Trade Protection, Stock Market Returns, and Welfare*

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Abstract

Tariff announcements during the U.S.-China trade war had large and broad effects on financial variables: stock prices fell, yields declined, and risk premia rose. The stock-price reactions were heterogeneous in the cross-section during 2018–19—firms that imported from, exported to, or sold in China experienced significantly worse returns than other firms. These cross-sectional differences in announcement-day returns forecast subsequent declines in profits, sales, employment, and investment. Using a specific factors model, we show that these asset price movements can help identify the welfare impact of tariffs. We estimate that the trade war substantially reduced U.S. welfare.

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KEYWORDS: Event Study, Specific Factors Model, Trade War, Policy Uncertainty

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1 Introduction

How do tariff announcements affect financial markets, and what do those market reactions tell us about the economic costs of trade protection? We address these questions using data from the U.S.-China trade war of 2018–2019, one of the largest disruptions to global trade in U.S. history. We document that tariff announcements during this period produced large, broad, and persistent declines in equity prices, reductions in yields, and increases in equity risk premia. These financial market reactions were not uniform across firms: companies that imported from, exported to, or sold in China experienced significantly worse returns than other firms, and we show that these cross-sectional differences in announcement-day returns predict subsequent declines in realized profits, sales, employment, and investment. Together, these findings establish that tariff announcements conveyed substantial information about the expected future costs of trade protection—information that we use, through the lens of a specific factors model, to estimate the aggregate welfare impact of the trade war.

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 policy action. To identify the tariff-announcement dates, we search for the first media mention of each tariff wave implemented by the U.S. or China during 2018–2019. We verify that these announcements represent genuine news by showing that stock prices were flat in the days before each announcement and moved sharply on the announcement day itself, with no reversal in the days that followed. We also show that markets barely responded to non-tariff executive actions and orders targeting China or President Trump's tweets about trade and China (except when they coincided with news of concrete tariff escalations or liberalizations), confirming that the large announcement-day returns we document specifically reflect information about tariff policy rather than general U.S.-China tensions.

We document a rich set of empirical findings about how financial markets responded to these announcements. The cumulative drop in the U.S. market across the eleven event dates was 11.5 percent—a 4.2 trillion dollar loss in firm equity value—while the Chinese stock market fell nearly twice as much, declining 20.6 percent in cumulative terms. These aggregate declines were broad: the full distribution of firm returns shifted to the left on announcement days, with the median firm losing over one percent of its value on Chinese announcement days alone. We show that the same asset-pricing patterns recur during the 2025–2026 episode, with markets falling by a similar cumulative magnitude on major tariff-increase days and rising sharply on tariff-liberalization days. This out-of-sample replication strengthens the interpretation that our event-study methodology captures genuine shifts in expectations about trade policy.

The cross-sectional variation is equally striking. Our empirical approach follows Hébert and Schreger (2017), who use event-study variation in firm-level returns to identify which firms bear the costs of sovereign default. We adapt this structure to trade policy and find that firms that imported from, exported to, or sold in China experienced significantly more negative abnormal returns on U.S. announcement days; on Chinese announcement days, the negative returns were concentrated among firms and industries with export exposure to China. These cross-sectional differences are fully preserved over a multi-year horizon, with no evidence of mean reversion. These results indicate that the announcement-day return differences are not transitory overreactions but genuine signals about lasting changes in firm prospects.

We also show that tariff announcements moved discount rates in a pattern consistent with a flight to safety. Treasury yields fell across the maturity curve, while option-implied bounds on the equity premium rose sharply. The fall in nominal yields does not simply reflect lower inflation expectations: decomposing nominal yields using inflation-indexed bonds and inflation swaps shows that real rates fell as well, while inflation compensation declined modestly. This inflation response suggests that markets incorporated not only the direct price effects of tariffs, but also forces that reduce expected inflation, such as weaker future demand and higher recession risk (Auclert et al., 2025), or improved fiscal revenues (Gómez-Cram et al., 2025). Together, the evidence points to lower safe rates but higher compensation for bearing equity risk.

