) \tag{A6}$$

or

$$\hat{L}_{ft} = \sigma(\hat{r}_{ft} - \hat{w}_t) = \sigma\left(\hat{r}_{ft} - \sum_{f'}\frac{L_{f'}}{L}\hat{r}_{f't}\right). \tag{A7}$$

□

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

Starting with equation (A4), we now can add an upward-sloping labor-supply curve by defining the log change in employment relative to some base level L as

$$\hat{L}_t = \hat{L}_t^s = \tilde{\sigma}\hat{w}_t,$$

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

$$\hat{w}_t = \sum_f \frac{L_f}{L}\hat{r}_{ft} - \frac{\tilde{\sigma}\hat{w}_t}{\sigma}$$

$$\hat{w}_t = \sum_f \frac{L_f}{L}\hat{r}_{ft} - \frac{\tilde{\sigma}}{\sigma}\sum_f \frac{L_f}{L}\hat{r}_{ft}$$

$$\hat{w}_t = \left(1 - \frac{\tilde{\sigma}}{\sigma}\right)\sum_f \frac{L_f}{L}\hat{r}_{ft},$$

which proves that wages will rise with changes in cash flow as long as $\tilde{\sigma} < \sigma$, i.e., the labor-supply response cannot be too large. Substituting this expression into equation (A7) gives us

$$\hat{L}_{ft} = \sigma(\hat{r}_{ft} - \hat{w}_t) = \sigma\left(\hat{r}_{ft} - \left(1 - \frac{\tilde{\sigma}}{\sigma}\right)\sum_f \frac{L_f}{L}\hat{r}_{ft}\right).$$

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

A.2 Proof of Proposition 2

Proposition. *2 The sum of log changes in the effective rates of protection ($\hat{p}_{ft}^e$) and adjusted productivity $\left(\frac{\hat{A}_{ft}}{1-\sum_i \omega_{ift}}\right)$ for a firm can be expressed as a linear function of the log changes in cash flows ($\hat{r}_{ft}$):*

$$\hat{p}_{ft}^e + \frac{\hat{A}_{ft}}{1 - \sum_i \omega_{ift}} = \left(\frac{\omega_{Vft}}{1 - \sum_i \omega_{ift}}\right)\hat{r}_{ft} + \left(\frac{\omega_{Lft}}{1 - \sum_i \omega_{ift}}\right)\sum_{f'}\frac{L_{f't}}{L}\hat{r}_{f't}.$$

3

Moreover, the log changes in firm cash flows ($\hat{r}_{ft}$) and wages ($\hat{w}_t$) can be expressed as linear functions of the log changes in effective rates of protection ($\hat{p}^e_{ft}$) and productivity ($\hat{A}_{ft}$):

$$\hat{w}_t = \sum_f \varphi_{ft} \left(\hat{p}^e_{ft} + \frac{\hat{A}_{ft}}{1 - \sum_i \omega_{ift}} \right) \ and$$

$$\hat{r}_{ft} = \left(\frac{1 - \sum_i \omega_{ift}}{\omega_{Vft}} \right) \left(\hat{p}^e_{ft} + \frac{\hat{A}_{ft}}{1 - \sum_i \omega_{ift}} \right) - \left(\frac{\omega_{Lft}}{\omega_{Vft}} \right) \sum_f \varphi_{ft} \left(\hat{p}^e_{ft} + \frac{\hat{A}_{ft}}{1 - \sum_i \omega_{ift}} \right),$$

where $\varphi_{ft} = L_{ft} \left(\frac{1 - \sum_i \omega_{ift}}{\omega_{Vft}} \right) / \sum_{f'} L_{f't} \left(\frac{1 - \sum_i \omega_{if't}}{\omega_{Vf't}} \right)$.

Proof. We begin by totally differentiation equation (1) and dividing both sides by p_{ft} to obtain

$$\omega_{Lft}\hat{w}_t + \omega_{Vft}\hat{r}_{ft} + \sum_i \omega_{ift}\hat{q}_{it} - \hat{A}_{ft} = \hat{p}_{ft}, \tag{A8}$$

where we have made use of the fact that

$$\omega_{Lft}\hat{a}_{Lft} + \omega_{Vft}\hat{a}_{Vft} + \sum_i \omega_{ift}\hat{a}_{ift} = -\hat{A}_{ft}.$$

Using the definition of effective rates of protection in equation (5) and Proposition (1), we can rearrange equation (A8) to arrive at the first equation in the proposition:

$$\hat{p}^e_{ft} + \frac{\hat{A}_{ft}}{1 - \sum_i \omega_{ift}} = \left(\frac{\omega_{Vft}}{1 - \sum_i \omega_{ift}} \right) \hat{r}_{ft} + \left(\frac{\omega_{Lft}}{1 - \sum_i \omega_{ift}} \right) \sum_{f'} \frac{L_{f't}}{L} \hat{r}_{f't}.$$

Then, it is straightforward to solve for $\hat{w}_t$ and $\hat{r}_{ft}$ in terms of $\hat{p}^e_{ft}$ and $\hat{A}_{ft}$. Specifically, we have

$$\left(\frac{\omega_{Lft}}{\omega_{Vft}} \right) \hat{w}_t + \hat{r}_{ft} = \left(\frac{1 - \sum_i \omega_{ift}}{\omega_{Vft}} \right) \left(\hat{p}^e_{ft} + \frac{\hat{A}_{ft}}{1 - \sum_i \omega_{ift}} \right)$$

$$\left[\sum_f \frac{L_{ft}}{L} \left(\frac{\omega_{Lft}}{\omega_{Vft}} \right) + 1 \right] \hat{w}_t = \sum_f \frac{L_{ft}}{L} \left(\frac{1 - \sum_i \omega_{ift}}{\omega_{Vft}} \right) \left(\hat{p}^e_{ft} + \frac{\hat{A}_{ft}}{1 - \sum_i \omega_{ift}} \right)$$

$$\left[\sum_f L_{ft} \left(\frac{1 - \sum_i \omega_{ift}}{\omega_{Vft}} \right) \right] \hat{w}_t = \sum_f L_{ft} \left(\frac{1 - \sum_i \omega_{ift}}{\omega_{Vft}} \right) \left(\hat{p}^e_{ft} + \frac{\hat{A}_{ft}}{1 - \sum_i \omega_{ift}} \right)$$

$$\hat{w}_t = \sum_f \varphi_{ft} \left(\hat{p}^e_{ft} + \frac{\hat{A}_{ft}}{1 - \sum_i \omega_{ift}} \right),$$

where Proposition (1) was used to derive the second line. Substituting the solution for $\hat{w}_t$ back into the first line, we get

$$\hat{r}_{ft} = \left(\frac{1 - \sum_i \omega_{ift}}{\omega_{Vft}} \right) \left(\hat{p}^e_{ft} + \frac{\hat{A}_{ft}}{1 - \sum_i \omega_{ift}} \right) - \left(\frac{\omega_{Lft}}{\omega_{Vft}} \right) \sum_f \varphi_{ft} \left(\hat{p}^e_{ft} + \frac{\hat{A}_{ft}}{1 - \sum_i \omega_{ift}} \right).$$

$\square$

A.3 Proof of Proposition 3

Proposition. *3 For an agent with log utility, the consumption-equivalent welfare effect of the deviation path $(\hat{C}_t)_{t=0}^{\infty}$ is*

$$\mathcal{C} = (1 - \rho) \sum_{t=0}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{C}_t \right],$$

where $\rho \equiv 1 - C_t/W_t$ denotes the consumption-to-wealth ratio..

Proof. The value function of an agent with log utility is

$$\mathcal{W}_0 = \sum_{t=0}^{\infty} \beta^t \mathrm{E}_0 \left[\ln C_t \right]$$

where β denotes the agent's subjective discount factor. The consumption-equivalent welfare effect $\mathcal{C}$ is defined as the percent change in consumption, in every state and every period, that is welfare-equivalent to the change in the agent's consumption path. Formally, $\mathcal{C}$ must solve:

$$\sum_{t=0}^{\infty} \mathrm{E}_0 \left[\frac{\beta^t}{C_t} \times C_t \mathcal{C} \right] = \sum_{t=0}^{\infty} \mathrm{E}_0 \left[\frac{\beta^t}{C_t} \times C_t \hat{C}_t \right]$$

$$\implies \left(\sum_{t=0}^{\infty} \beta^t \right) \mathcal{C} = \sum_{t=0}^{\infty} \mathrm{E}_0 \left[\beta^t \hat{C}_t \right]$$

$$\implies \mathcal{C} = (1 - \beta) \sum_{t=0}^{\infty} \mathrm{E}_0 \left[\beta^t \hat{C}_t \right].$$

To conclude the proof, note that, with log-utility, the consumption-to-wealth ratio is equal to $1 - \beta$, and so have $\rho = \beta$. The reason we use the notation ρ rather than β is that ρ is the relevant discount factor in the more general case of Epstein-Zin utilities (see Section B.3). $\qquad \square$

A.4 Proof of Proposition 4

Proposition. *4 Around a baseline path in which the ratio of cash flow to firm value, $r_{ft}V_f/\Pi_{ft}$, is equal to the constant consumption-to-wealth ratio, C_t/W_t, we have:*

$$\hat{\Pi}_{f0} = (1 - \rho) \sum_{t=0}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{r}_{ft} \right] - \sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{ft} \right]$$

Proof. Differentiating the PDV relationship (12) gives

$$
\begin{aligned}
\hat{\Pi}_{f0} &= \frac{1}{\Pi_{f0}}\mathrm{E}_0\left[\sum_{t=0}^{\infty}\frac{r_{ft}V_f}{R_{f1}\ldots R_{ft}}\left(\hat{r}_{ft}-\sum_{s=1}^{t}\hat{R}_{fs}\right)\right]\\
&= \frac{1}{\Pi_{f0}}\mathrm{E}_0\left[\sum_{t=0}^{\infty}\frac{r_{ft}V_f}{R_{f1}\ldots R_{ft}}\hat{r}_{ft}\right]-\frac{1}{\Pi_{f0}}\sum_{t=1}^{\infty}\mathrm{E}_0\left[\left(\sum_{s=t}^{\infty}\frac{r_{fs}V_f}{R_{f1}\ldots R_{fs}}\right)\hat{R}_{ft}\right]\\
&= \frac{1}{\Pi_{f0}}\mathrm{E}_0\left[\sum_{t=0}^{\infty}\frac{r_{ft}V_f}{R_{f1}\ldots R_{ft}}\hat{r}_{ft}\right]-\frac{1}{\Pi_{f0}}\sum_{t=1}^{\infty}\mathrm{E}_0\left[\frac{1}{R_{f1}\ldots R_{ft}}\mathrm{E}_t\left[\sum_{s=t}^{\infty}\frac{r_{fs}V_f}{R_{ft+1}\ldots R_{fs}}\right]\hat{R}_{ft}\right]\\
&= \sum_{t=0}^{\infty}\mathrm{E}_0\left[\frac{r_{ft}V_f}{\Pi_{ft}}\frac{\Pi_{ft}/\Pi_{f0}}{R_{f1}\ldots R_{ft}}\hat{r}_{ft}\right]-\sum_{t=1}^{\infty}\mathrm{E}_0\left[\frac{\Pi_{ft}/\Pi_{f0}}{R_{f1}\ldots R_{ft}}\hat{R}_{ft}\right]
\end{aligned}
$$

where the second line uses the fact that $\Pi_{ft}=\mathrm{E}_t\left[\sum_{s=t}^{\infty}\frac{r_{fs}V_f}{R_{ft+1}\ldots R_{fs}}\right]$, following (12). We then use the assumption that on the baseline path $r_{ft}V_f/\Pi_{ft}$ is constant and equal to C_t/W_t (if not, all of our equalities should be understood as being first-order approximations around this baseline path, as in Campbell and Shiller (1988)).[1] In particular, using the definition of ρ above, we can write $(\Pi_{ft}-r_{ft}V_f)/\Pi_{ft}=\rho$, which implies:

$$
R_{ft+1}=\frac{\Pi_{ft+1}}{\Pi_{ft}-r_{ft}V_f}=\frac{1}{\rho}\frac{\Pi_{ft+1}}{\Pi_{ft}}
$$

