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TRADE PROTECTION, STOCK-MARKET RETURNS, AND WELFARE

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ABSTRACT

This paper develops a methodology to assess the expected impact of trade-policy announcements on aggregate welfare using financial market reactions. We use an infinite-horizon specific factors model of production to map the present discounted value of firm cash flows into aggregate welfare. We show that the policy-induced movement in the present value of firm cash flows—a variable that can be estimated from financial data—encapsulates the welfare impact of the tariffs. After applying our framework to the data, we find that the U.S.-China trade war lowered U.S. welfare by three percent.

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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 effects on productivity and welfare in the long-run.[2] 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 around the policy announcement. Financial data is particularly well suited to quantify the equilibrium 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 by examining movements in asset prices on days in which tariffs were announced. 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 4.12 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 happened in 2019—over a year after the trade war began. Furthermore, markets

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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.

[2]See, for instance, Perla et al. (2021).

hardly responded to non-tariff executive actions and orders, which suggests that 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 input purchases 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 likely active. Using Greenland et al. (2024)'s empirical specification, 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 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 analytic solutions for how movements in expected firm cash flows map into movements in expected firm-level effective rates of protection, sales, wages, employment, and both quantity and revenue total factor productivity (TFPR).

We then integrate the production structure of the specific factors model into one that will allow us to model 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 in each future period away from this 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. We then show that the present value of consumption can be written as the present value of expected cash flows and tariff revenues. Moreover, in this framework, we can specify the welfare impact of a policy in terms of its impact on expected log consumption as well as on its higher-order cumulants like variance, skewness, and kurtosis. Finally, we follow Campbell and Shiller (1988) to show that we can write the present discounted value of cash flows as the sum of the policy-induced change in firm value and the change in the expected discount rate. The change in firm value can be estimated from stock-price movements arising from a tariff announcement, and the movement in discount rates

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can be measured using the vector-autoregression (VAR) methodology of Campbell and Vuolteenaho (2004).

With our estimates of the implied movements of each firm's cash flow in hand, we turn to measuring the implied impact of the tariffs on welfare. We identify three main reasons why equity-price drops might overstate movements in firm cash flow. First, when firms are debt-financed, small drops in cash flow can lead to large drops in market value, and hence large observed drops in market value may only imply small drops in cash flow. This problem requires us to adjust changes in firm equity values using their initial leverage. Second, movements in the market value of Compustat firms overstates movements in the market value of all firms in the U.S. economy because the Compustat sample of firms overweights large firms, and these firms had lower market returns than small firms. This problem requires us to reweight the Compustat sample of firms so we can infer what happened to cash flows of a sample of firms that match the industry-size distribution of firms in the U.S. economy. Finally, increases in discount rates tend to amplify drops in firm market value relative to the actual changes in firm cash flows.

The leverage and sampling adjustments imply that changes in firm value were -6.7 percent, just over half as big as the 11.5 percent market decline on tariff-announcement days. Of this fall in firm value, 3.1 percentage points can be explained by higher discount rates, which means that the impact of the tariffs on cash flows drove welfare down by 3.6 percent. Finally, in order to be conservative, we assume that the tariff revenues arising from the trade war equal 2017 import values multiplied by the increase in tariffs. This is an upper bound because tariffs likely caused import values to fall. However, this upper bound implies that increased tariff revenues could not have raised welfare by more than 0.6 percent, which yields our upper bound estimate of the welfare loss of 3.0 percent. This estimate is robust to a wide range of alternative specifications. Finally, this number only captures the welfare effect of tariffs through changes in the first moment of log consumption. This corresponds to the welfare effect of an agent with log utility. If the representative agent has a relative risk aversion higher than one and tariff announcements increase the variance or decrease the skewness of log consumption, we show that our number underestimates the extent to which the tariff announcements decreased aggregate welfare.

This result raises the question of why market participants believed the tariffs would have a large effect on the economy, but conventional economic models suggest they would have small effects. The higher estimated losses in this exercise relative to those in conventional analyses likely arise from two main sources. First, our identifying assumptions differ from those commonly used in estimating the impact of tariffs on welfare. Conventional analyses make strong assumptions about the pass-through of tariffs into prices, the timing of output-, input-, and factor-price changes, the absence of dynamic effects, the structure of input-output linkages, how tariffs affect "unexposed" firms, how TFP is affected by tariffs, and the roles played by trade policy uncertainty and consumption volatility. It is well known that welfare estimates can be very sensitive to these assumptions. Our model relaxes these assumptions. In particular, the assumption that protection does not affect productivity or aggregate growth is likely to be particularly consequential. For example, Perla et al. (2021) show that trade liberalization generates large welfare gains if it also can affect the incentive of firms to invest in new technologies. Second, while

we are rigorous in our estimation of the impact of tariff announcements on expected cash flows, we make no assumptions about why they moved cash flows as much as they did. As a result, our approach likely incorporates other secondary impacts of unilaterally levying tariffs on the world trading system, political stability, policy uncertainty, macro policy, etc. While conventional analyses are excellent at providing an estimate of welfare effects through the lens of a particular model, the approach has difficulty computing the total impact of tariffs that arises from their effect on other policies. The gain in precision associated with only examining a narrow channel through which tariffs affect welfare comes at the cost of not being able to discuss alternative channels. By not taking a stand on why the expected cash flows fall following a tariff announcement, we allow for trade policy to have complex interactions with other variables in the global economy. In this sense, our approach can be seen as complementary to existing ones. Standard exercises examine one mechanism through which tariffs affect firms, whereas our approach allows for many possibilities.

Related Literature Our work is closely related to the voluminous literature on stock-market event studies that use trade data (Grossman and Levinsohn (1989), Hartigan et al. (1986), Breinlich (2014), Fisman et al. (2014), Moser and Rose (2014), Breinlich et al. (2018), Crowley et al. (2019), Huang et al. (2023), and Greenland et al. (2024)). We differ in the use of a general equilibrium model to interpret the data. Greenland et al. (2024) is particularly relevant in that they show that positive firm abnormal returns in response to lower trade uncertainty through the granting of permanent normal trade relations in 2000, led to future increases in firm employment, sales, productivity, and profits. Our approach yields a theoretical foundation for their regressions, and their results validate our assumption that movements in expected cash flows are tightly linked to movements in future accounting profits and other non-financial variables. We also document a significant link between firm stock returns and future movements in non-financial variables using a structural approach to measuring the impact of policy announcements.