We then develop a model that maps these financial market reactions into an estimate of aggregate welfare. We adapt Jones (1975)'s industry-level specific factors model to the firm level. In this setup, payments to firm-specific factors equal firm cash flows, i.e., revenues less variable costs. We embed this production structure into an infinite-horizon model of consumer welfare. Since wages in each period can be expressed as a function of firm cash flows, consumption in each period can be written as a function of firm cash flows and tariff revenues, and the consumption-equivalent welfare change can be written as the present discounted value (PDV) of expected cash-flow and tariff-revenue changes. Following Campbell and Shiller (1988), the PDV of cash flows equals the sum of the policy-induced change in firm market values and the change in expected discount rates—both of which we estimate from financial data. We validate these cash-flow estimates in the cross-section by showing that the firm-level cash-flow deviations we estimate from stock prices predict subsequent realized declines in accounting profits with coefficients statistically indistinguishable from one. This result supports the interpretation that financial markets processed tariff announcements rationally, pricing in real economic costs that subsequently materialized in the data.

We estimate that the trade war reduced U.S. welfare by 3.9 percent in our baseline specification and use the model to understand why the market reactions imply welfare losses far larger than those from conventional static models. Decomposing the cash-flow effect into a static price effect, a dynamic price effect, and a productivity effect, we find that the static price effect—which corresponds to the welfare estimate from standard trade models—is small. The bulk of the estimated welfare loss comes from the dynamic price and productivity effects: markets appear to have believed that tariffs would generate large, negative future shocks to firm productivity, of the kind that feature prominently in dynamic trade models but are absent from static ones.

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

The specific factors model, which forms the basis of our approach, has also been used extensively in empirical estimation (cf., Topalova (2010), Kovak (2013), and Dix-Carneiro and Kovak (2017)). These papers have shown that many of the large effects of trade policy changes on wages often take a decade or more to be fully apparent in the data. Our paper provides a complementary way of thinking about the long-term effects of a policy change in terms of expected wages. In particular, most papers in this literature only look at the impact of output tariffs, so tariffs are assumed to always raise the effective rate of protection. However, in our setup, tariffs can affect input prices as well, so the imposition of tariffs can either raise the effective rate of protection by increasing firm output prices or lower it by raising the cost of the firm's imported intermediate inputs.

Our paper is related to the vast empirical trade literature over the last two decades showing that trade liberalizations have big effects on per capita income and productivity. These studies have shown that *firm-level* TFP is very sensitive to ERP and import competition more generally.[1] We also identify large impacts of trade policy on TFP, but our identification is based on using stock-price data filtered through a general equilibrium model. Our work is also related to the macro literature evaluating the impact of trade

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

on income that has found evidence of large impacts of trade on productivity, income, and growth (cf., Frankel and Romer (1999); Alcalá and Ciccone (2004); Feyrer (2019); Wacziarg and Welch (2008); Waugh (2019)). Although our work also finds large impacts of trade on productivity and welfare, an important difference between our work and the macro literature is that we build these estimates up from firm-level data on stock prices and use a general equilibrium setup to obtain our estimates. We also contribute to the burgeoning literature on understanding the importance of protection for the economy through macro or policy uncertainty channels (Baker et al. (2016); Pierce and Schott (2016); Handley and Limão (2017); Caldara et al. (2019); Greenland et al. (2024)) as increased uncertainty is one potential explanation for our larger welfare effect, through either the dynamic price effect or the productivity effect.

We also build off the literature documenting the impact of the trade war on firm prices (cf., Amiti et al. (2020); Fajgelbaum et al. (2020); Flaaen et al. (2020); Amiti et al. (2019); Cavallo et al. (2021)). These papers have found that during the U.S.-China trade war, tariff passthrough into import prices was close to complete, consistent with our finding that higher U.S. tariffs negatively affected importers.

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

2 Stylized Facts

This section documents four stylized facts about the tariff announcements that motivate our theory and welfare analysis. First, we describe the announcements themselves and document that both the U.S. and Chinese stock markets reacted negatively to tariff announcements. We show that announcement-day returns were not driven by coincident non-tariff news, that markets fully incorporated each announcement within a single trading day, and that cross-sectional differences in announcement-day returns were fully preserved in firm valuations over a multi-year horizon, making it unlikely they can be explained by a market overreaction. Second, we show that tariff protection benefited domestic firms only when it was applied broadly across the major foreign suppliers of a product, and had little effect—or even a negative effect—when targeted only at Chinese exporters. Third, we show that firms directly exposed to China through importing, exporting, or multinational sales had significantly more negative abnormal returns on tariff-announcement days. Fourth, we show that tariff announcements affected discount rates by driving down nominal and real Treasury yields and breakeven inflation while raising the equity-premium bound obtained from option prices.