Plugging this into the previous equation gives:

$$
\hat{\Pi}_{f0}=(1-\rho)\sum_{t=0}^{\infty}\rho^t\mathrm{E}_0\left[\hat{r}_{ft}\right]-\sum_{t=1}^{\infty}\rho^t\mathrm{E}_0\left[\hat{R}_{ft}\right]
$$

$\square$

B Model Extensions

B.1 Adding Growth

The baseline model that we analyze does not allow for growth, but we can easily change it to a model in which productivity rises by ϕ each period. We demonstrate that the only effect of increasing productivity in this setup is to cause output, wages, and payments to the specific factor to rise by ϕ each period. We do this by showing that if output grows at a rate ϕ and prices do not change, then all factor and product markets will clear, and firms will continue to earn zero profits. We then show that if output grows at a rate ϕ, firms have no incentive to change prices, which means that we have identified an equilibrium. We model growth in our setup by assuming that firm output in each period is given by

$$
y_{ft}=h\left(\phi^t V_f,\phi^t L_{ft},m_{ift}\right),
$$

---

[1]The underlying assumption is that, on the baseline path, consumption growth is i.i.d. and the cash flow of each firm grows at the same rate as aggregate consumption.

where $\phi \geq 1$ is a parameter that determines TFP growth. Since labor and the specific factor are paid the value of their marginal product, we can write the wage and rental rate equations as

$$w_t = \phi^t h_L p_{ft} \quad \text{and} \quad r_{ft} = \phi^t h_V p_{ft}.$$

Thus, if firms do not change their employment levels and prices do not change, we will have $\Delta \ln w_t = \Delta \ln r_{ft} = \phi$. This result implies that real incomes will rise by ϕ, which means that if demand is homothetic and prices do not change, output will rise by ϕ. We also know from Proposition 1 that each firm will continue to employ the same number of workers as in period 0 if wages and rental rates rise by the same amount.

The new factor market clearing conditions in each time period will be

$$\sum_f \frac{a_{Lf0}}{\phi^t} \left(\phi^t y_{f0} \right) = L, \text{ and}$$

$$\frac{a_{Vf0}}{\phi^t} \left(\phi^t y_{f0} \right) = V_f.$$

An important implication of these equations is that if markets clear in period 0, they will also clear in period t.

Finally, we show that an equilibrium featuring no changes in prices from those in period 0 will also satisfy the zero-profit condition. In order to do this, we first show that the unit-input requirement for materials doesn't change because separability of the production function means that

$$a_{ift} = \frac{m_{ift}}{y_{ft}} = \frac{a_{if0} y_{ft}}{y_{ft}} = a_{if0}.$$

One implication of this result is that intermediate input use grows at the same rate as output growth, i.e., $\Delta \ln m_{ift} = \Delta \ln y_{ft} = \phi$. If output in period t is given by $\phi^t y_{ft}$ and prices do not change, then the zero-profit condition (equation 1) can be written as

$$a_{Lft} w_t + a_{Vft} r_{ft} + \sum_i a_{ift} q_{it} = p_{ft}$$

$$\frac{a_{Lf0}}{\phi^t} \left(\phi^t w_0 \right) + \frac{a_{Vf0}}{\phi^t} \left(\phi^t r_{f0} \right) + \sum_i a_{if0} q_{it} = p_{ft}$$

$$a_{Lf0} w_0 + a_{Vf0} r_{f0} + \sum_i a_{if0} q_{it} = p_{ft}.$$

Since we know that these equations hold in period 0, we know that if $q_{it} = q_{i0}$, then $p_{ft} = p_{f0}$. Intermediate input prices will not change if labor and specific factor productivity growth affects all firms equally because intermediate input usage, consumer demand, and supply will all grow at a rate of ϕ.

B.2 Nesting the Neoclassical Static Welfare Effects in Our Setup

The neoclassical welfare effects are based on three additional assumptions: tariff changes are permanent (trivially true in a two-period model); they have no productivity effects (i.e., $\hat{A}_{ft} = \hat{A}_f = 0$); and there are only two periods so, $\hat{p}_{ft}^e = \hat{p}_f^{e\tau}$, and $\hat{r}_{ft} = \hat{r}_f^\tau$, where $\hat{r}_f^\tau$ and

$\hat{p}_f^{e\tau}$ denote the tariff-induced changes in firm cash flow and ERP *under the assumption that tariffs do not affect productivity*. We can see why these assumptions would yield different estimates than those in our setup by starting with equation (11) and noting that the first term in the equation gives us the role that cash flow plays in determining welfare:

$$\mathcal{C}_{\hat{r}} \equiv \sum_f \frac{wL_f + r_f V_f}{C}\left((1-\rho)\sum_{t=0}^{\infty} \rho^t \mathrm{E}_0[\hat{r}_{ft}] \right).$$

We can then use Proposition 2 to rewrite this as

$$\mathcal{C}_{\hat{r}} = \sum_f \frac{wL_f + r_f V_f}{C}\left((1-\rho)\sum_{t=0}^{\infty} \rho^t \mathrm{E}_0\left[\left(\frac{1-\sum_i \omega_{if}}{\omega_{Vf}}\right)\left(\hat{p}_{ft}^e + \frac{\hat{A}_{ft}}{1-\sum_i \omega_{if}}\right) \right] \right)$$

$$- \sum_f \frac{wL_f + r_f V_f}{C}\left(\frac{\omega_{Lf}}{\omega_{Vf}} \sum_f \varphi_f \mathrm{E}_0\left[\left(\hat{p}_{ft}^e + \frac{\hat{A}_{ft}}{1-\sum_i \omega_{if}}\right) \right] \right)$$

We can rewrite this as

$$\mathcal{C}_{\hat{r}} = \sum_f \frac{wL_f + r_f V_f}{C}\left((1-\rho)\sum_{t=0}^{\infty} \rho^t \mathrm{E}_0\left[\left(\frac{1-\sum_i \omega_{if}}{\omega_{Vf}}\right)\left(\hat{p}_{ft}^e + \frac{\hat{A}_{ft}}{1-\sum_i \omega_{if}}\right) \right] \right)$$

$$- \sum_f \frac{wL_f + r_f V_f}{C}\left(\frac{\omega_{Lf}}{\omega_{Vf}} \sum_f \varphi_f \mathrm{E}_0\left[\left(\hat{p}_{ft}^e + \frac{\hat{A}_{ft}}{1-\sum_i \omega_{if}}\right) \right] \right)$$

$$= \sum_f \frac{wL_f + r_f V_f}{C}\left((1-\rho)\sum_{t=0}^{\infty} \rho^t \mathrm{E}_0\left[\left(\frac{1-\sum_i \omega_{if}}{\omega_{Vf}}\right)\hat{p}_{ft}^e - \frac{\omega_{Lf}}{\omega_{Vf}}\sum_f \varphi_f \hat{p}_{ft}^e \right] \right)$$

$$+ \sum_f \frac{wL_f + r_f V_f}{C}\left((1-\rho)\sum_{t=0}^{\infty} \rho^t \mathrm{E}_0\left[\left(\frac{1-\sum_i \omega_{if}}{\omega_{Vf}}\right)\frac{\hat{A}_{ft}}{1-\sum_i \omega_{if}} - \frac{\omega_{Lf}}{\omega_{Vf}}\sum_f \varphi_f \frac{\hat{A}_{ft}}{1-\sum_i \omega_{if}} \right] \right)$$

$$= \sum_f \frac{wL_f + r_f V_f}{C}\left((1-\rho)\sum_{t=0}^{\infty} \rho^t \mathrm{E}_0\left[\left(\left(\frac{1-\sum_i \omega_{if}}{\omega_{Vf}}\right) - \frac{\omega_{Lf}}{\omega_{Vf}}\sum_f \varphi_f \right)\hat{p}_{ft}^e \right] \right)$$

$$+ \sum_f \frac{wL_f + r_f V_f}{C}\left((1-\rho)\sum_{t=0}^{\infty} \rho^t \mathrm{E}_0\left[\left(\left(\frac{1-\sum_i \omega_{if}}{\omega_{Vf}}\right) - \frac{\omega_{Lf}}{\omega_{Vf}}\sum_f \varphi_f \right)\frac{\hat{A}_{ft}}{1-\sum_i \omega_{if}} \right] \right)$$

$$= \sum_f \frac{wL_f + r_f V_f}{C}\left(\left(\frac{1-\sum_i \omega_{if}}{\omega_{Vf}}\right) - \frac{\omega_{Lf}}{\omega_{Vf}} \right)\left((1-\rho)\sum_{t=0}^{\infty} \rho^t \mathrm{E}_0\left[\hat{p}_{ft}^e \right] \right)$$

$$+ \sum_f \frac{wL_f + r_f V_f}{C}\left(\left(\frac{1-\sum_i \omega_{if}}{\omega_{Vf}}\right) - \frac{\omega_{Lf}}{\omega_{Vf}} \right)\left((1-\rho)\sum_{t=0}^{\infty} \rho^t \mathrm{E}_0\left[\frac{\hat{A}_{ft}}{1-\sum_i \omega_{if}} \right] \right)$$

$$= \sum_f \frac{wL_f + r_f V_f}{C}\left((1-\rho)\sum_{t=0}^{\infty} \rho^t \mathrm{E}_0\left[\hat{p}_{ft}^e \right] \right) + \sum_f \frac{wL_f + r_f V_f}{C}\left((1-\rho)\sum_{t=0}^{\infty} \rho^t \mathrm{E}_0\left[\frac{\hat{A}_{ft}}{1-\sum_i \omega_{if}} \right] \right)$$

where we use the fact that $\sum_f \varphi_f = 1$ to move from second line to the third line, and $\omega_{Vf} = 1 - \sum_i \omega_{if} - \omega_{Lf}$ to move from the third line to the fourth line. We can rewrite this

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equation as

$$\mathcal{C}_{\hat{r}} = \sum_f \frac{wL_f + r_f V_f}{C} \hat{p}_{f0}^e$$

$$+ \sum_f \frac{wL_f + r_f V_f}{C} \left(\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{p}_{ft}^e - \hat{p}_{ft-1}^e \right] \right)$$

$$+ \sum_f \frac{wL_f + r_f V_f}{C} \left((1-\rho) \sum_{t=0}^{\infty} \rho^t \mathrm{E}_0 \left[\frac{\hat{A}_{ft}}{1 - \sum_i \omega_{if}} \right] \right).$$

which proves (23).