The specific factors model, which forms the basis of our approach, has also been used extensively in empirical estimation in recent years (c.f., Topalova (2010), Kovak (2013), and Dix-Carneiro and Kovak (2017)). These papers have shown that many of the large effects of trade policy changes on wages often take a decade to be fully apparent in the data. Our paper provides a complementary way of thinking about the long-term effects of a policy change in terms of expected wages. 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, we allow tariffs to affect input prices as well, so the imposition of tariffs can either raise the effective rate of protection (ERP) 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.[3] We also identify large impacts of trade policy on revenue TFP,

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[3]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 our identification is based on using stock-price data filtered through a general equilibrium model. Our paper is also related to the macro literature evaluating the impact of trade on income that has found evidence of large impacts of trade on productivity and income (c.f., Frankel and Romer (1999); Alcalá and Ciccone (2004); Feyrer (2019)). These studies find that the elasticity of per capita income with respect to trade ranges from 0.5 to 3 and that most of the effect arises through trade's impact on productivity. Although our work also finds large impacts of trade on productivity and welfare, an important difference between our work and the macro literature is that we build these estimates up from firm-level data on stock prices and use a structural general equilibrium setup to obtain our estimates.

We also contribute to the burgeoning literature on understanding the importance of protection 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)). Like these papers, our paper also suggests that trade policy announcements can have impacts that arise through uncertainty or changing the macro environment, but we differ in our use of financial data to identify the shocks and the use of a general equilibrium model. Our paper is also related to work on the China shock. For example, Autor et al. (2013) and Caliendo et al. (2019) show how trade with China affected U.S. employment, wages, and welfare, but our work focuses on trade policy announcements. In the financial literature, Barrot et al. (2019) show that firms in industries with lower shipping costs tend to have higher average returns, suggesting that foreign productivity shocks are associated with times where the marginal utility of consumption for investors is high.

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

2 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, in the cross-section, while the data indicates that the distribution of all stock returns shifted to the left, the announcements have a relatively larger negative effect on directly exposed firms. More precisely, 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

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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. Bloom et al. (2016) find that Chinese import competition accounts for 14 percent of European technology upgrading.

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: 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.

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.

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 using a one-day window.[4] 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, we see that 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 in our event windows, we also report the cumulative stock-market returns around tariff-announcements after controlling for the set of macroeconomic release 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. Moreover, we have checked that there were no monetary policy announcements surrounding our tariff policy announcements.

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[4]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
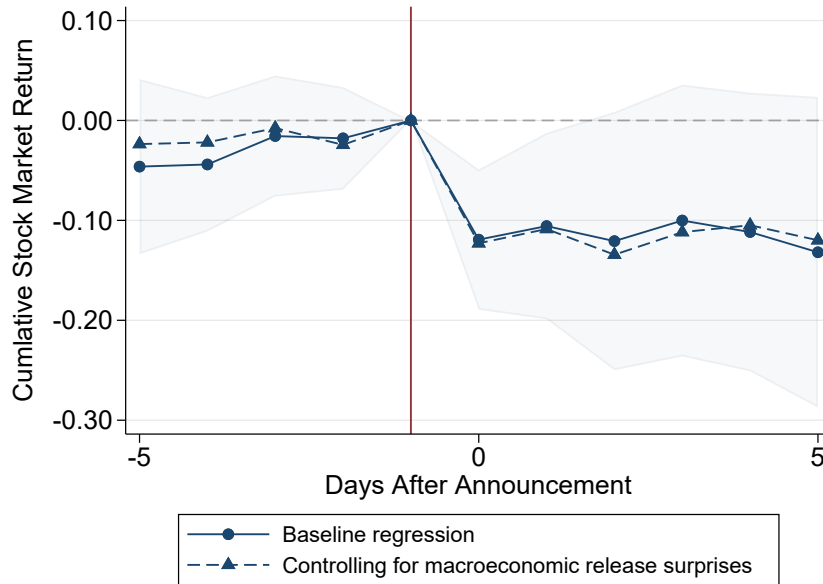
Note: This figure plots the cumulative log stock-market return starting the day before the announcement. Formally, we estimate the following regression on all trading days between 2017 and 2019: $\ln R_{M,t} = \alpha + \sum_{s=-4}^{5} \beta_s D_{s,t} + \epsilon_t$, where $D_{s,t} = 1$ if day t is s days 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.

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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
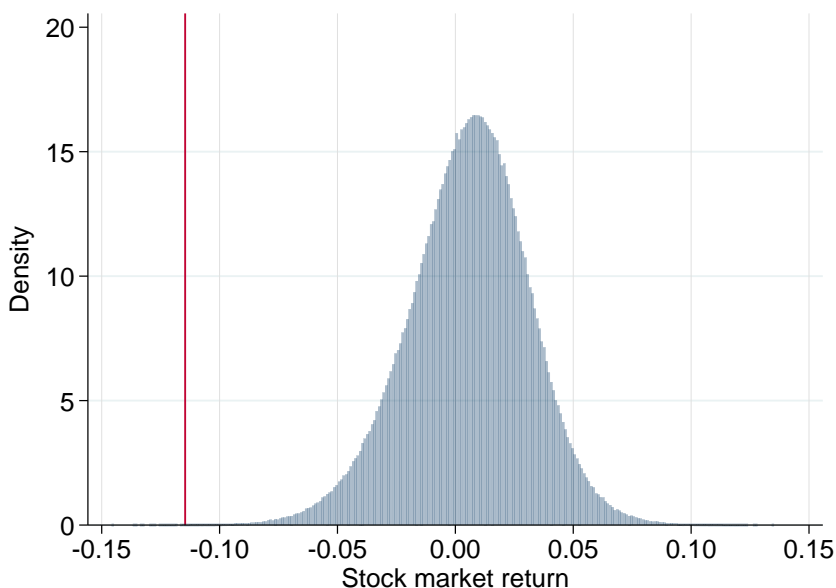
Note: The figure compares the cumulated log stock-market return over our 11 announcement days (in red) with the density of cumulated log stock-market returns obtained over 11 random days between 2017 and 2019 (in blue). The stock-market return is the value-weighted market-portfolio return from CRSP.