2.1 The Tariff Announcements

Over the course of the 2018-19 trade war, the U.S. implemented tariffs in waves. The average tariff rate on all U.S. imports rose by approximately 4 percentage points, driven by high tariffs on a wide range of Chinese imports, for which the average tariff rate increased by 15 percentage points. For each of these new tariffs, we found the earliest announcement date in the media using Factiva and Google search. In addition, we 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 tariff waves, and not just threats. Our choice of event dates has the advantage of being comprehensive and objective, in that we do not use events based on actions or statements that do not correspond to observable changes in tariffs.[2]

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 the following trading day if the announcement 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, which were implemented on February 7, 2018 on China and, in this case, more broadly on other countries. The second event date (March 1, 2018) is the announcement of steel and aluminum tariffs, which were also broadly applied and imposed on March 23, 2018. All subsequent U.S. tariff actions apply only to China. At the start of the trade war, the U.S. announced new tariffs on China so quickly that China sometimes did not have time to retaliate before the next round 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. imposed steel and

[2] The tariffs announced by both sides remained in place throughout our sample period, with some minor exceptions. On the US side, no tariffs that were actually implemented were reduced during 2018–2019; the few cases of apparent scaling-back involved delays in implementation or reductions in the list of targeted goods rather than rollbacks of tariffs already in force. On the Chinese side, the main exception was the suspension of China's 25 percent retaliatory tariff on US autos (imposed July 6, 2018), which was paused for 90 days starting January 2019 and subsequently extended—a concession made in direct response to the US postponing its own planned escalation from 10 to 25 percent on $200 billion of Chinese goods. Substantial reductions by either side came only later, under the Phase 1 agreement of February 2020, when the US reduced some of the September 2019 tariffs from 15 to 7.5 percent, and China made reciprocal concessions (Bown, 2020). These reductions fall outside our event-study sample window, which ends in 2019. Within that window, the tariffs announced on both sides were largely implemented and remained in place.

Table 1: Stock-Market Returns on Tariff-Announcement Days

Event Date	Country	Description	US (x100)	CHN (x100)
23jan2018	US	U.S. imposes tariffs on solar panels and washing machines	0.3	1.1
01mar2018	US	U.S. imposes steel and aluminum tariffs	-1.1	0.6
22mar2018	US	U.S. imposes $60B in annual tariffs on China	-2.4	-1.0
23mar2018	CHN	China retaliates and announces tariffs on 128 U.S. exports	-1.9	-2.9
15jun2018†	CHN	China announces retaliation against U.S. tariffs on $50B of imports	-0.2	-3.6
19jun2018	US	U.S. announces imposition of tariffs on $200B of Chinese goods	-0.4	-3.6
02aug2018†	CHN	China unveils retaliatory tariffs on $60B of US Goods	0.5	-1.7
06may2019	US	U.S. to raise tariffs on $200B of Chinese goods up to 25%	-0.4	-6.0
13may2019†	CHN	China to raise tariffs on $60B of U.S. goods starting June 1	-2.5	-0.6
01aug2019†	US	U.S. imposes a 10% tariff on another $300B of Chinese goods	-0.9	-1.5
23aug2019†	CHN	China retaliates with higher tariffs on soy and autos	-2.5	-1.4
Cumulative	US		-5.0	-10.4
Cumulative	CHN		-6.5	-10.2
Cumulative	All		-11.5	-20.6

Note: The table reports log returns ($\ln R_{MKT,t} \times 100$) for the U.S. value-weighted market portfolio from CRSP and the China Securities Index 300 on each tariff announcement day. The Event Date is the first day markets could trade on the announcement. † indicates events where the U.S. or Chinese announcement occurred after the close of the Chinese market. Because of the time-zone difference between the U.S. and China, we use the return on the following trading day for the Chinese market in these cases. Country indicates whether the U.S. or China announced the tariff action.

aluminum tariffs on March 23, 2018, prompting China to announce retaliatory tariffs that same day. China then retaliated on June 15, 2018, by hitting $50 billion of U.S. exports to China. After these initial announcements, a pattern emerged in which the U.S. would announce new tariffs, and China would 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 B.1.

2.2 Aggregate Stock Market Response

Stock markets reacted consistently to these tariff announcements. Table 1 reports the U.S. value-weighted stock-market return from CRSP on each of the tariff-announcement dates. We see that the stock market fell on all event dates except one U.S. event date and one Chinese event date, with a total drop of 11.5 percent across all events.[3] These announcements had an even larger effect on the China Securities Index 300, which reacted with

[3]We chose a one-day window because tariffs are sometimes announced and then their scope and details are explained later in the day, which makes it difficult to identify the precise time of the announcement. Our choice of a one-day window for analyzing stock market responses is also consistent with 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.

about twice the severity, declining a total of 20.6 percentage points on the announcement days. The larger impact on Chinese stock prices is consistent with U.S. tariffs mattering more for the export-dependent Chinese economy than for the U.S. economy.