B.3 Welfare with Epstein-Zin Preferences

In the main text, we derive an expression for the consumption-equivalent welfare effect of a deviation path for an agent with log utility. We now generalize this expression for a representative agent with Epstein-Zin preferences. The key takeaway of this section is that, when the agent's risk aversion differs from one, the welfare effect depends not only on the effect of the policy on expected log consumption (as in the log utility case) but also on the effect of the policy on higher-order cumulants of log consumption.

We first prove the following lemma which expresses the consumption-equivalent welfare effect in terms of the household's stochastic discount factor for arbitrary preferences.

Lemma 1. *The consumption-equivalent welfare effect of the deviation path* $(\hat{C}_t)_{t=0}^{\infty}$ *is*

$$\mathcal{C} = \frac{\sum_{t=0}^{\infty} \mathrm{E}_0 \left[M_{0 \to t} C_t \hat{C}_t \right]}{\sum_{t=0}^{\infty} \mathrm{E}_0 \left[M_{0 \to t} C_t \right]},$$

where $M_{0 \to t}$ *denotes the household's Stochastic Discount Factor (SDF).*

Proof. Denote $\mathcal{W}_0$ the welfare of the household at time t. Totally differentiating with respect to the deviation path for consumption $(\hat{C}_t)_{t=0}^{\infty}$ gives:

$$d\mathcal{W}_0 = \mathrm{E}_0 \left[\sum_{t=0}^{\infty} \frac{\partial \mathcal{W}_0}{\partial C_t} C_t \hat{C}_t \right].$$

where $\partial \mathcal{W}_0 / \partial C_t$, a stochastic derivative, corresponds to the effect of increasing consumption in states realized at time t for welfare at time 0.

The consumption-metric welfare effect $\mathcal{C}$ is defined as the constant log deviation of consumption that yields the same welfare change; that is

$$\mathrm{E}_0 \left[\sum_{t=0}^{\infty} \frac{\partial \mathcal{W}_0}{\partial C_t} C_t \mathcal{C} \right] = \mathrm{E}_0 \left[\sum_{t=0}^{\infty} \frac{\partial \mathcal{W}_0}{\partial C_t} C_t \hat{C}_t \right].$$

Solving for $\mathcal{C}$ gives:

$$\mathcal{C} = \frac{\mathrm{E}_0 \left[\sum_{t=0}^{\infty} \frac{\partial \mathcal{W}_0}{\partial C_t} C_t \hat{C}_t \right]}{\mathrm{E}_0 \left[\sum_{t=0}^{\infty} \frac{\partial \mathcal{W}_0}{\partial C_t} C_t \right]}.$$

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To conclude, notice that, for any available asset i with return $R_{i,0\to t}$ between 0 and t, an optimizing agent must be indifferent between consuming a bit more today and investing a bit more in asset i between 0 and t, which implies

$$\frac{\partial \mathcal{W}_0}{\partial C_0} = \mathrm{E}_t\left[\frac{\partial \mathcal{W}_0}{\partial C_t} R_{i,0\to t}\right].$$

Hence, $\frac{\partial \mathcal{W}_0/\partial C_t}{\partial \mathcal{W}_0/\partial C_0}$ corresponds to the household's SDF, $M_{0\to t}$, and dividing the numerator and denominator of our expression for $\mathcal{C}$ proves the lemma. $\qquad\square$

We now consider the case where the representative agent has Epstein-Zin preferences. Formally, the value function of the agent is defined recursively as follows:

$$\mathcal{W}_t = \left((1-\beta)\frac{C_t^{1-1/\psi}}{1-1/\psi} + \beta\left(\mathrm{E}_t\left[\mathcal{W}_{t+1}^{1-\gamma}\right]^{\frac{1}{1-\gamma}}\right)^{1-1/\psi}\right)^{\frac{1}{1-1/\psi}}.$$

where β is the subjective discount factor (SDR); γ determines the agent's relative risk aversion (RRA); and ψ is the elasticity of intertemporal substitution (EIS). The log utility case discussed in the main text corresponds to $\psi = \gamma = 1$. We also assume that log consumption growth is i.i.d. on the baseline path, which, as proved below, implies that the consumption-to-wealth ratio is constant on the baseline path. If this assumption is not satisfied, the proposition below should be understood as a first-order approximation that is valid as long as the baseline path is close to this balanced growth path.

Proposition 5. *For an agent with arbitrary Epstein-Zin preferences, the consumption-equivalent welfare effect of the deviation path $(\hat{C}_t)_{t=0}^{\infty}$ is*

$$\mathcal{C} = (1-\rho)\sum_{t=0}^{\infty}\rho^t\mathrm{E}_0\left[\frac{C_t^{1-\gamma}}{\mathrm{E}_0\left[C_t^{1-\gamma}\right]}\hat{C}_t\right],$$

where $\rho \equiv 1 - C_t/W_t$ denotes the consumption-to-wealth ratio and γ denotes the agent's relative risk aversion (RRA).

Proof. Denote $M_{t\to t+k}$ the household SDF between t and $t+k$ and $W_t = \mathrm{E}_t[\sum_{k=0}^{\infty} M_{t\to t+k}C_{t+k}]$ the PDV of consumption (or, equivalently, total wealth). As shown, for instance, in Martin (2013), a household with Epstein-Zin preferences has an SDF of the form:

$$M_{t\to t+k} = \left(\beta^k\left(\frac{C_{t+k}}{C_t}\right)^{-1/\psi}\right)^{\theta}\left(R_{W,t\to t+k}^{-1}\right)^{1-\theta}, \tag{B1}$$

where $\theta \equiv (1-\gamma)/(1-1/\psi)$ and $R_{W,t+1} \equiv \frac{W_{t+1}}{W_t-C_t}$ denotes the return on the wealth portfolio between t and $t+1$ and $R_{W,t\to t+k} = R_{W,t+1}\ldots R_{W,t+k}$ denotes the cumulative return on the wealth portfolio between t and $t+k$. In the special case where $\psi = 1/\gamma$ (separable preferences), equation (B1) gives the familiar expression $M_{t\to t+k} = \beta^k\left(C_{t+k}/C_t\right)^{-\gamma}$.

This expression for the SDF can be simplified when log consumption is i.i.d (which is the case on the baseline path). Indeed, in this case, we can guess (and verify later) that the consumption-to-wealth ratio is constant over time, in which case the return on the wealth portfolio simplifies to:

$$
\begin{aligned}
R_{W,t+1} &= \frac{W_{t+1}}{W_t - C_t} \\
&= \frac{W_t}{W_t - C_t} \times \frac{W_{t+1}}{W_t} \\
&= \frac{1}{\rho} \frac{C_{t+1}}{C_t},
\end{aligned}
$$

where the last line uses the definition of $\rho \equiv 1 - C_t/W_t$. Combining with (B1) allows us to simplify the expression for the SDF along the baseline path:

$$
\begin{aligned}
M_{t \to t+k} &= \left(\beta^k \left(\frac{C_{t+k}}{C_t} \right)^{-1/\psi} \right)^\theta \left(\rho^k \frac{C_t}{C_{t+k}} \right)^{1-\theta} \\
&= \beta^{\theta k} \rho^{(1-\theta)k} \left(\frac{C_{t+k}}{C_t} \right)^{-\gamma},
\end{aligned} \tag{B2}
$$

where the second line uses the fact that $\theta(1 - 1/\psi) = (1 - \gamma)$. We now verify that the consumption-to-wealth ratio is indeed constant along the baseline path. Using the definition of total wealth, we get

$$
\begin{aligned}
W_t &= E_t \left[\sum_{k=0}^{\infty} M_{t \to t+k} C_{t+k} \right] \\
&= C_t \sum_{k=0}^{\infty} \beta^{\theta k} \rho^{(1-\theta)k} E_t \left[\left(\frac{C_{t+k}}{C_t} \right)^{1-\gamma} \right] \\
&= C_t \sum_{k=0}^{\infty} \beta^{\theta k} \rho^{(1-\theta)k} E_t \left[\left(\frac{C_{t+k}}{C_{t+k-1}} \right)^{1-\gamma} \left(\frac{C_{t+k-1}}{C_{t+k-2}} \right)^{1-\gamma} \cdots \left(\frac{C_{t+1}}{C_t} \right)^{1-\gamma} \right] \\
&= C_t \sum_{k=0}^{\infty} \beta^{\theta k} \rho^{(1-\theta)k} E_t \left[\left(\frac{C_{t+k}}{C_{t+k-1}} \right)^{1-\gamma} \right] E_t \left[\left(\frac{C_{t+k-1}}{C_{t+k-2}} \right)^{1-\gamma} \right] \cdots E_t \left[\left(\frac{C_{t+1}}{C_t} \right)^{1-\gamma} \right] \\
&= C_t \sum_{k=0}^{\infty} \beta^{\theta k} \rho^{(1-\theta)k} E_0 \left[\left(\frac{C_1}{C_0} \right)^{1-\gamma} \right]^k \\
&= C_t \sum_{k=0}^{\infty} \left(\beta^\theta \rho^{1-\theta} E_0 \left[\left(\frac{C_1}{C_0} \right)^{1-\gamma} \right] \right)^k \\
&= C_t \frac{1}{1 - \beta^\theta \rho^{1-\theta} E_0 \left[\left(\frac{C_1}{C_0} \right)^{1-\gamma} \right]},
\end{aligned}
$$

where the fourth and fifth lines use the fact that consumption growth is independently and identically distributed across periods along the baseline path and the last line uses

the formula for the infinite sum of a geometric sequence. Hence, we have proven that the wealth-to-consumption ratio W_t/C_t is constant along the baseline path.