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 mere signaling of potentially worsening relations between the U.S. and China. The difference between levying tariffs on China 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 are unrelated to tariffs.[5] We report the stock returns for each of these

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

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 which 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 (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

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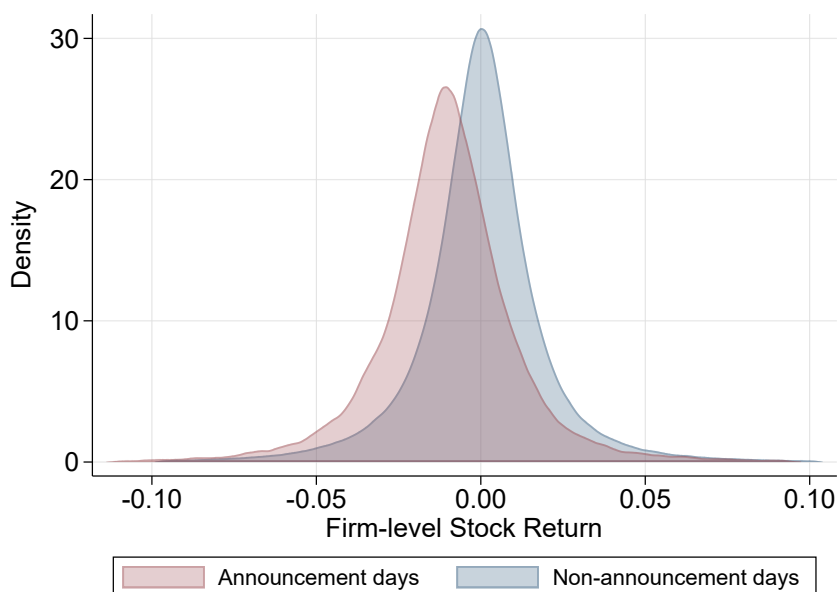
Note: The figure compares the average density of firm-level returns on announcement days (in red) and non-announcement days (in blue). We first residualize firm-level returns with respect to a set of day fixed effects (while still leaving a dummy corresponding to announcement days). We then plot the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

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 see that 31 percent of all listed firms in the U.S. import directly or indirectly from China. In the last row of the table, we construct a variable, "Firm Exposed to China" if any firm in the firm's network exported to or imported from China or if the firm had positive revenues from China (possibly from affiliate sales). We see that 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, we see that 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 untreated firms. Third, both Chinese and U.S. 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

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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.

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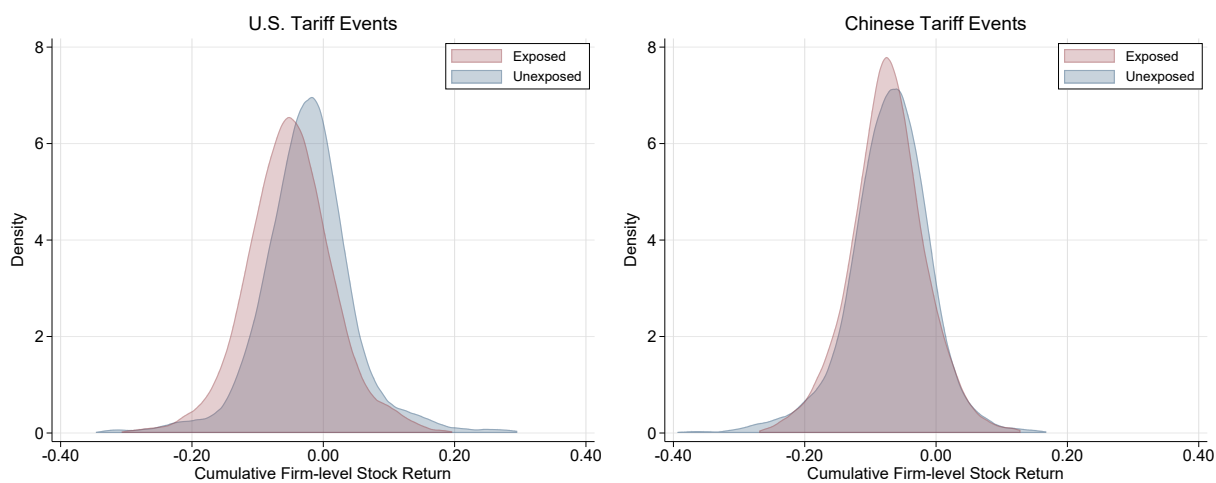
Note: This figure plots the kernel densities of cumulative abnormal returns of firms exposed to China (light red) and unexposed (light blue) during one-day windows around tariff announcements. Exposed firms are firms that export to, import from, or have positive revenues in China.

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 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, sales, employment, 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)	(2)	(3)	(4)
	$\ln(\text{Profit}_{ft})$	$\ln(\text{L}_{ft})$	$\ln(\text{Sales}_{ft})$	$\ln(\text{Sales/L})_{ft}$
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 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
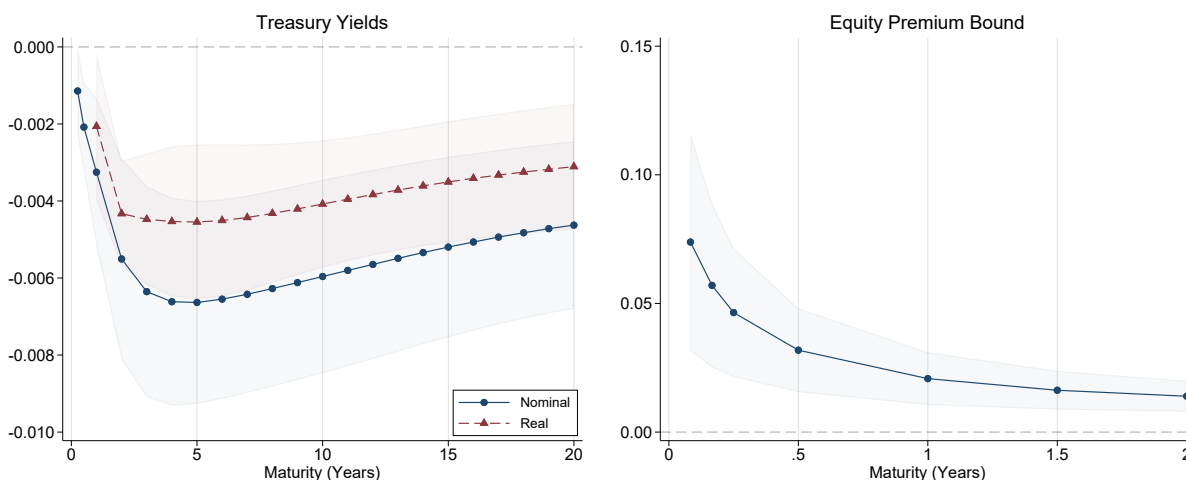
Note: Each figure reports the cumulated daily change of variables over all days with a tariff announcement, after controlling for surprises in macroeconomic releases. The first subfigure reports the change in the nominal and real yield curves, using data from FRED (for nominal yields at the 3-month, 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. Similarly to the VIX index, 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. Similarly to Table 1, 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 one outlier event: almost all announcements tend to decrease real yields and increase the equity-premium bound. Similarly to Figure 1, Appendix Figure E.1 reports the dynamic effect of announcements on these variables over a ten-day window. This figure shows that the change in these variables is concentrated on the days of the announcements, which seems to refute the idea that the market under or overreacted 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, firm sales, employment, prices, effective rates of protection (ERP), and TFP. 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 present discounted value (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 rederive the model under the assumption 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 (where production decisions in each period would mimic those of a static model in the absence of any policy shocks). In our model, time is discrete and indexed by t; and there is a continuum 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 differentiated intermediate inputs $m_{1ft}, \ldots, m_{nft}$. Firms maximize profits taking the output price as