We also analyze intraday stock returns in Appendix B.2 and find no evidence that prices moved systematically in the days before or after announcements. We typically see prices move sharply at the time of each announcement, though there is sometimes evidence that the market began or ended its move a few hours before or after an announcement. However, the data make it clear that markets processed information about tariff announcements within the trading day of the announcement. These results suggest that, if there were confounding informational releases, they consistently occurred coincident with, or at most within a couple of hours of, tariff announcements and must have mattered more for Chinese firm valuations than for U.S. ones.

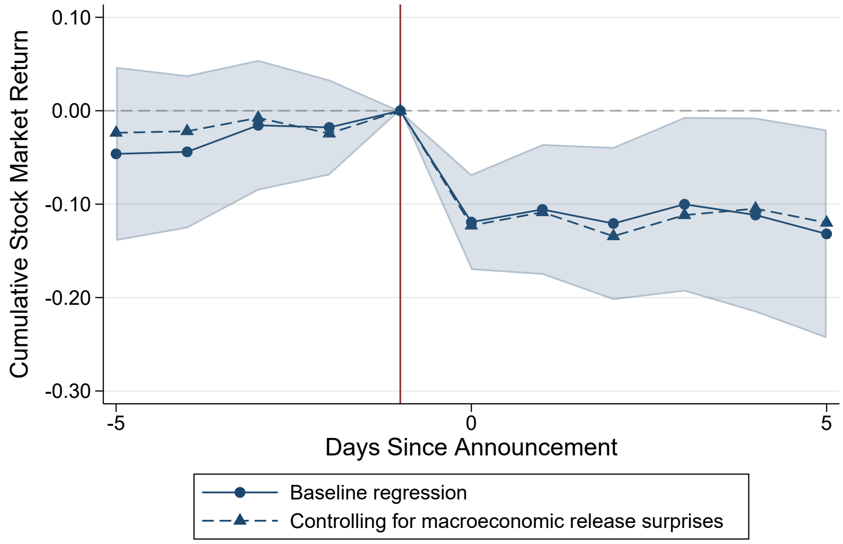
Pre- and post-announcement returns Figure 1 plots the cumulative stock-market return over a ten-day window around the tariff announcements so that we can better understand the dynamics of the stock market surrounding these announcements. The data reveal that over the four trading days before the events, stock price movements were quite small on average—there is little evidence of anything out of the ordinary in the market before the announcements. However, as Table 1 showed, there were significant cumulative declines of over 10 percent on the announcement days.[4] 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 data releases happening on the same day. While no monetary policy announcements occured on our event days, we also report 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.

Comparing tariff announcements to other announcements. Our event dates are limited to announcements of concrete tariff actions, not political rhetoric. To verify that we are not missing important information, we collected all tweets by President Trump during

[4]Because daily stock returns exhibit fat tails, however, asymptotic inference may not provide reliable finite-sample coverage. We therefore also construct bootstrap confidence intervals that do not rely on normality: we randomly draw 11 days with replacement from all trading days in 2017–2019, aggregate their log returns, and repeat one million times. Less than 0.01 percent of draws produced a lower cumulative return, strongly rejecting the hypothesis that the negative stock-market response on tariff-announcement days arose by chance.

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: $\ln R_{MKT,t} = \alpha + \sum_{s=-4}^{5} \theta_s D_{s,t} + \epsilon_t$, where $D_{s,t} = 1$ if day t is s days after an announcement and $D_{s,t} = 0$ otherwise. $\ln R_{MKT,t}$ denotes the logged value-weighted stock market return. We then plot the cumulative return of the stock market as $\sum_{k=s+1}^{-1} \hat{\theta}_k$ if $s < -1$, 0 for $s = -1$, and $\sum_{k=0}^{s} \hat{\theta}_k$ if $s > -1$ (in words, a point to the left of the eve of the announcement represents the cumulative return from that day to the eve, while a point to the right represents the cumulative return from the eve to that day). The dashed line reports the results of the same procedure controlling for economic surprises, i.e. $\ln R_{MKT,t} = \alpha + \sum_{s=-4}^{5} \theta_s D_{s,t} + \sum_{d=1}^{D} \gamma_d ES_{d,t} + \epsilon_t$ 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. Estimates and standard errors are scaled by the number of announcement days and should therefore be interpreted as the cumulative effect of all announcements.