Finally, we can combine this equation with the definition of $\rho = 1 - C_t/W_t$ to solve for ρ in terms of the household preferences and of the distribution of consumption growth:

$$\rho = \beta^\theta \rho^{(1-\theta)} E_0 \left[\left(\frac{C_1}{C_0} \right)^{1-\gamma} \right]$$

$$\implies \rho = \beta E_0 \left[\left(\frac{C_1}{C_0} \right)^{1-\gamma} \right]^{\frac{1}{\theta}}.$$

Plugging this into (B2) gives a simplified expression for the SDF along the baseline path:

$$M_{0 \to t} = \beta^t \left(\frac{C_t}{C_0} \right)^{-\gamma} E_0 \left[\left(\frac{C_t}{C_0} \right)^{1-\gamma} \right]^{1/\theta - 1}$$

$$= \rho^t \frac{\left(\frac{C_t}{C_0} \right)^{-\gamma}}{E_0 \left[\left(\frac{C_t}{C_0} \right)^{1-\gamma} \right]}.$$

Combining this formula for the SDF with the expression for the welfare effect $\mathcal{C}$ obtained in Lemma 1 gives:

$$\mathcal{C} = \frac{\sum_{t=0}^{\infty} E_0 \left[\rho^t \frac{\left(\frac{C_t}{C_0} \right)^{1-\gamma}}{E_t \left[\left(\frac{C_t}{C_0} \right)^{1-\gamma} \right]} \hat{C}_t \right]}{\sum_{t=0}^{\infty} E_0 \left[\rho^t \frac{\left(\frac{C_t}{C_0} \right)^{1-\gamma}}{E_0 \left[\left(\frac{C_t}{C_0} \right)^{1-\gamma} \right]} \right]}$$

$$= (1 - \rho) \sum_{t=0}^{\infty} \rho^t E_0 \left[\frac{\left(\frac{C_t}{C_0} \right)^{1-\gamma}}{E_0 \left[\left(\frac{C_t}{C_0} \right)^{1-\gamma} \right]} \hat{C}_t \right],$$

where the second line obtains after simplifying the denominator in the first line to $\sum_{t=0}^{\infty} \rho^t = 1/(1-\rho)$. $\qquad \square$

This proposition generalizes Proposition 3 stated in the main text, which corresponds to the special case of log utility $\gamma = \psi = 1$. With general Epstein-Zin preferences, the consumption-equivalent welfare effect $\mathcal{C}$ can be expressed as a time-discounted, weighted average of the deviations in log consumption. The first set of weights, $(1-\rho)\rho^t$, adjusts for the agent's discounting over time (they sum to one across time) while the weights $\frac{C_t^{1-\gamma}}{E_0[C_t^{1-\gamma}]}$ represent the agent's discounting of different states of nature (they sum up to one across states of nature in a given period).

To better understand the effect of general Epstein-Zin preferences for welfare, note that we can rewrite the consumption-equivalent welfare effect $\mathcal{C}$ as the sum of two terms:

$$\mathcal{C} = (1-\rho) \sum_{t=0}^{\infty} \rho^t \mathrm{E}_0\left[\hat{C}_t\right] + (1-\rho) \sum_{t=1}^{\infty} \rho^t \mathrm{cov}_0\left(\frac{C_t^{1-\gamma}}{\mathrm{E}_0\left[C_t^{1-\gamma}\right]}, \hat{C}_t\right). \tag{B3}$$

The first term corresponds to the welfare effect for an agent with log utility (the one discussed in Proposition 3). The second term corresponds to the normalized covariance of $C_t^{1-\gamma}$ and changes in log consumption. This second term is zero if $\gamma = 1$ (e.g., log utility) or if deviations in log consumption are independent of the realization of consumption along the baseline path. The following corollary expresses this second term as the sum of deviations in the higher-order cumulants of log consumption.

Corollary 1. *For an agent with arbitrary Epstein-Zin preferences, the consumption-equivalent welfare effect of the deviation path $(\hat{C}_t)_{t=0}^{\infty}$ is*

$$
\begin{aligned}
\mathcal{C} = & (1-\rho) \sum_{t=0}^{\infty} \rho^t \mathrm{E}_0\left[\hat{C}_t\right] \\
& + \frac{1-\gamma}{2} \sum_{t=1}^{\infty} (1-\rho)\rho^t d\left(\mathrm{Var}_0 \ln C_t]\right) \\
& + \frac{(1-\gamma)^2}{3!} \sum_{t=1}^{\infty} (1-\rho)\rho^t d\left(\textit{Skewness}_t[\ln C_t] \cdot \mathrm{Var}_0[\ln C_t]^{3/2}\right) \\
& + \frac{(1-\gamma)^3}{4!} \sum_{t=1}^{\infty} (1-\rho)\rho^t d\left(\textit{Excess Kurtosis}_0[\ln C_t] \cdot \mathrm{Var}_0[\ln C_t]^2\right) \\
& + \ldots
\end{aligned}
$$

When the representative agent has a risk aversion different from one, the consumption-equivalent welfare effect depends not only on the change in expected log average consumption, but also on the change in the higher-order cumulants of log consumption, such as its variance, skewness, and kurtosis. In particular, if $\gamma > 1$, the representative agent is more risk averse than log utility and dislikes increases in even cumulants of log consumption (e.g., variance or kurtosis) while enjoying increases in odd cumulants (e.g., skewness). The converse is true if $\gamma < 1$. One implication is that, if agents have greater risk aversion (i.e., $\gamma > 1$), and if tariffs increase the even cumulants of log consumption (like variance) or decrease odd cumulants (like skewness), then our baseline welfare effect, which corresponds to the first-term in on the right-hand side, will underestimate the full welfare loss.

Proof. First, note that one can rewrite the expression for welfare given in Proposition 3 as:

$$\mathcal{C} = (1-\rho) \sum_{t=0}^{\infty} \rho^t \frac{d \ln \mathrm{E}_0\left[C_t^{1-\gamma}\right]}{1-\gamma}.$$

The *cumulant-generating function* (CGF) of a random variable g is defined as the function $\theta \to \ln \mathrm{E}\left[e^{\theta g}\right]$. It is well known that the CGF can be expanded as a power series in θ:

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$$\ln \mathrm{E}\left[e^{\theta g}\right] = \sum_{l=1}^{\infty} \frac{\theta^l}{l!} \kappa_l,$$

where κ_l corresponds to the the l-th *cumulant* of the variable g. In particular, the first cumulant corresponds to the mean of g and the second cumulant corresponds to its variance. Applying this definition with $g = \ln C_t$ and $\theta = 1 - \gamma$ gives:

$$\ln \mathrm{E}_0\left[C_t^{1-\gamma}\right] = \sum_{l=1}^{\infty} \frac{(1-\gamma)^l}{l!} \kappa_{l,0\to t},$$

where $\kappa_{l,0\to t}$ denotes the l-th cumulant of log consumption at time t from the point of view of time 0. Combining the last two equations gives:

$$
\begin{aligned}
\mathcal{C} &= (1-\rho) \sum_{t=0}^{\infty} \rho^t \frac{1}{1-\gamma} \sum_{l=1}^{\infty} \frac{(1-\gamma)^l}{l!} d\kappa_{l,0\to t} \\
&= (1-\rho) \sum_{t=0}^{\infty} \rho^t d\kappa_{1,0\to t} + (1-\rho) \sum_{t=0}^{\infty} \rho^t \frac{1}{1-\gamma} \sum_{l=2}^{\infty} \frac{(1-\gamma)^l}{l!} d\kappa_{l,0\to t} \\
&= (1-\rho) \sum_{t=0}^{\infty} \rho^t \mathrm{E}_0\left[\hat{C}_t\right] + (1-\rho) \sum_{t=1}^{\infty} \rho^k \sum_{l\geq 2} \frac{(1-\gamma)^{l-1}}{l!} d\kappa_{l,0\to t},
\end{aligned}
$$

where the last line uses the fact that the deviation of the average log consumption (its first cumulant) can be written as the average deviation of log consumption. To conclude, simply replace the first four cumulants using the definition of variance, skewness, and excess kurtosis. □

C Data and Measurement

C.1 Event Dates

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

Table C.1: Details on Event Dates

Event Date	Implementation Date	Country	News Link
23jan2018*	07feb2018	US	Washington Post
01mar2018*	23mar2018	US	Reuters
22mar2018	06jul2018	US	NYT
23mar2018	02apr2018	China	CNBC
15jun2018	06jul2018	China	NPR
19jun2018	24sep2018	US	WSJ
02aug2018	24sep2018	China	Reuters
06may2019**	15jun2019	US	DW
13may2019	01jun2019	China	CNBC
01aug2019	01sep2019	US	CNBC
23aug2019	01sep2019	China	CNBC

Note: Event dates with the first news release on a weekday after trading hours (4:00 PM EST) are flagged by an asterisk (*). Event dates with the first news release on a weekend are flagged by two asterisks (**). In these instances, the trading day for the event is the first trading day after the news release, which is listed as the event date in the table.

C.2 Summary of Data Sources

Table C.2: Summary of Data Sources

Variable	Construction
Book Leverage	*Source: CRSP-Compustat Annual Merged Dataset (2017)* Book leverage is total debt including current [**dt**] *divided by* assets (total) [**at**], **dt**/**at**.
Cash Flow to Asset Ratio	*Source: CRSP-Compustat Annual Merged Dataset (2017)* The Cash Flow-to-Asset Ratio is operating income after depreciation [**oiadp**] *plus* interest and related expense (total) [**xintq**] *all divided by* assets (total) [**at**]; (**oiadp** + **xintq**)/**at**.

Variable	Construction
China Revenue Share	*Source: FactSet Geographic Revenue Exposure (2017)* These data report revenue shares from major markets (including China) for 3,134 firms (identified by PERMNO). If we cannot match a firm to this dataset, we try to match using tickers. If we cannot match a firm using either PEMRNO or the ticker to one in the Datamyne dataset, we assume that its China revenue share is zero. More details are provided in Section C.3.
China Importer/ Exporter	*Source: Datamyne dataset of the value and quantity of exports to and imports from China (via sea) by U.S. firms in 2017, Supply chain data from Capital IQ* We combine the Datamyne dataset with supply chain data to determine whether each firm imported from or exported to China (via sea) in 2017 either directly or through a subsidiary/supplier. Refer to Section C.3 for details on variable construction.

Variable	Construction
Economic Surprise Variables (ES_t)	*Source: Daniel Lewis based on Lewis et al. (2019)*
	The difference between a macroeconomic data release value and the Bloomberg median of economists' forecast on the previous day. The 65 series we use to construct our economic surprise variables are ISM manufacturing, ISM non-manufacturing, ISM prices, construction spending, durable goods new orders, factory orders, initial jobless claims, ADP payroll employment, non-farm payrolls, unemployment rate, total job openings, consumer credit, non-farm productivity, unit labor costs, retail sales, retail sales less auto, federal budget balance, trade balance, import price index, building permits, housing starts, industrial production, capacity utilization, business inventories, Michigan consumer sentiment, PPI core, PPI, CPI core, CPI, Empire State manufacturing index, Philadelphia Fed BOS, GDP (advance estimate), GDP (second estimate), GDP price index, personal income, personal spending, PCE price index, core PCE price index, wholesale inventories, new home sales, CB consumer confidence, leading economic index, employment cost index, Wards total vehicle sales, continuing claims retail sales ex auto and gas, NAHB housing market index, change in manufacturing 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.
Equity-Premium Bound (EPB_t)	*Source: OptionMetrics, dataset with prices of actively traded option on the S&P 500 (ticker SPX)*
	We follow Martin (2017) method for constructing EPB_t.