given.[6] 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 $c_{ft}(w_t, r_{ft}, q_{1t}, ..., q_{nt})$, where the arguments correspond to the wage (w_t), the shadow price of the firm's fixed factor (r_{ft}), and prices of a set of intermediate inputs ($q_{1t}, ..., q_{nt}$). Shephard's Lemma tells us that the unit-input requirements are given by the derivative of the cost function; that is, $a_{Lft} = \frac{\partial c_{ft}}{\partial w_t}$, $a_{Vft} = \frac{\partial c_{ft}}{\partial r_{ft}}$, and $a_{ift} = \frac{\partial c_{ft}}{\partial q_{it}}$, where $a_{Lft}, a_{Vft}, a_{ift}$ denote the unit-input requirements for labor, fixed factor, and intermediate input i, respectively. We assume that each firm f sets the price of its output p_{ft} equal to its marginal cost so

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

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 will adjust 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); that is, $r_{ft}V_f = (p_{ft} - a_{Lft}w_t - \sum_i a_{ift}q_{it})y_{ft}$.

In order to model the impact of a policy change, we start with a "baseline" equilibrium in which all cost functions, product prices, and input prices are unchanging over time (i.e., $c_{ft} = c_f$, $p_{ft} = p_f$, and $q_{it} = q_i$), and then treat a policy shock as a policy that shifts input and output prices away from this baseline in each period. Since, in the baseline equilibrium, aggregate employment (L), each firm's specific factor (V_f), and input and output prices 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 in Appendix B that we can easily modify the setup to allow for productivity growth without changing any of our propositions.

We model a tariff change as causing a set of log-change deviations in output and input prices ($\hat{p}_{it}, \hat{q}_{it}$) in the period t baseline values ($p_{ft} = p_{f0}$ and $q_{it} = q_{i0}$). 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

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[6]As long as the marginal productivity of V_f tends to infinity as V_f tends to zero, each firm's production is positive in equilibrium.

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 that the share of expenditures on intermediate inputs in costs are unchanging. This assumption enables us to write the factor intensity of production (a_{Vft}/a_{Lft}) as a function of the elasticity of substitution between the specific factor and labor (σ):[7]

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

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, 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 $\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\square$

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 line follows immediately from this equation and the fact that the amount of the specific factor is fixed, so the left-hand side of equation (4) is just $-\hat{L}_{ft}$.[8]

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

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[7]Importantly, this assumption does not imply that the elasticity of substitution between imports and labor is one. For example, suppose that production is given by a Cobb Douglas function: $Y_f = V_f^{\alpha_1} L_f^{\alpha_2} Q_f^{(1-\alpha_1-\alpha_2)}$, where Y_f is output of firm f; Q_f is a composite intermediate used by the firm; and the α_i are parameters between zero and one that satisfy $\alpha_1 + \alpha_2 < 1$. In this case, the elasticity of substitution between the composite input and labor is one. If the composite intermediate input is a function of domestic and imported intermediates (D_f and I_f), so $Q_f = g(D_f, I_f)$, the elasticity of substitution between labor and imported intermediates, could take on values greater than one. For example, if domestic and imported inputs are highly substitutable, the elasticity of substitution between labor and imported intermediates will also be high because the ratio of imported intermediates to labor will fall rapidly when the price of imports rises.

[8]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.

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 flow.[9] Wages move one-for-one with the employment-weighted average of log changes in cash flow.[10]

As in Jones, the remaining propositions require that the share of expenditures on total intermediate inputs are a constant fraction of sales. We do this by defining ω_{Lf}, ω_{Vf}, and ω_{if} as the expenditure shares of firm f on labor, the specific factor, and input i expressed as a share of total revenue and assuming $\sum_i \omega_{ift} = \sum_i \omega_{ifs}$ for all s and t.[11]

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):

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

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. Jones (1975) assumed that the observed movements in prices were due to tariff changes, but he never modeled how tariffs passed through into domestic product prices. This assumption creates an empirical conundrum when taking the model to data because although the model tells us how movements in firm *prices* (and hence ERP) affect factor prices, a major limitation of his approach is that it is impossible to rigorously map *tariff changes* into ERP changes without making strong assumptions.[12]

An advantage of our approach is that we can use movements in cash flow to conduct comparative statics exercises and measure a policy's impact on many variables, including ERP, without making any assumptions about how tariffs affect ERP. We therefore do not need to model tariff passthrough. We proceed by first recalling a result from Jones (1975), who proved that the movement in the returns to each specific factor (i.e., changes in cash flow) can be written as

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[9]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.

[10]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.

[11]The assumption that $\sum_i \omega_{ift} = \sum_i \omega_{ifs}$ is standard whenever one wants to analyze a value-added production function and is common in the macro literature whenever TFP is defined as the residual from subtracting capital and labor input growth from output growth (see, for example, Hsieh and Klenow (2009)).