2016–2019 that mention trade, tariffs, or China and that could be interpreted as a threat of escalation. We then measure stock market reactions in a one-hour window around each tweet (when the tweet occurs during trading hours) or in the close-to-open return (when it occurs outside trading hours). Appendix Table B.4 reports these results. The cumulative market effect of escalation tweets that fall outside our announcement windows is small (-0.47 percent over one-hour windows and 0.20 percent in close-to-open windows), which is negligible relative to the -11.5 percent cumulative return on our announcement days. This confirms that tweets not tied to concrete policy actions had negligible effects and supports our decision to focus on actual tariff announcements.

The difference between levying tariffs on China and non-tariff actions is also clearly visible when we examine stock price movements on days in 2017-2019 when the U.S.

announced executive orders and actions targeting China that were unrelated to tariffs.[5] We report the stock returns for each of these dates in Appendix Table B.5. We find that non-tariff actions had little 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.

Tariff announcements caused broad declines in stock returns. These aggregate stock-market declines on tariff-announcement days were broad-based across firms, rather than driven by a small number of large firms. To show this, Figure 2 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 shifts left on tariff-announcement days and that there is a left tail of firms disproportionately hurt by the announcements. Table 2 reports the results of quantile regressions on daily stock returns on a dummy for U.S. announcement days and Chinese announcement days, which shows that both Chinese and U.S. tariff announcements shifted the distribution of returns down. The median return fell by 1.45 percent on Chinese announcement days and by only 0.71 percent on U.S. days. These regressions also reveal that both types of announcements increased the negative skew in the distribution, with the tenth percentile falling by 50 to 95 percent more than the ninetieth percentile.

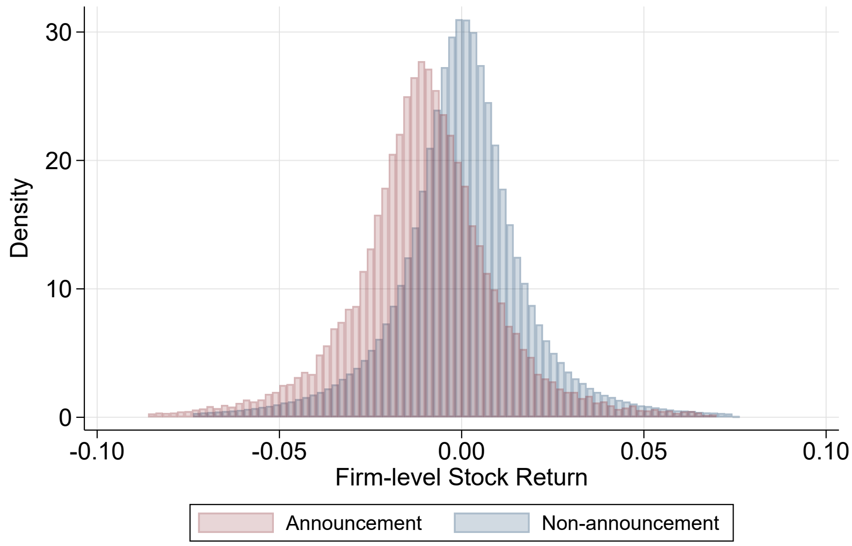
Table 2: Effect of Tariff Announcements on the Cross-Sectional Distribution of Returns

	(1) OLS	(2) p10	(3) p25	(4) p50	(5) p75	(6) p90
US announcement	-0.64***	-0.84***	-0.79***	-0.71***	-0.57***	-0.43***
	(0.02)	(0.04)	(0.02)	(0.01)	(0.02)	(0.04)
CHN announcement	-1.47***	-1.75***	-1.60***	-1.45***	-1.27***	-1.17***
	(0.03)	(0.04)	(0.02)	(0.01)	(0.02)	(0.04)
N	1,837,498	1,837,498	1,837,498	1,837,498	1,837,498	1,837,498

Note: This table reports quantile regressions of log returns (multiplied by 100) on announcement days versus non-announcement days. To focus on within-day variation, we first residualize firm-level returns on a full set of day fixed effects, and then re-center the residuals by adding the group average separately for announcement and non-announcement days.