Variable	Construction
Firm	*Source: CRSP-Compustat Annual Merged Dataset (2017)* A firm is defined by its Compustat Global Company Key or GVKEY. In our sample, the GVKEY codes map one-to-one to the unique identifier and permanent identifier to security or PERMNO in CRSP. As such, we are able to use PERMNO (`permno`) and GVKEY (`gvkey`) interchangeably across datasets.
Firm Employment L_f	*Source: CRSP-Compustat Annual Merged Dataset (2017)* The employment variable in Compustat [`emp`] includes the following items: all part-time and seasonal employees; and all employees of consolidated subsidiaries, both domestic and foreign. The employment variable excludes consultants, contract workers, and employees of unconsolidated subsidiaries.
Firm Returns ($\ln R_{ft}$)	*Source: CRSP U.S. Stock Database* We define log firm returns as the *log* of one *plus* net returns [`ret`]; $\ln(1 + \texttt{ret})$.
Labor and Specific Factor Shares (θ_{Lf} and θ_{Vf})	*Source: Compustat and BEA Input-Output table* Firm cash flow as a share of revenue is calculated by dividing accounting cash flows with gross sales [`sale`] in 2017, obtained from Compustat. We use the BEA's 450-by-450 industry (6-digit NAICS) IO table in 2012 to construct labor and materials shares of revenue. In Section C.3, we describe how we combine all of these shares to construct the labor and specific factor shares of value added (θ_{Lf} and θ_{Vf}).

Variable	Construction
Ratio Between Market Value of Equity and Market Value of Assets κ_f	*Source: CRSP-Compustat Annual Merged Dataset (2017)* κ_f is defined as the ratio between the market value of equity and the market value of total assets (equity + debt). The market value of equity (or market capitalization) is defined below. The market value of assets is the sum of the market value of equity and the value of debt, constructed as total assets [**at**] *minus* stockholder equity [**seq**] *minus* cash and short-term investments [**che**]; $\mathbf{at} - \mathbf{seq} - \mathbf{che}$. If cash and short-term investments is missing, we replace it with zero. Finally, we winsorize κ_f to be between 0.1 and 1.0.
Market Value of Equity	*Source: CRSP-Compustat Annual Merged Dataset (2017)* We use the 2017 Market Value of Equity of a firm is [**mkval**]. When this variable is unavailable we use the *product of* annual price close (fiscal) [**prcc_f**] *and* common shares outstanding [**csho**]; $\mathbf{prcc\_f} \times \mathbf{csho}$.
Profit	*Source: CRSP-Compustat Annual Merged Dataset (2017)* Profit is "operating income after depreciation" [**oiadp**] *minus* "interest and related expense (total)" [**xint**]; $\mathbf{oiadp} - \mathbf{xint}$.
Property, Plant, and Equipment (PPE) per worker	*Source: CRSP-Compustat Annual Merged Dataset (2017)* PPE per worker is property, plant, and equipment (gross total) [**ppegt**] *divided by* employees [**emp**]; $\mathbf{ppegt}/\mathbf{emp}$.

Variable	Construction
Treasury Yield (1- to 30-Month Maturity)	**1. Maturity: 3, 4, and 12 months** *Source: Board of Governors of the Federal Reserve System, {3-Month, 6-Month, 1-Year} Treasury Bill Secondary Market Rate, Discount Basis; retrieved from FRED, Federal Reserve Bank of St. Louis*
	We obtain the nominal yields with the following maturities from FRED: 3-Month [**DTB3**], 6-Month [**DTB6**], and 12-Month [**DTB1YR**].
	2. Maturity: all remaining maturities up to 30 months *Source: daily US yield curve data up to 2019 dataset from Gürkaynak et al. (2007); dataset retrieved from Refet Gürkaynak's website*
	The US yield curve dataset was published alongside Gürkaynak et al. (2007) and is updated regularly. At the time of writing, the dataset reports nominal and real yields up until October 25, 2019, at different monthly maturities ranging from one to thirty months. Nominal yields in the paper refers to "Zero-Coupon Yield (Continuously Compounded)" [**SVNY***xx*].
Real Yields (1- to 30-Month Maturity)	*Source: daily US TIPS curve data up to 2019 dataset from Gürkaynak et al. (2010); dataset retrieved from Refet Gürkaynak's website*
	The US yield curve dataset was published alongside Gürkaynak et al. (2010) and is updated regularly (data up to 10/25/2019). Real yields is "TIPS Yield Zero Coupon (Continuously Compounded)" [**TIPSY***xx*].
Tobin's Q	*Source: CRSP-Compustat Annual Merged Dataset (2017)*
	Tobin's Q is market capitalization *plus* book value of total assets [**at**] *minus* book value of common equity [**ceq**], *all divided* by the book value of total assets [**at**].
U.S. Import Value	*Source: U.S. Census Bureau*
	We obtain 2017 U.S. import values for each good (HTS10) and exporting country from the U.S. Census Bureau.

Variable	Construction
U.S. Tariff Rates	*Source: U.S. Trade Representative (USTR), and U.S. International Trade Commission (USITC).*
	In the paper, the tariff rate in year y for an HS10 product and exporting country refers to the tariff rate in effect in December of year y. We use the December 2017 and 2019 tariff rates applied to each product (HTS10) and exporting country.
U.S. Firm-size Distribution (Goods and Services)	*Source: U.S. Census Bureau, "Number of Firms, Number of Establishments, Employment, and Annual Payroll by Small/Large Enterprise Employment Sizes for the United States and States, NAICS Sectors: 2017" dataset*
	The dataset reports reports the number of employees by sector (NAICS2) and employment bin.

C.3 Construction of China-Exposure Variables

We consider three ways in which firms were 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. 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 2017 (either obtained through sales of subsidiaries or exports) that arise from sales in China, as reported in FactSet.

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, use a binary exposure measure. Our "China Import" dummy is one if the firm or its supply network imported from China in 2017 and zero otherwise. We also construct a "China Export" dummy analogously

for exports. Second, the Datamyne data only 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.

China Revenue Share   The China revenue share variable is from FactSet. There are two potential issues we note. First, firms sometimes report geographic revenue shares for more aggregated geographies than countries (e.g., Asia/Pacific). In these cases, FactSet imputes the undisclosed revenue share for a country using that country's GDP weight within a more aggregate geographic unit for which the data are disclosed (e.g., China's GDP share within Asia/Pacific region). FactSet provides a confidence factor that ranges from 0.5 to 1, with 1 indicating no imputation. Fortunately, within our sample of firms, the mean confidence factor for the China revenue share is 0.996 with a range of 0.98 to 1, and our China revenue share variable comes mostly from direct disclosures.

Table C.4: Descriptive Statistics

	N	Mean	SD	p25	p50	p75
Ratio of Equity to Total Assets κ	3,463	0.65	0.30	0.43	0.71	0.94
China Importer Dummy	2,437	0.31	0.46	0.00	0.00	1.00
China Exporter Dummy	2,437	0.04	0.20	0.00	0.00	0.00
China Revenue Share	2,437	0.03	0.07	0.00	0.00	0.02

Note: The China Importer and China Exporter dummies equal 1 for firms that import or export to China. China Revenue Share is the share of a firm's revenues that come from China.

D   Details on Reweighting the Compustat-CRSP Sample

We now detail how we reweight the sample of firms in our Compustat-CRSP sample to approximate the distribution of firms in the U.S. across sectors and employment size. We first describe the method used in our baseline results, which uses a non-parametric approach. We then describe an alternative method, used as a robustness exercise, that uses a more parametric approach with a finer employment grid.

D.1   Baseline Method

We start by dividing the set of firms in our sample into 18 industries (defined by their first 2-digit NAICS code) and four employment bins (0-500, 501-5,000, 5,001-20,000, 20,001+). For the 2-digit NAICS industries 11 (agriculture), 61 (education), 62 (health care), and 81 (other services), we only use two employment bins, below or above 20000, to ensure that there are enough firms within each bin.

We compute the average deviation in firm value in sector s and employment bin b for event j as:

$$\hat{\Pi}_{sb0}^{j} \equiv \sum_{f' \in \Omega_{sbj}} \frac{L_f}{\sum_{f' \in \Omega_{sbj}} L_{f'}} \Pi_{f0}^{j}.$$

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where Ω_{sbj} denotes the set of firms in industry sector s and employment bin b with a non-missing return on event j and Π^j_{f0} denotes the change in firm value over the day in which event j happens. We then compute the overall deviation in firm value in sector s and employment bin b as the sum of the average deviation on all tariff-announcement days j in our sample

$$\hat{\Pi}_{sb0} \equiv \sum_{j=1}^{J} \hat{\Pi}^j_{sb0}.$$

The average deviation in firm value in sector s is given by

$$\hat{\Pi}_{s0} \equiv \sum_{b \in \Omega^B_s} \frac{L_{sb}}{\sum_{b' \in \Omega^B_s} L_{sb'}} \hat{\Pi}_{sb0},$$

where Ω^B_s is the set of employment bins b in sector s and L_{sb} denotes the overall employment in bin b and sector s in the U.S. economy, provided by the Statistics of U.S. Businesses (SUSB, U.S. Census Bureau). As a final step, we compute the overall deviation in firm value for the whole economy as

$$\hat{\Pi}_0 \equiv \sum_{s \in \Omega^S} \frac{VA_s}{C} \hat{\Pi}_{s0},$$

where Ω^S denotes the set of sectors, VA_s is the value added of sector s and C is personal consumption expenditures, all obtained from the BEA.

D.2 Alternative Method

Under this alternative methodology, we divide the set of firms in our sample into 18 industries (defined by their first 2-digit NAICS code) and a finer grid of ten employment bins (defined by nine employment thresholds 500, 750, 1000, 1500, 2000, 2500, 5000, 10000, and 20000). With this finer employment grid, some {sector s, employment bin b, announcement j} cells have zero or very few firms. To handle this issue, we first regress, within each event and sector, the deviation in firm value on log employment and log employment squared. We then use the predicted values from this regression to construct the average deviation in firm value for each {sector s, employment bin b, announcement j} cell. The final step is similar to the previous method: we obtain the overall deviation in firm value in the economy by taking an employment-weighted average within each sector, and then a value-added weighted average across sectors.

E Details on Estimating Changes in Discount Rates

E.1 Stylized Facts

In Table 1, we reported stock-market returns event-by-event. In the same spirit. Appendix Table E.1 reports the change in nominal yields, real yields, and in the equity-premium bound event-by-event. This shows that our results are not driven by some outlier event: almost all announcements tend to decrease real yields and increase the equity-premium bound.

## Table E.1: Change in Discount Rates on Tariff-Announcement Days

Event Date	Δ T-Bill (3m) (x100)	Δ Nominal Yields (10y) (x100)	Δ Real Yields (10y) (x100)	Δ EPB (12m) (x100)
23jan2018	-0.01	-0.03	-0.03	0.02
01mar2018	-0.03	-0.06	-0.04	0.23
22mar2018	-0.02	-0.07	-0.05	0.35
23mar2018	0.02	-0.00	0.00	0.29
15jun2018	0.00	-0.01	-0.02	0.07
19jun2018	0.00	-0.03	-0.03	0.10
02aug2018	-0.01	-0.02	-0.01	-0.04
06may2019	0.01	-0.03	-0.03	0.11
13may2019	-0.02	-0.07	-0.04	0.29
01aug2019	-0.01	-0.13	-0.05	0.12
23aug2019	-0.03	-0.09	-0.08	0.45
Cumulative	-0.10	-0.54	-0.36	1.98

Note: The table reports the daily change in each variable on each announcement day. We obtain the daily yield-to-maturity on 3-month T-Bill from FRED, the daily nominal and real yield-to-maturity on 10-year Treasuries from Gürkaynak et al. (2007), and the daily equity-premium bound from OptionMetrics, using the methodology of Martin (2017).