[12]Examples of common assumptions include: firms use no intermediate inputs, perfect or constant passthrough of tariffs into prices, no heterogeneity in firm-level input-output matrices, no effects of tariffs on exchange rates, no impact of tariffs on productivity, etc. Another common approach to measuring ERP is to follow Corden (1966) and define it as the change in the output tariff less an input-share weighted average of the input tariff changes all divided by the share of value added in sales. Despite the popularity of this approach, Ethier (1977) proves that the Corden tariff-based measure of ERP and the Jones price-based measure of ERP cannot be rigorously linked.

$$\hat{r}_{ft} = \left(\varphi_{ft} + \frac{1}{\theta_{Vft}} \sum_{f' \neq f} \varphi_{f't} \right) \hat{p}^e_{ft} - \frac{\theta_{Lft}}{\theta_{Vft}} \sum_{f' \neq f} \varphi_{f't} \hat{p}^e_{f't} \text{ and } \hat{w}_t = \sum_f \varphi_{ft} \hat{p}^e_{ft}, \qquad (6)$$

where

$$\varphi_{ft} \equiv \frac{L_{ft}}{\theta_{Vft}} \Big/ \sum_{f'} \frac{L_{f't}}{\theta^V_{f't}},$$

θ_{Lft} and θ_{Vft} are the wage bill and cash flow expressed as a share of value added:

$$\theta_{Lft} \equiv \frac{\omega_{Lft}}{(1 - \sum_i \omega_{ift})}, \text{ and } \theta_{Vft} \equiv \frac{\omega_{Vft}}{(1 - \sum_i \omega_{ift})}. \qquad (7)$$

The first term in equation (6) captures the direct link between a firm's change in cash flow and its ERP. Intuitively, the shadow price of a firm's specific factor will rise if its ERP rises and falls if the ERPs of other firms rise because this causes them to bid up the wage. Two important properties of the mapping between ERP and factor prices, which we will use later, are that it is linear and homogeneous of degree 1, which means that factor prices will not change if the ERP does not change.

As we prove in the following proposition, movements in cash flow provide a sufficient statistic for the changes in the ERP.

Proposition 2. *The log change in the ERP for a firm ($\hat{p}^e_{ft}$) can be expressed as a linear function of the log changes in cash flows*

$$\hat{p}^e_{ft} = \theta_{Vf} \hat{r}_{ft} + \theta_{Lf} \sum_{f'} \frac{L_{f'}}{L} \hat{r}_{f't}$$

and is equivalent to the log change in its revenue total factor productivity:

$$\widehat{TFPR}_{ft} \equiv \hat{p}_{ft} + \widehat{TFP}_{ft} = \hat{p}^e_{ft},$$

where $\widehat{TFP}_{ft} \equiv \hat{y}_{ft} - \theta_{Lf} \hat{L}_{ft} - \theta_{Vf} \hat{V}_{ft}$. The log changes in revenue for a firm can also be expressed as linear functions of the log changes in cash flows:

$$\hat{p}_{ft} + \hat{y}_{ft} = (\theta_{Lft} \sigma + \theta_{Vft}) \hat{r}_{ft} + \theta_{Lft} (1 - \sigma) \sum_{f'} \frac{L_{f't}}{L} \hat{r}_{f't}.$$

Proof. See Appendix A.2 □

Proposition 2 proves that the ERP is simply TFPR. The intuition for this result stems from the fact that cash flow equals the payments to the firm's specific factor, which implies that $\hat{p}^e_{ft} = \theta_{Vft} \hat{r}_{ft} + \theta_{Lft} \hat{w}_t$. The left-hand side will only be positive if aggregate payments to factors rise, which can only happen if a firm's revenue is growing faster than its costs, i.e., TFPR is rising.

If we had information on firm-level input-output linkages (ω_{ift}) and the changes in intermediate input prices of importers ($\hat{q}^*_{ft}$), we could recover movements in all prices ($\hat{p}_{ft}$), quantities ($\hat{y}_{ft}$), and TFPQ ($\widehat{TFP}_{ft}$) for all firms. We prove this in the following proposition:

Proposition 3. *The vectors of log changes in firm output prices* $(\hat{\boldsymbol{p}}_t)$, *output* $(\hat{\boldsymbol{y}}_t)$, *and TFP* $\left(\widehat{\boldsymbol{TFP}_t}\right)$ *can be expressed as linear functions of the vectors of log changes in cash flows* $(\hat{\boldsymbol{r}}_t)$ *and imported intermediate input prices* $\left(\hat{\boldsymbol{q}}_t^*\right)$:

$$\hat{\boldsymbol{p}}_t = \mathbf{A_1}\hat{\boldsymbol{r}}_t + \mathbf{A_2}\hat{\boldsymbol{q}}_t^*$$
$$\hat{\boldsymbol{y}}_t = \mathbf{A_3}\hat{\boldsymbol{r}}_t - \mathbf{A_2}\hat{\boldsymbol{q}}_t^*$$
$$\widehat{\boldsymbol{TFP}_t} = \mathbf{A_4}\hat{\boldsymbol{r}}_t - \mathbf{A_2}\hat{\boldsymbol{q}}_t^*,$$

where the elements of matrices $\mathbf{A_1}, \mathbf{A_2}, \mathbf{A_3},$ *and* $\mathbf{A_4}$ *only depend on the baseline factor shares in revenue and value added* (ω_f, θ_f), *shares of total employment* (L_f/L), *and the elasticity of substitution between labor and the specific factor* (σ).

Proof. See Appendix A.3 ☐

These propositions demonstrate that a researcher with knowledge of how a policy change would affect cash flows $(\hat{\boldsymbol{r}}_t)$ can solve for a wide variety of equilibrium variables such as changes in wages, employment, sales, ERP, and TFPR. Thus, to the extent that stock returns covary with expected cash flows, we should expect real firm outcomes to covary with stock returns as Table 4 shows actually happens. Moreover, Proposition 3 tells us that if one also knew how intermediate input prices shifted in response to the policy, one could also solve the model for all price, quantity, and TFP changes as well. We build off these insights in the next sections, which show how to map movements in cash flows into welfare shifts and how to measure these cash flow movements using stock-market data.