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

Figure 2: Effect of Tariff Announcements on the Cross-Section of Firm-Level Returns



Note: The figure compares the distribution of firm-level returns on announcement days (red) versus non-announcement days (blue). To focus on within-day variation, we first residualize firm-level returns on a full set of day fixed effects, and then re-center the residuals by adding the group average separately for announcement and non-announcement days. We then plot the histogram of these residuals for each group, trimming observations outside of the 1st–99th percentile range.

2.3 Cross-sectional Evidence

In this section, we explore which industry and firm characteristics predict larger or smaller stock-price responses to tariff announcements. Trade theory and prior empirical work identify several characteristics that determine how tariffs affect firms. First, we can expect firms that import from China to lose from an increase in US-imposed tariffs because their input prices will rise. Second, firms that compete with China in the US market will likely benefit if it raises their Chinese competitors' tariff-inclusive prices. Third, Chinese retaliation may negatively affect US exporters by raising the tariff-inclusive price of their output and therefore lowering the demand they face. In addition, because China retaliation also occurred through non-tariff measures, including slower approval procedures, increasing inspection rates, and creating a legal framework to impose blacklists, export bans, asset freezes, and bans on cooperation (Pinchis-Paulsen, 2020), U.S. multinationals with sales in China may also have been adversely affected. Fourth, we can expect all tariffs to affect big firms because they are typically both large exporters and importers.

We therefore examine whether firms with the characteristics discussed above experienced more negative abnormal returns on tariff-announcement days.[6] Our empirical ap-

[6]We derive abnormal returns from a standard CAPM in Appendix Section B.6.

proach follows a growing literature that uses event studies to examine the cross-section of firm-level stock-price responses to identified macroeconomic shocks, including monetary policy shocks (Bernanke and Kuttner, 2005; Gorodnichenko and Weber, 2016) and sovereign default risk (Hébert and Schreger, 2017).

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 affiliate sales	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 B.5 for the construction of these variables. The sample is restricted to firms in the balanced event-study panel.

Our analysis focuses on the set of U.S.-incorporated firms in the CRSP-Compustat linked dataset, which we combine with Capital IQ and FactSet data to identify each firm's network of subsidiaries, major suppliers, and affiliates.[7] We also use bill of lading data from Datamyne to determine whether any firm in the network imported from or exported to China by sea in 2017 (See Appendix B.5 for details). Table 3 shows that only 10 percent of the firms in our sample import directly from China, and only 2 percent export directly to China. However, if we take subsidiaries into account, these numbers rise to 25 and 4 percent, respectively. When we add imports by all firms in the supply chain, we find that 31 percent of all listed firms in the U.S. import directly or indirectly from China. In the last row of the table, we construct a variable, "Firm Exposed to China" if any firm in the firm's network exported to or imported from China or if the firm had positive revenues from China (possibly from affiliate sales). Our results show that 52 percent of all firms were exposed to China through one or more of these channels.

Identifying how tariff announcements affect firm value is difficult, since the same announcement that protects a firm or industry often also raises its input costs. We begin by isolating the protection channel, regressing industry-level abnormal returns on a protec-

[7] The sample is limited to firms that (i) are traded on each of our eleven tariff-announcement days, (ii) have at least 120 trading days in 2017 (so that we can reliably estimate firm-level market betas), and (iii) can be matched to Compustat for balance-sheet variables.

Table 4: Firm Abnormal Returns and Protection

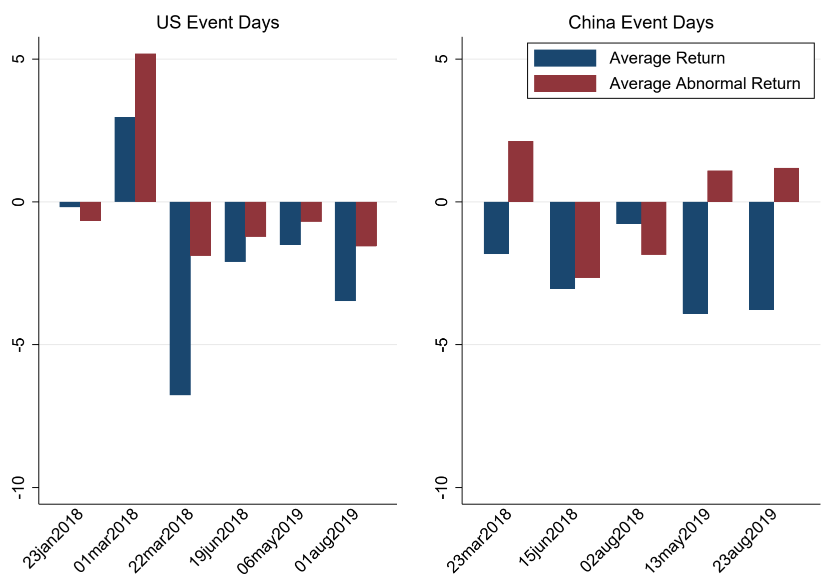
	(1) Cumulative	(2) 23Jan18	(3) 01Mar18	(4) 22Mar18	(5) 19Jun18	(6) 06May19	(7) 01Aug19
Protection	3.21*	0.23	4.27***	-0.23	-0.55***	-0.36**	-0.15
	(1.74)	(0.73)	(1.50)	(0.19)	(0.15)	(0.14)	(0.32)
N	5,841	5,841	5,841	5,841	5,841	5,841	5,841