In Figure 1, we reported the dynamic effect of announcements on stock-market returns over a five-day window. In the same spirit, Appendix Figure E.1 reports the dynamic effect of announcements on the change in nominal yields, real yields, and the equity-premium bound over a five-day window. This figure shows that the change in these variables is concentrated on the days of the announcements, which supports the notion that a one-day window is long enough to capture the overall effect of announcements.

Figure E.1: The Dynamics of Discount Rates around Tariff Announcements
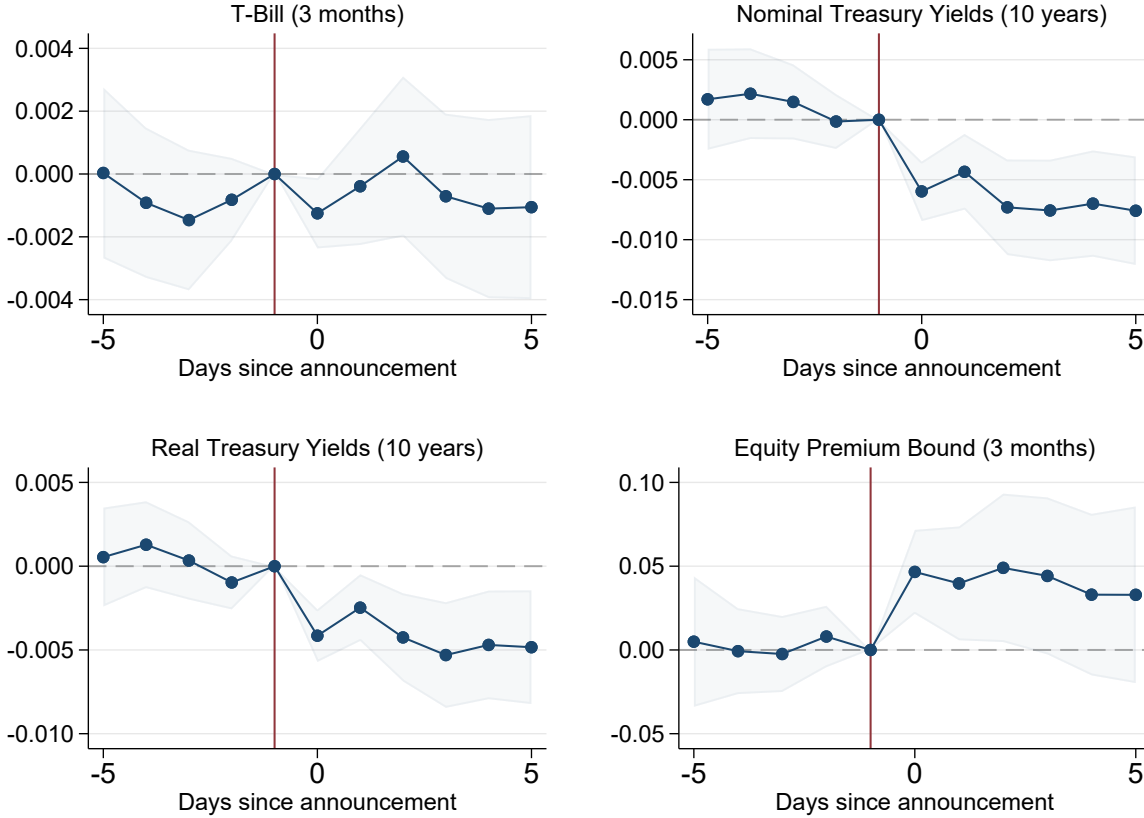
Note: This figure plots the cumulative change in each variable from the day before the announcement. Formally, we estimate the following regression on all trading days between 2017 and 2019: $\Delta Y_t = \alpha + \sum_{s=-4}^{5} \beta_s D_{s,t} + \sum_{d=1}^{D} \gamma_d \times ES_{d,t} + \epsilon_t$, where $D_{s,t} = 1$ if day t is s days after an announcement; $D_{s,t} = 0$ otherwise and $ES_{d,t}$ denotes the surprise in macroeconomic releases. We then plot the cumulative change in Y_t from the eve of the announcement to the horizon s as $11 \sum_{k=s+1}^{-1} \hat{\beta}_k$ if $s < -1$ and $11 \sum_{k=0}^{s} \hat{\beta}_k$ if $s > -1$. Shaded areas correspond to the 95 percent confidence interval computed using robust standard errors.

E.2 VAR

We now describe more precisely how we construct the set of variables used in the VAR discussed in (19). The log risk-free rate $\ln R_{\text{risk-free},t}$, corresponds to the annualized yield of 3-month T-Bills (DTB3 in FRED) minus the growth of the CPI price index (CPIAUCSL in FRED) in the previous year. The excess market return $\ln R_{EM,t}$ corresponds to the log return of CRSP value-weighted stock market minus the risk-free rate implied by the yield of 3-month T-Bills. The term spread TS is the annualized yield-to-maturity of ten-year treasuries (SVENY10 in Gürkaynak et al. (2007)) minus the annualized yield of 3-month T-Bills. The equity-premium bound corresponds to the annualized equity premium for the 3-month horizon constructed using the methodology of Martin (2017), using data from OptionMetrics. The value spread, VS, is the log difference in log book-to-market value between the top 10 percent and the bottom 10 percent of firms ranked by book to

market equity, constructed using data from Fama-French library. The credit spread, CS, is the difference between the yield of BAA bonds, from Moody's Seasoned Baa Corporate Bond Yield, and the log risk-free rate. The log price-dividend ratio, $\ln PD$, is the logarithm of a smoothed average price-dividend ratio, constructed as the dividends distributed by the value-weighted CRSP portfolio in the past year divided by its current price. In some robustness tests, we also add the return of the small-minus-big portfolio SMB (i.e., a portfolio of long small firms and short big firms) and the return of the high-minus-low portfolio HML (i.e., a portfolio of long high book-to-market equity and short low book-to-market equity) from Fama-French data library.

Table E.2: Effect of Tariff Announcements on VAR variables (One-Day Window)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\log R_{\text{risk-free}}$	$\log R_{EM}$	TS	EPB	VS	CS	$\log PD$	SMB	HML
Event	-0.000**	-0.125***	-0.005***	0.046***	0.092***	-0.001***	-0.127***	0.016	-0.041**
	(0.000)	(0.040)	(0.001)	(0.013)	(0.030)	(0.000)	(0.039)	(0.015)	(0.017)
N	753	754	753	753	753	753	753	754	754

Note: The table reports the sum of β_j in the regression (22). The sample includes all trading days from 2017 to 2019. Robust standard errors in parentheses.

Table E.3: Effect of Tariff Announcements on VAR variables (Three-Day Window)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\log R_{\text{risk-free}}$	$\log R_{EM}$	TS	EPB	VS	CS	$\log PD$	SMB	HML
Event	-0.000	-0.112*	-0.003	0.039	0.051	-0.000	-0.130**	0.027	-0.023
	(0.000)	(0.066)	(0.002)	(0.024)	(0.048)	(0.000)	(0.066)	(0.031)	(0.029)
N	753	754	753	753	753	753	753	754	754

Note: The table reports the sum of β_j in the regression (22), using three-day windows around announcement. The sample includes all trading days from 2017 to 2019. Robust standard errors in parentheses.

Table E.4: Robustness Exercises for Changes in Future Discount Rates

Specification	Deviations in Discount Rates $\rho\boldsymbol{B}(I-\rho\boldsymbol{B})^{-1}d\boldsymbol{x}_0$			
	Risk-free Rate	Excess Returns	SMB	HML
	$\sum\rho^t\mathrm{E}_0\left[\hat{R}_{\text{risk-free},t}\right]$	$\sum\rho^t\mathrm{E}_0\left[\hat{R}_{EM,t}\right]$	$\sum\rho^t\mathrm{E}_0\left[\hat{R}_{SMB,t}\right]$	$\sum\rho^t\mathrm{E}_0\left[\hat{R}_{HML,t}\right]$
Baseline	-0.021	0.089		
Without TS	-0.017	0.090		
Without EPB	-0.013	0.083		
Without VS	0.003	0.076		
Without CS	-0.008	0.084		
Without $\log PD$	-0.023	0.047		
FF 3-Factor Model	-0.009	0.074	0.026	0.006
3-Days Window	-0.005	0.088		

Note: The table reports $\rho\boldsymbol{B}(I-\rho\boldsymbol{B})^{-1}d\boldsymbol{x}_0$, where $\boldsymbol{x}_0$ is reported in Table E.2 (using a one-day window) and Table E.3 (using a three-day window).

E.3 Robustness to Using a Factor Model for Firm Discount Rates

In the baseline results, we made the simplifying assumption that the log deviation in the interest rate paid on firm debt was the same as the log deviation in the risk-free rate and that the deviation in the required return on firm equity was given by its beta exposure to the stock market times the deviation in the expected excess return on the market (CAPM). For robustness, we also experiment with relaxing these two assumptions.

First, we use the Fama-French 3-factor model instead of the CAPM to estimate the discount rate on firm equity. This effectively allows the discount rate of a firm equity to depend not only on its exposure to the stock market (as in the CAPM) but also on its size and book-to-market values. More precisely, we replace the second equation in (17) by

$$\mathrm{E}_0\left[\hat{R}_{ft}^E\right] = \mathrm{E}_0\left[\hat{R}_{\text{risk-free},t}\right] + \beta_{f,M}\mathrm{E}_0\left[\hat{R}_{M,t} - \hat{R}_{\text{risk-free},t}\right]$$
$$+ \beta_{f,SMB}\mathrm{E}_0\left[\hat{R}_{SMB,t}\right] + \beta_{f,HML}\mathrm{E}_0\left[\hat{R}_{HML,t}\right],$$

where SMB denotes the portfolio of small minus big firms while HML denotes the portfolio of high minus low book-to-market values and the set of betas $(\beta_{f,M}, \beta_{f,SMB}, \beta_{f,HML})$ is obtained as the slope coefficients in a multivariate regression of firm excess returns on $\left(\hat{R}_{M,t} - \hat{R}_{\text{risk-free},t}\right)$, $\hat{R}_{SMB,t}$, and $\hat{R}_{HML,t}$. Combining this equation with (16) implies the following equation for the deviation in firm discount rates:

$$\underbrace{\sum_{t=1}^{\infty}\rho^t\mathrm{E}_0\left[\hat{R}_{ft}\right]}_{\substack{\text{Deviation in firm } f \\ \text{discount rates}}} = \underbrace{\sum_{t=1}^{\infty}\rho^t\mathrm{E}_0\left[\hat{R}_{\text{risk-free},t}\right]}_{\substack{\text{Deviation in future} \\ \text{risk-free rates}}} + \kappa_f\beta_{f,M}\underbrace{\sum_{t=1}^{\infty}\rho^t\mathrm{E}_0\left[\hat{R}_{M,t} - \hat{R}_{\text{risk-free},t}\right]}_{\substack{\text{Deviation in future} \\ \text{excess stock market returns}}} \quad (\text{E1})$$

$$+ \kappa_f\beta_{f,SMB}\underbrace{\sum_{t=1}^{\infty}\rho^t\mathrm{E}_0\left[\hat{R}_{SMB,t}\right]}_{\substack{\text{Deviation in future} \\ \text{SMB returns}}} + \kappa_f\beta_{f,HML}\underbrace{\sum_{t=1}^{\infty}\rho^t\mathrm{E}_0\left[\hat{R}_{HML,t}\right]}_{\substack{\text{Deviation in future} \\ \text{HML returns}}}.$$

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We then use a VAR that includes the return of SMB and HML portfolios, $R_{SMB,t}$ and $R_{HML,t}$, to jointly estimate the deviation in future risk-free rates, future excess stock-market returns, future expected SMB returns, and future expected HML returns. As reported in Table E.4, we find that tariff announcements slightly increase the expected return of the SMB portfolio; that is, tariff announcements have a larger effect on the discount rate of small firms relative to big firms.