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:

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

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:

$$\hat{C}_t = \frac{wL}{C}\hat{w}_t + \sum_f \frac{r_f V_f}{C}\hat{r}_{ft} + \frac{TR}{C}\hat{TR}_t. \tag{8}$$

The policy change can be thought of as affecting an infinite sequence of changes in wage, cash flow, and tariff revenue: $\hat{w}_t$, $\hat{r}_t$, 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 log change in consumption (in every state and every period) that would compensate the agent for the effect of the policy change.

To characterize this consumption-equivalent welfare effect, we assume that 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). Finally, we assume that log consumption growth is i.i.d. on the baseline path.[13] As shown in the proof of the proposition, this ensures that the ratio of consumption, C_t, to the present value of consumption, W_t, is constant along the baseline path.

Proposition 4. *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, which is constant in the baseline economy.

Proof. See Appendix A.4

This proposition expresses the welfare effect as a time-discounted, weighted average of the deviations in consumption. The first set of weights, $(1-\rho)\rho^t$, adjust for the agent's discounting over time (they sum to one across time) while the weights $\frac{C_t^{1-\gamma}}{\mathrm{E}_0\left[C_t^{1-\gamma}\right]}$ represent the agent's discounting of different states of nature (they sum up to one across states of nature in a given period). This implies that positive deviations in log consumption are particularly important for welfare if they happen close to the current period or if they happen in states of nature in which $C_t^{1-\gamma}$ is particularly high (i.e., states in which consumption is low when $\gamma > 1$). $\qquad\square$

To better understand this formula, we can rewrite the consumption-equivalent welfare effect as the sum of two terms:

---

[13]If this is not the case, 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.

$$\mathcal{C} = \underbrace{(1-\rho) \sum_{t=0}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{C}_t \right]}_{\equiv \, \mathcal{C}^{\text{first-order}}} + \underbrace{(1-\rho) \sum_{t=1}^{\infty} \rho^t \mathrm{cov}_0 \left(\frac{C_t^{1-\gamma}}{\mathrm{E}_0 \left[C_t^{1-\gamma} \right]}, \hat{C}_t \right)}_{\equiv \, \mathcal{C}^{\text{higher-order}}}. \tag{9}$$

The first term, $C^{\text{first-order}}$, corresponds to the weighted change in average log consumption. The second term, $C^{\text{higher-order}}$, corresponds to the normalized covariance of $C_t^{1-\gamma}$ and changes in log consumption. This second term is null if $\gamma = 1$ or if deviations in log consumption are independent of the realization of consumption along the baseline path. The corollary below gives an equivalent expression for the second term.

Corollary 1. *The consumption-equivalent welfare effect of the deviation path $(\hat{C}_t)_{t=0}^{\infty}$ due to higher-order terms is:*

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

Proof. See Appendix A.5. $\qquad\qquad\square$

This corollary says that, while $C^{\text{first-order}}$ captures the welfare effect of the policy through changes in average log consumption, $\mathcal{C}^{\text{higher-order}}$ captures its effect through changes in its higher-order cumulants, such as the variance, skewness, and kurtosis of log consumption. In particular, if $\gamma > 1$, the representative agent dislikes an increase in even cumulants (e.g., variance or kurtosis) but enjoys an increase in odd cumulants (e.g., skewness). The converse is true if $\gamma < 1$. In the rest of the paper, we will focus on measuring $C^{\text{first-order}}$, which corresponds to the welfare effect in the intermediate case of log utility, when $\gamma = 1$. As shown by Corollary 1, if the true model is one in which agents do not like increased consumption variance or fear extreme negative outcomes (negative skewness) (i.e., $\gamma > 1$), and if tariffs increase the variance of log consumption or decrease its skewness, then our measured welfare effect $C^{\text{first-order}}$ 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 first-order impact

on consumption-equivalent welfare ($\mathcal{C}^{\text{first-order}}$) in terms of the present value 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 and Firm Values and Discount Rates

We begin by decomposing the first-order welfare effect into how much is due to each source of household income. Substituting equation (8) into equation (9), we obtain an expression for the first-order welfare effect in terms of the discounted value of policy-induced changes in wages, cash-flows, and tariffs:

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

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

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:

$$\mathcal{C}^{\text{first-order}} = \sum_f \frac{wL_f + r_f V_f}{C} \left((1 - \rho) \sum_{t=0}^{\infty} \rho^t \mathrm{E}_0[\hat{r}_{ft}] \right) + \frac{TR}{C} \left((1 - \rho) \sum_{t=0}^{\infty} \rho^t \mathrm{E}_0 \left[\widehat{TR}_t \right] \right). \quad (10)$$

This equation expresses the first-order welfare effect as the sum of two terms: the present value of the deviation in (expected) firm cash flows and the present value of the deviation in tariff revenues.

The first term in equation (10) 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:[14]

$$\Pi_{f0} = \mathrm{E}_0 \left[\sum_{t=0}^{\infty} \frac{r_{ft} V_f}{R_{f1} \ldots R_{ft}} \right]. \quad (11)$$

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 present value of firm cash-flows and a deviation in the present value of firm discount rates:

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

Proposition 5. *Around a baseline path in which the cash-flow-to-firm-value ratio, $r_{ft}V_f/\Pi_{ft}$ is equal to the constant consumption-to-wealth ratio, C_t/W_t, we have:*

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

Proof. See Appendix A.6. □

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.[15] We can solve for the present value 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 present value 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 (10) allows us to write the aggregate welfare effect as a sum of three components:

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

(12)

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 may lead to noisy estimates, as unrelated news is released over time. As a robustness exercise, we also experiment with a three-day window, and we find that our results are qualitatively similar.