Notes: Protection is an indicator equal to one if the industry receives positive output-tariff protection associated with that announcement event. Each column reports the coefficient on the protection indicator from an industry-level pooled event-study regression of daily abnormal returns (multiplied by 100). Column (1) reports the cumulative coefficient across U.S. announcement days, and columns (2)-(7) report the event-specific coefficients for January 23, 2018, March 1, 2018, March 22, 2018, June 19, 2018, May 6, 2019, and August 1, 2019. The data are collapsed to the industry-date level, and abnormal returns are computed as the 2017 market-value-weighted average across firms within the industry, in percentage points. Standard errors are clustered by NAICS industry and reported in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

tion indicator that equals 1 if the tariff on the *output* of the industry increased, in Table 4. In column (1), where we present the total effect, cumulated across all U.S. events, we find a positive coefficient. That is, raising tariffs on a firm's output sector is associated with positive abnormal returns. Looking at coefficients separately for each of the U.S. events, we find that the positive aggregate effect is driven by the January 23, 2018 tariffs on solar panels and washing machines and especially the March 1, 2018 tariffs on aluminum and steel. The coefficient for January 23rd is imprecisely measured, likely reflecting the fact that the solar panel and washing machine tariffs only protected a subset of domestic producers within the relevant NAICS categories — for instance, the washing machine NAICS code also includes other electrical and nonelectrical household appliances whose domestic producers gained no competitive benefit from the tariff. Moreover, the same January 23 announcement also imposed a 50 percent tariff on washing machine parts, which would have raised input costs for domestic producers and thereby offset some of the competitive benefit conferred by the output tariff, further attenuating the estimated effect. The aluminum and steel tariffs, by contrast, suffered much less from these limitations: they covered essentially all import-competing producers within those NAICS industries and were less likely to be offset by input cost increases, and the estimated effect on abnormal returns is correspondingly large and statistically significant — 4.27 percentage points in column (3).

All tariff announcements after the first two dates had negative or insignificant coefficients. This pattern likely reflects a key difference in the scope of the tariffs. The first two announcement dates involved tariffs applied to all major countries exporting a few targeted products, meaning that U.S. firms competing with those imports could only substitute toward domestic production, boosting the expected profits of domestic producers. By contrast, the later tariffs were levied exclusively on Chinese exporters across a broad range of industries. Because importers could substitute toward suppliers in other countries, U.S. producers gained little competitive benefit from the tariffs. At the same time, the breadth of the industries covered meant that many firms faced higher input costs, either from paying the tariffs directly or from reorganizing their supply chains. Together, these two features — limited protection benefit and widespread input cost increases — likely explain why the China-specific tariffs reduced expected firm profits.

Figure 3: Firm Returns in the Aluminum and Steel Industries by Event Date



Note: The figure plots the average returns (in blue) and average abnormal returns (in red) of firms in the steel and aluminum industries (NAICS: 331110, 331210, 331313, 331315, 331318, 332919), weighted by firm market value in 2017, on each of our event days. The returns are reported in percentages.