This implies that, relative to the CAPM, our Fama-French 3-factor model returns an estimate for firm-level discount rates that is higher for small firms (firms with $\beta_{f,SMB} > 0$) and lower for big firms (firms with $\beta_{f,SMB} < 0$). These changes would average out if we were doing a value-weighted average of firms in our sample. However, because we overweight smaller firms, this leads to a lower aggregate deviation in firm discount rates by 1.1 percentage points. As a result, the overall decline in welfare is mechanically reduced by 1.1 percentage points.

Second, we assume that the log deviation in the interest rate paid on firm debt is equal to the log deviation in the yields of BAA bonds rather than the risk-free rate on debt; that is, we replace the first equation in (17) by

$$\mathrm{E}_0\left[\hat{R}_{ft}^D\right] = \mathrm{E}_0\left[\hat{R}_{\text{risk-free},t}\right] + \mathrm{E}_0\left[\widehat{CS_t}\right],$$

where CS_t denotes the credit spread (the difference between the yield on BAA bonds and the risk-free rate). In terms of methodology, this means that we need to augment our measure of the deviation in future risk-free rates by the deviation in future credit spread, as estimated by the VAR. As reported in Table 8, we find that our measure of welfare hardly changes; that is, our VAR estimates relatively little deviation in credit spread following announcement shocks.

F   Additional Tables

Table F.1: Effect of Tariff Announcements on the Components of Cash Flow and Stock Returns

| | Deviation in ... | | | | | |
| | Discount-Rate | Asset-Value | logR | Discount-Rate | Asset-Value | logR |
	(1)	(2)	(3)	(4)	(5)	(6)
China Importer	0.38***	-2.35***	-2.59***	0.26***	-0.70***	-0.30
	(0.10)	(0.28)	(0.35)	(0.07)	(0.22)	(0.28)
China Exporter	-0.47***	-0.70	-2.01***	-0.31***	0.34	-0.36
	(0.17)	(0.49)	(0.72)	(0.11)	(0.38)	(0.60)
China Revenue Share	6.57***	-12.09***	-10.22***	4.40***	-9.36***	-7.43***
	(1.14)	(2.22)	(2.23)	(0.77)	(2.00)	(2.01)
N	26,807	26,807	26,807	26,807	26,807	26,807
Events	U.S.	U.S.	U.S.	China	China	China

Note: All dependent variables are multiplied by 100. A firm f's deviation discount rate on trading day t corresponds to the term $\sum_{t=1}^{\infty} \rho^t E_0[\hat{R}_{ft}]$ in the theory section. A firm's asset value on a trading day t is market value plus debt. The deviation in a firm f's cash flow on the day t, denoted by $\hat{r}_{ft}$, is the sum of its deviation in the discount rate and deviation in asset value. This table uses a one-day window around each event, enforces a balanced panel of firms, and drops firms in the financial sector. China Importer is a dummy that equals one if the firm or any of its subsidiaries or suppliers import from China. China Exporter is a dummy that equals one if the firm or subsidiaries export to China. China Revenue Share is the share of the firm's revenue from China, reported in percentage points. Columns 1-3 presents the sum of the coefficients across each of the U.S. event days; and columns 4-6 are the sum of the coefficients across each of the China event dates. Standard errors are in parenthesis. Asterisks correspond to the following levels of significance: ***$p < 0.01$,** $p < 0.05$,* $p < 0.1$.

Table F.2: Relationship between Changes in Returns and Future Observables (with Controls Reported)

	(1)	(2)	(3)	(4)
	$\ln(\text{Profit}_{ft})$	$\ln(\text{L}_{ft})$	$\ln(\text{Sales}_{ft})$	$\ln(\text{Sales/L})_{ft}$
Post $\times$ ln R_f	0.23***	0.07***	0.12***	0.04**
	(0.04)	(0.01)	(0.02)	(0.02)
Post $\times$ PPE per Worker$_f$	-0.00	-0.00	-0.00	0.00
	(0.02)	(0.01)	(0.01)	(0.01)
Post $\times$ ln(Mkt. Val. of Equity$_f$)	0.02	-0.01	0.03***	0.03***
	(0.02)	(0.01)	(0.01)	(0.01)
Post $\times$ $\frac{\text{Cash Flows}}{\text{Assets}}_f$	-0.39***	0.02***	-0.08***	-0.09***
	(0.03)	(0.01)	(0.01)	(0.01)
Post $\times$ Book Leverage$_f$	0.05***	-0.03***	-0.02**	0.01
	(0.02)	(0.01)	(0.01)	(0.01)
Post $\times$ Tobin's Q$_f$	0.08***	0.07***	0.08***	0.00
	(0.02)	(0.01)	(0.01)	(0.01)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.915	0.976	0.962	0.873
Observations	11940	17032	16760	16736

Note: Data is at the firm-annual level for the period 2013 to 2021, from Compustat and CRSP. Profit is defined as operating income after depreciation less interest and related expenses. We follow Greenland et al. (2024)'s specification in defining $\ln R_f$ as the log of one plus the average return on 5 days surrounding the tariff-announcement dates across all event dates in 2017-2019; however, instead of using abnormal returns, we just simply use the actual return. In this table, $\ln R_f$ is then multiplied by 100. The Post dummy takes a value of one in 2019, 2020, and 2021. All columns include the following control variables at the start of the sample (i.e., 2013) interacted with the Post dummy as covariates: Property, Plant, and Equipment (PPE) per worker, market capitalization, cash-flow-to-asset ratio, book leverage and Tobin's Q. The controls are winsorized at the 1 percent level and then demeaned and divided by their standard deviation. See Appendix C.2 for details on variable constructions. Standard errors are in parenthesis. ***$p < 0.01$,** $p < 0.05$,* $p < 0.1$.

G   Measuring the Static and Dynamic Price Effects

In this section, we describe how we compute the effective rate of protection, in order to calculate the first two terms in (23).

G.1   Construction of Industry-level Tariffs

The first step is to construct the log change in the tariff on outputs in each 6-digit NAICS industry $j \in J$. We begin with the U.S. statutory tariff rates τ_{hct} at the HTS10 h - country c level in year-month t. We compute the log change in the output tariff for each industry j as the import-value weighted average of log changes in the HTS10-country level tariff rates, using fixed annual 2017 import value weights:

$$\hat{\tau}_j \equiv \sum_{h \in H_j} \sum_c \frac{mv_{hc,2017}}{\sum_{h' \in H_j} \sum_{c'} mv_{h'c',2017}} \Delta \ln(1 + \tau_{hc}), \tag{G1}$$

where H_j is the set of HTS10 codes that map to NAICS 6-digit industry j; $mv_{hc,2017}$ is the annual import value of goods in HTS10 code h imported from country c in 2017; and

$\Delta \ln(1 + \tau_{hc}) = \ln(1 + \tau_{hc,2019Dec}) - \ln(1 + \tau_{hc,2017Dec})$ is the log-change in ad-valorem tariff rates from December 2017 to December 2019. Thus, the change in output tariff $\hat{\tau}_j$ captures the average change in tariff rates applied to imported goods produced in industry j.

We compute the tariffs in a counterfactual exercise in which the U.S. applies additional tariff rates of 60 percentage points on imports from China and 20 percentage points on imports from all other countries as

$$\hat{\tau}_j^a \equiv \sum_{h \in H_j} \sum_c \frac{mv_{hc,2017}}{\sum_{h' \in H_j} \sum_{c'} mv_{h'c',2017}} \Delta \ln(1 + \tau_{hc}^a), \tag{G2}$$

where $\Delta \ln(1 + \tau_{hc}^a) = \ln(1 + \tau_{hc,2017Dec} + 0.6) - \ln(1 + \tau_{hc,2017Dec})$ if $c = $ China, and $\Delta \ln(1 + \tau_{hc}^a) = \ln(1 + \tau_{hc,2017Dec} + 0.2) - \ln(1 + \tau_{hc,2017Dec})$ otherwise.

G.2 Effective Rates of Protection Calculation

We use equation (5) to estimate how U.S. import tariff changes map into firm-level ERP $(\hat{p}_{f0}^e)$ in a static model. Since firm-level intermediate-input use data are not available, we use industry-level data, i.e., we assume that the shift in the ERP for all firms in industry j is given by

$$\hat{p}_j^e = \frac{\hat{p}_j^\tau - \sum_{i \in J} \omega_{ij} \hat{q}_i^\tau}{1 - \sum_{i \in J} \omega_{ij}}, \tag{G3}$$

where $\hat{p}_j^\tau$ are estimates of how U.S. import tariff changes affected prices of U.S. outputs in industry j, and $\hat{q}_i^\tau$ are estimates of how U.S. import tariff changes affected input prices i. The ω_{ij}'s denote the cost-share of intermediate input i used in the production of output in industry j.[2] We assign industry-level changes in ERP to each firm based on the industry it produces, i.e., $\hat{p}_{f0}^e = \hat{p}_j^e \quad \forall f \in j$.

Calculating ERP is challenging because it requires many assumptions about passthrough from tariffs into domestic prices in a world with complex input-output linkages. We estimate the ERP in two ways.