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:

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[15]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.

$$\ln R_{f,t} = \alpha_f + \sum_{j=1}^{J} \beta_{f,j} D_t^j + \sum_{d=1}^{D} \gamma_{f,d} ES_{d,t} + \epsilon_{f,t}. \tag{13}$$

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

$$\hat{\Pi}_{f0} \equiv \sum_{j=1}^{J} \kappa_f \beta_{f,j} \tag{14}$$

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 (12)) 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 (12)) 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

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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
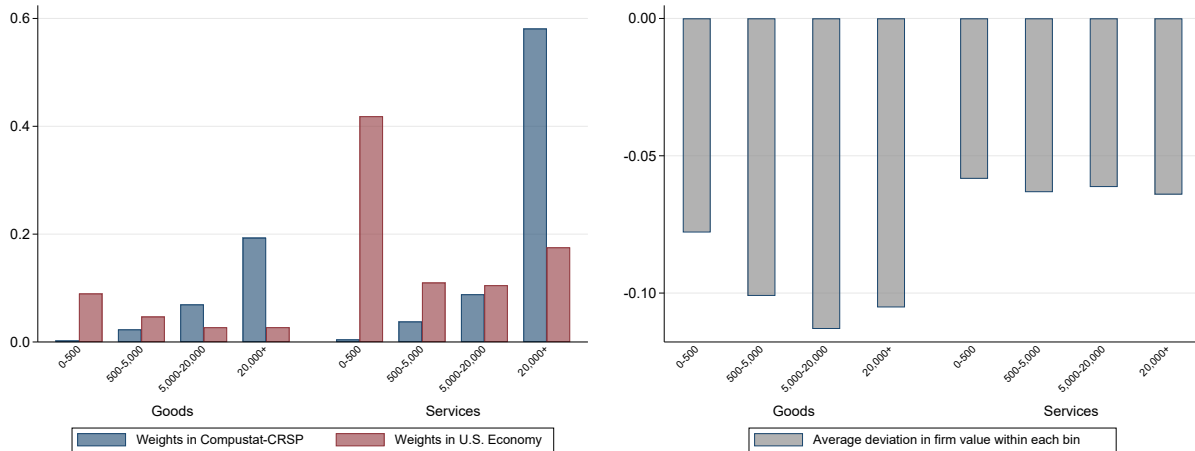
Note: For goods (2-digit NAICS: 11, 21, and 31-33) and services (remaining 2-digit NAICS) sectors in 2017.

We find that tariff announcements caused aggregate firm values to fall 6.5 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 (14), 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 5.2.

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 (12). The challenge in computing this term is in obtaining an expression for the change in discount rates induced by the policy $\left(\sum_{t=0}^{\infty} \rho^t E_0 \left[\hat{R}_{ft}\right]\right)$. 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 $(\hat{R}_{ft}^E)$:

$$E_0 \left[\hat{R}_{ft}\right] = (1 - \kappa_f) E_0 \left[\hat{R}_{f,t}^D\right] + \kappa_f E_0 \left[\hat{R}_{f,t}^E\right], \tag{15}$$

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):

$$\mathrm{E}_0\left[\hat{R}_{f,t}^D\right] = \hat{R}_{\text{risk-free},t}, \tag{16}$$
$$\mathrm{E}_0\left[\hat{R}_{f,t}^E\right] = \hat{R}_{\text{risk-free},t} + \beta_{f,M}\left(\hat{R}_{M,t} - \hat{R}_{\text{risk-free},t}\right)$$

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 (15) and aggregating over time gives the following expression for the deviation in firm f discount rate:

$$\underbrace{\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0\left[\hat{R}_{ft}\right]}_{\text{Deviation in firm } f \text{ discount rates}} = \underbrace{\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0\left[\hat{R}_{\text{risk-free},t}\right]}_{\text{Deviation in future risk-free rates}} + \kappa_f \beta_{f,M} \underbrace{\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0\left[\hat{R}_{M,t} - \hat{R}_{\text{risk-free},t}\right]}_{\text{Deviation in future excess stock-market returns}}. \tag{17}$$

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 $\boldsymbol{x}_t$, 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:

$$\boldsymbol{x}_{t+1} = \boldsymbol{a} + \boldsymbol{B}\boldsymbol{x}_t + \boldsymbol{u}_{t+1}. \tag{18}$$

This VAR structure allows us to express the expected effect of a policy announcement on $\boldsymbol{x}_t$ in terms of its effect on $\boldsymbol{x}_0$: $\mathrm{E}_0[d\boldsymbol{x}_t] = \boldsymbol{B}^t d\boldsymbol{x}_0$. Hence, the VAR structure implies the following equation for the deviation in future risk-free rates and excess returns defined in equation (17):[16]

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

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

$$\underbrace{\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{\text{risk-free},t} \right]}_{\text{Deviation in future risk-free rates}} = \boldsymbol{e}_1' \rho \boldsymbol{B} (\boldsymbol{I} - \rho \boldsymbol{B})^{-1} d\boldsymbol{x}_0, \tag{19}$$

$$\underbrace{\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{M,t} - \hat{R}_{\text{risk-free},t} \right]}_{\text{Deviation in future excess returns}} = \boldsymbol{e}_2' \rho \boldsymbol{B} (\boldsymbol{I} - \rho \boldsymbol{B})^{-1} d\boldsymbol{x}_0, \tag{20}$$

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 (17)) 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 (18) at the quarterly frequency where the vector x_t contains seven variables:

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

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 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 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 quar-

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

ter.[17] 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 (18), 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 our 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

$$\Delta \boldsymbol{x}_t = \boldsymbol{\alpha} + \sum_{j=1}^{J} \boldsymbol{\beta_j} D_t^j + \sum_{d=1}^{D} \boldsymbol{\gamma}_d ES_{d,t} + \boldsymbol{\epsilon}_t, \qquad (21)$$

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

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

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 (21). 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 (19) and (20). 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 $(= -2.1 + 8.9)$.[18] 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 very consistent with existing results on their relative importance for the unconditional variance of returns (see, for instance, Campbell (2003)).

Table 7: Estimated Changes in Future Discount Rates

	Deviation in Future Risk-free Rates $\sum_{t=1}^{\infty} \rho^t E_0 \left[\hat{R}_{\text{risk-free},t} \right]$	Deviation in Future Excess Returns $\sum_{t=1}^{\infty} \rho^t E_0 \left[\hat{R}_{M,t} - \hat{R}_{\text{risk-free},t} \right]$
Baseline	-0.021	0.089

Note: The table reports the deviation in risk-free rate, $\boldsymbol{e}_1' \rho \boldsymbol{B} (I - \rho \boldsymbol{B})^{-1} d\boldsymbol{x}_0$, and the deviation in the equity premium, $\boldsymbol{e}_2' \rho \boldsymbol{B} (I - \rho \boldsymbol{B})^{-1} d\boldsymbol{x}_0$. Note that the matrix $\boldsymbol{B}$ is reported in Table 5 while the vector $d\boldsymbol{x}_0$ 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.