Lower Bound Tariff Effect: First, we obtain a lower bound for the static price effect by assuming that output prices do not change when tariffs are applied, i.e., $\hat{p}_j^\tau = 0$, and the input price, $\hat{q}_i^\tau$, is equal to the change in the tariffs on imported inputs. The input price assumption is based on the findings in Amiti et al. (2019) and Fajgelbaum et al. (2020). They estimated passthrough of U.S. tariffs on U.S import prices and the impact of Chinese tariffs on U.S. export prices. Both studies find 100 percent passthrough of tariffs into tariff-inclusive import prices. In this scenario, $\hat{p}_j^\tau$ is set equal to zero, and the ERP is calculated as follows:

$$\hat{p}_j^{e1} = \frac{-\sum_{i \in J} \omega_{ij} \lambda_i \hat{\tau}_i}{1 - \sum_{i \in J} \omega_{ij}}. \tag{G4}$$

We use the 2017 IO table to identify all of the inputs i used to produce output j. We set $\hat{q}_i^\tau$ equal to $\lambda_i \hat{\tau}_i$ in equation G3, where λ_i is the share of imports of input i in total absorption of input i (where absorption is calculated as production less exports plus imports). We multiply the cost share of each intermediate input i used to produce output j (ω_{ij}) by λ_i

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[2]Total output is calculated as the sum of total intermediate input cost, compensation of employees, and gross operating surplus in the BEA's IO Table from 2017.

so that the tariff change is only applied to imported inputs and not to domestic inputs. The price of the imported input increases by the full amount of the tariff $\hat{\tau}_i$ (calculated in equation (G1)). Note that the tariffs on inputs are at the BEA IO level, which is a little more aggregated than NAICS 6-digit. Using this calculation of ERP, we assign the same value to each firm within a NAICS 6-digit industry in our Compustat sample, and reweight the industries to reflect the distribution of firms in the aggregate economy as we did in our baseline welfare calculations and described in Section D.

Upper Bound Tariff Effect: In our second specification, we assume that higher import prices also raise U.S. output prices, so that $\hat{p}_j^\tau > 0$. Specifically, we set

$$\hat{p}_j^{e2} = \frac{\gamma \lambda_j \hat{\tau}_j - \sum_{i \in J} \omega_{ij} \left[\lambda_i \hat{\tau}_i + (1 - \lambda_i) (\gamma \lambda_i \hat{\tau}_i) \right]}{1 - \sum_{i \in J} \omega_{ij}}. \tag{G5}$$

In this calculation, we allow for prices of domestic input i to also increase when there is an increase in tariffs on input i. The amount we adjust domestic input prices is based on the estimates in Table 4 of Amiti et al. (2019), which found that domestic prices increased by $\gamma \lambda_i$ with $\gamma = 0.4$. i.e. $\hat{p}_j^\tau = \gamma \lambda_j \hat{\tau}_j$. Total input prices, therefore, rise by the sum of the the direct tariff effect on the share of imported intermediates in the industry $\lambda_i \hat{\tau}_i$ plus the share of domestically sourced intermediate inputs multiplied by the increase in tariffs due to higher domestic prices $(1 - \lambda_i) (\gamma \lambda_i \hat{\tau}_i)$.

Estimating the Static Price Effect: We use tariff changes between 2017 and 2019 to assign these industry-level changes in ERP to firms in our sample and then use the reweighting scheme in Section D. We use equation (G4) to obtain an estimate for the welfare impact equal to -0.3 of a percent for the static price effect in equation (23). Our upper bound estimate of the uses equation (G5) to compute the ERP and produces an estimate of the welfare impact given in equation (23) of -0.17%.

Estimating the Lower Bound the Dynamic Price Effect: We assume that the worst case scenario for future ERP is a tariff scheme in which the U.S. applies additional tariff rates of 60 percentage points against China and 20 percentage points against all other countries. We denote these tariffs by $\hat{\tau}_j^a$. Using these hypothetical output tariffs to calculate the changes in ERP in equation (G4), the resulting static price effect is -2.19%. If we instead use equation (G5) to calculate the changes in ERP, the resulting static price effect is -1.01%

H   Treatment Effects

In this section, we provide more details of the estimation of the treatment effects. To estimate the size of the treatment effect, we use an event study, where we project firm-level deviations in cash flow on a set of our three firm-level characteristics associated with China exposure (importer dummy, exporter dummy, as well as Chinese revenue shares), allowing for different coefficients for each announcement day and each exposure type.

$$\text{CF}_{ft} \equiv \sum_{t=0}^{\infty} (1-\rho) \rho^t \text{E}_0 \left[\hat{r}_{ft} \right] = \alpha_t + \sum_j \sum_i \gamma_{ij} Z_{if} D_{jt} + \epsilon_{ft}, \tag{H1}$$

where the left-hand side variable is the expected present discounted value of firm cash flow, which can be measured using Proposition 4, estimated using the method described

in Sections 4.2 and 4.3; α_t is a day fixed effect; D_{jt} is a dummy variable that is one if day t is the same as announcement day j; $Z_{if} \in \{$Importer, Exporter, China Revenue Share$\}$ is a measure of firm f's exposure to China; γ_{ij} is parameter to be estimated; and ϵ_{ft} is an i.i.d. error term.

Table H.1: Impact of U.S. Tariff Announcements on Cash Flows

	(1) Cumulative	(2) 23Jan18	(3) 1Mar18	(4) 22Mar18	(5) 19Jun18	(6) 06May19	(7) 01Aug19
China Importer	-1.97***	-0.25***	-0.33***	-0.27***	-0.12	-0.52***	-0.47***
	(0.26)	(0.07)	(0.11)	(0.08)	(0.10)	(0.07)	(0.14)
China Exporter	-1.17***	-0.19**	0.15	-0.23**	-0.43***	-0.19*	-0.27
	(0.41)	(0.08)	(0.16)	(0.10)	(0.11)	(0.11)	(0.28)
China Revenue Share	-5.52***	-0.57*	-2.55***	-1.23***	-1.62***	-2.30***	2.74**
	(1.77)	(0.34)	(0.73)	(0.40)	(0.42)	(0.44)	(1.19)

Note: The dependent variable is residualized cash flow (CF_{ft}) multiplied by 100, which is constructed by summing $\hat{\Pi}_{f0}$ (constructed using equation (15)) and the change in the discount rate (which is based on the change in the VAR variables on announcement days after controlling for economic surprises). This table uses a one-day window around each event. China Importer is a dummy that equals one if the firm or any of its subsidiaries or suppliers import from China. China Exporter is a dummy that equals one if the firm or subsidiaries export to China. China Revenue Share is the share of the firm's revenue from China. Column 1 reports the sum of the coefficients across each of the U.S. event days. There are 26,807 observations. Standard errors are in parenthesis. Asterisks correspond to the following levels of significance: ***$p < 0.01$,** $p < 0.05$,* $p < 0.1$.

Table H.1 presents the results for each of the six U.S. tariff events, and Table H.2 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 (H1). Thus, all event dates in both tables are estimated jointly in one regression. The coefficients should be interpreted as the effect of the announcement on the expected cash flows of exposed firms relative to unexposed firms. For example, the coefficient of -0.33 on the China importer dummy in column 3 of Table H.1 implies that on the March 1, 2018 steel and aluminum announcement day, firms that imported from China experienced declines in their expected cash flows that were on average 0.33 percentage points lower than other firms. The numbers in column 1 provide our estimate of the cumulative impact over all U.S. events and all days in the event windows ($\sum_j \hat{\gamma}_{ij}$). We can see from the first column of this table that the cumulative impact of the U.S. announcements was to lower the expected cash flows of U.S. importers by 1.97 percentage points relative to firms that did not import from China. Similarly, the relative fall in expected cash flows of exporters were 1.17 percentage points more than those of non-exporters, and firm's selling in China saw their expected cash flows fall by 0.06 percentage points for every percentage point of revenue share they obtained from China. The coefficient on China Revenue Share implies that a firm with the average sales exposure to China (three percent of revenue) experienced a fall in expected cash flow of 0.18 percentage points lower than a firm with no sales in China across all of the U.S. events.

The cumulative impact of the U.S. events, shown in the first column of Table H.1, indicates that in general U.S. tariff announcements had large, negative, and significant

impacts on the cash flows of importers, exporters, and firms selling in China. Although the effects are not precisely measured for every event and measure of exposure, 16 of the 18 event-day coefficients are negative, which indicates that U.S. tariff announcements typically had negative effects on the expected cash flows of firms exposed to China relative to unexposed firms. When we sum across all events, the cumulative effect is negative and significant for each type of exposure.

Interestingly, U.S. tariff announcements caused expected cash flows to decline not only for importing firms but also for firms exporting or selling in China more generally. These negative coefficients on the exporter or sales variables are likely due to three (not mutually exclusive) reasons. The first is that markets may have anticipated that U.S. tariffs would provoke Chinese retaliatory tariffs, thereby lowering the abnormal return of exporters. Second, market participants may have anticipated that U.S. tariffs would also provoke Chinese retaliatory non-tariff barriers that could lower revenues obtained by exporting or multinational sales. Third, it is also possible that U.S. tariffs weakened the Chinese economy, which could lower expected profits for U.S. firms selling there.

Table H.2: Impact of Chinese Tariff Announcements on Cash Flows

	(1) Cumulative	(2) 23Mar18	(3) 15Jun18	(4) 02Aug18	(5) 13May19	(6) 23Aug19
China Importer	-0.45**	0.02	-0.02	0.21*	-0.28***	-0.37***
	(0.20)	(0.08)	(0.07)	(0.11)	(0.09)	(0.08)
China Exporter	0.03	0.16	-0.05	-0.49***	0.36***	0.05
	(0.30)	(0.10)	(0.11)	(0.15)	(0.13)	(0.13)
China Revenue Share	-4.95***	-0.85	-0.23	1.26	-4.06***	-1.08***
	(1.49)	(0.60)	(0.36)	(0.78)	(0.75)	(0.36)

Note: The dependent variable is residualized cash flow (CF_{ft}) multiplied by 100, which is constructed by summing $\hat{\Pi}_{f0}$ (constructed using equation (15)) and the change in the discount rate (which is based on the change in the VAR variables on announcement days after controlling for economic surprises). This table uses a one-day window around each event. China Importer is a dummy that equals one if the firm or any of its subsidiaries or suppliers import from China. China Exporter is a dummy that equals one if the firm or subsidiaries export to China. China Revenue Share is the share of the firm's revenue from China. Column 1 reports the sum of the coefficients across each of the Chinese event days. There are 26,807 observations. Standard errors are in parenthesis. Asterisks correspond to the following levels of significance: ***$p < 0.01$,** $p < 0.05$,* $p < 0.1$.

Turning to the Chinese announcements, column 1 of Table H.2 shows that Chinese retaliation on average significantly lowered expected cash flows for firms selling in China (either by exporting or through multinationals). We do not see an effect on exporting per se, but this result may reflect the fact that export revenues are captured in the China Revenue Share variable so we may have a multicollinearity problem. Interestingly, we see that tariff announcements also lowered expected cash flows of firms importing from China, perhaps because of the tit-for-tat retaliation structure of the trade war in which Chinese retaliation provoked more U.S. tariffs. Overall, Chinese retaliation announcements led to a significant 0.45 percentage point drop in the expected cash flows of firms importing from China and another 0.05 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 tariff announcements on a firm exposed to China through multiple channels. We estimate that a firm that imported from and exported to China and obtained 3 percent of its revenue from sales to China would have had its expected cash flows lowered by 3.9 percent when we sum across all event days. The large magnitude of this result suggests that the tariff announcement had a sizable negative impact on the expected cash flows of exposed firms.[3]

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[3]Appendix Table F reports the cumulative effect for the tariff-announcement effects on firm values, discount rates, and stock prices.