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

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[18]This calculation can be seen as an application of Equation (17) for a firm with $\kappa_f = 1$ and $\beta_f = 1$.

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 very consistent results on the evolution of discount rates following tariff announcements: the real risk-free rate decreases, especially at longer 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.[19]

Figure 7: Effect of Tariff Announcements on Discount Rates: VAR versus Reduced-Form
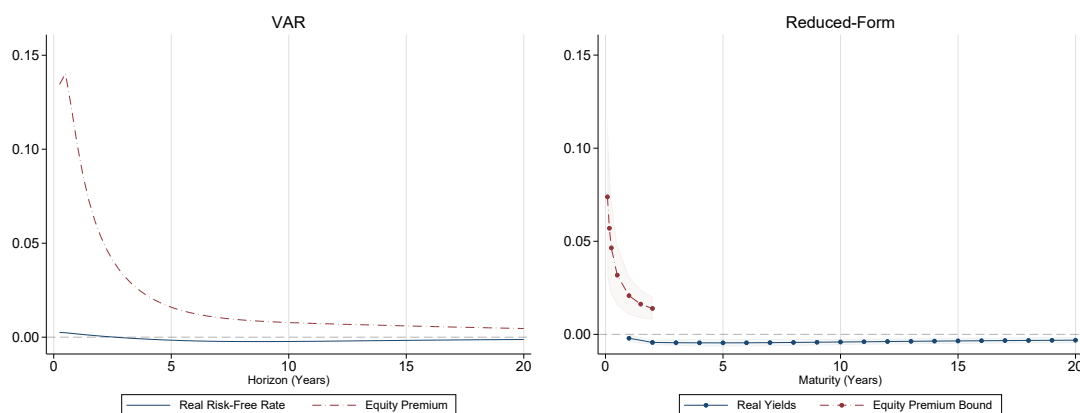
Note: The figure in the left panel plots the effect of tariff announcements on the annualized (real) risk-free rate and excess stock-market return between 0 and t; that is, $(4/T)\sum_{t=1}^{T} \mathrm{E}_0[\hat{R}_{\text{risk-free},t}] = (4/T)\sum_{t=1}^{T} e_1' B^t dx_0$ and $(4/T)\sum_{t=1}^{T} \mathrm{E}_0[\hat{R}_{M,t} - \hat{R}_{\text{risk-free},t}] = (4/T)\sum_{t=1}^{T} e_2' B^t dx_0$. 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 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 (15)): as firms issue a mix of debt and

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[19]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.

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 (12) 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 (12) described above, across all announcement days: the deviation in firm values, the deviation in firm discount rates, and the deviation in tariff revenues.

5.1 Baseline Results

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.

5.2 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.

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. announcement window				
3-day window	-0.057	0.046	0.006	-0.005
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 first-order welfare effect of trade announcements, $\mathcal{C}^{\text{first-order}}$, as well as its three components defined in equation (12): the aggregate deviation in firm values, the aggregate deviation in firm discount rates, and the effect on tariff revenues.

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.

Announcement Window   In the baseline results, we estimated firm deviation in firm values and discount rates using a one-day window around tariff announcements. As a robustness check, we now explore using a longer three-day window. This alternative procedure affects not only the estimates for the deviation in firm value (as the effect of announcements on firm returns differ when using a three-day window) but also the deviation in firm discount rates (as the effect of announcements on the VAR variables differ when using a three-day window). In particular, Appendix Table E.3 reports the change in the VAR variables obtained over a three-day window around announcement days. Relative to the estimates obtained with a one-day window reported in Table 6, we find quantitatively similar, but much noisier, effects—in particular, most changes in the VAR variables become insignificant with a three-day window. As reported in Table 8, using a three-day window leads us to find a smaller drop in firm value and a larger increase in discount rates, which implies a smaller magnitude for the welfare effect of tariff announcements. Nevertheless, the overall impact remains large compared to conventional analyses.

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 robustness 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.

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). 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.. More precisely, we replace the second equation in (16) 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 (15) implies the following equation for the deviation in firm discount rates:

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

$$\tag{22}$$

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

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 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 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 (16) 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.

5.3 Treatment Effects

We can obtain a sense of how important the impact of tariff announcements on firms in general vs. the differential impact of tariffs on "exposed" vs. "unexposed" firms by comparing our estimates to a "naive" difference-in-difference estimate. This approach estimates the differential deviation in firm values and discount rates between firms exposed to China relative to unexposed firms. We find that the treatment effect accounts for only about a quarter of the aggregate drop in firm cash flows.

Event Study 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.

$$\mathrm{CF}_{ft} \equiv \sum_{t=0}^{\infty}(1-\rho)\rho^k \mathrm{E}_0\left[\hat{r}_{ft}\right] = \alpha_t + \sum_j \sum_i \gamma_{ij} Z_{if} D_{jt} + \epsilon_{ft}, \tag{23}$$

where the left-hand side variable is the expected present discounted value of firm cash flow, which can be measured using Proposition 5, 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 9: Impact of US 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 (14)) 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 9 presents the results for each of the six U.S. tariff events, and Table 10 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 (23). 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 9 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 9, 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.

Turning to the Chinese announcements, column 1 of Table 10 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 con-

Table 10: 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 (14)) 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: $^{***}p < 0.01,^{**} p < 0.05,^* p < 0.1$.

sidering 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.[20]

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 provide a rigorous methodology to estimate the expected impact of a policy change using the reaction of financial markets to policy announcements. Seen through the lens of an infinite-horizon specific factors model, we show that the change in firm cash flows is a sufficient statistic for identifying expected movements in sales, wages, total factor productivity, and, therefore, in aggregate welfare.

Our estimates are large compared to conventional measures. One likely reason is that our welfare measure captures all of the dynamic and stochastic impacts of tariffs on the economy (i.e., effects that are far in the future or specific to certain states of nature). An-

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

other likely reason is that our welfare effect captures all of the indirect effects of changes in trade policy, in particular their impacts on the likelihood of further deterioration in trade policies through retaliations. While our framework does not pin down the exact mechanism driving these results, the fact that the drop in welfare computed from the differential stock returns of exposed firms accounts for only a quarter of the aggregate drop in welfare suggests that changes in the overall economic environment play an important role.

Our paper also opens up paths for future research. 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, sales, productivity, prices, etc. These links may help future researchers better understand the mechanisms driving our results.

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