Figure 3 illustrates how the tariff announcements both protected and raised costs for firms in the steel and aluminum industry by plotting the average returns and average abnormal returns for these firms on each event date. On January 23, when the U.S. announced tariffs on solar panels and washing machines, there was little movement in either measure, likely reflecting the small number of steel and aluminum firms affected by those particular products. The pattern shifts sharply on March 1, when the U.S. announced protection specifically for steel and aluminum: average abnormal returns rose by more than 5 percentage points, a clear signal that markets expected these firms to benefit. Average returns were more muted, however, because the 1.1 percent broad market decline documented in Table 1 partially offset the firm-specific gains. All subsequent U.S. tariff announcements targeted a broad range of intermediate inputs, causing both types of returns to fall and eroding the earlier gains. Chinese retaliation compounded these losses — Table 1 shows that retaliatory announcements drove U.S. equity markets down by 6.5 percent — resulting in a net decline in steel and aluminum stock prices over the course of the trade war.

Table 5: Abnormal Returns and Exposure

Panel A. U.S. Announcement Days							
	Industry Measures			Firm Measures			
	(1) China Imported Input Intensity (P75)	(2) China Export Share (P75)	(3) Manufacturing Industry (=1)	(4) China Importer (=1)	(5) China Exporter (=1)	(6) China Revenue Share (P75)	(7) Size (P75)
Exposure	-1.78***	-2.12***	-1.30***	-3.12***	-3.95***	-2.36***	-4.11***
	(0.52)	(0.63)	(0.48)	(0.36)	(0.65)	(0.38)	(0.33)
N	5,841	5,841	5,841	26,807	26,807	26,807	26,807
Panel B. China Announcement Days							
	Industry Measures			Firm Measures			
	(1) China Imported Input Intensity (P75)	(2) China Export Share (P75)	(3) Manufacturing Industry (=1)	(4) China Importer (=1)	(5) China Exporter (=1)	(6) China Revenue Share (P75)	(7) Size (P75)
Exposure	-0.15	-1.53***	0.35	-0.43	-0.96**	-0.19	-1.33***
	(0.49)	(0.58)	(0.52)	(0.26)	(0.46)	(0.28)	(0.26)
N	5,841	5,841	5,841	26,807	26,807	26,807	26,807

Notes: Each column reports a separate pooled regression of daily abnormal returns (multiplied by 100) on interactions between the event-day dummies and the exposure variable shown at the top of the column, with date fixed effects. The reported coefficient is the sum of the event-specific interaction coefficients across the relevant set of announcement days: U.S. announcement days in Panel A and China announcement days in Panel B. The dependent variable is the firm's daily abnormal return, in percentage points. China Import Intensity (P75), China Export Share (P75), China Revenue Share (P75), and Size (P75) are indicators that equal 1 if the relevant variable is above the 75th percentile in the sample. China imported input intensity is the share of imported inputs from China in total inputs, including goods, services, and wages. China export share is the share of exports to China. Manufacturing Industry (=1) is an indicator that equals 1 if the firm's NAICS code begins with 3. China Importer (=1) is an indicator that equals 1 if the firm or any of its subsidiaries imported from China in 2017. China Exporter (=1) is an indicator that equals 1 if the firm or its subsidiaries exported to China in 2017. For the industry-level measures in columns (1)-(3), the data are collapsed to the industry-date level, and abnormal returns are computed as the 2017 market-value-weighted average across firms within the industry. Accordingly, the reported N in columns (1)-(3) is the number of industry-date observations rather than firm-date observations. Standard errors are clustered by NAICS industry for columns (1)-(3) and by firm for columns (4)-(7), and are reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Next, we examine the cross-sectional impact of U.S. and Chinese tariff announcements on industries and firms with different types of exposure to China. In Table 5, we consider three industry-level and four firm-level exposure measures. First, we define "China imported input intensity" as the value of imported inputs from China in the industry divided by the industry's total expenditures on materials, labor, and services.[8] Second,

[8]We identify the intermediate inputs of each industry using the BEA input-output table for 2017. Fol-

we define China export share as the industry's value of exports to China divided by its total shipments. Third, we construct a dummy variable that equals one if the industry is part of the manufacturing sector. At the firm level, we use dummy variables for whether a firm or its subsidiary imported from or exported to China and whether a firm's revenue share from sales in China was above the 75th percentile of the distribution, based on the information shown in Table 3. Because these measures may not capture all trading relationships — for instance, they exclude firms that import or export by air — we also include the number of employees as a complementary proxy for trade exposure, consistent with evidence that larger firms are more likely to import and export.

The first column reports the results of regressing industry abnormal returns on tariff announcement days on a dummy that equals 1 if the industry is above the 75th percentile of the distribution of China imported input intensity. In Panel A, we see that U.S. tariff announcements had a large negative impact on industries that were heavily dependent on imported inputs from China. Industries in the top quartile of this distribution had abnormal returns that fell by 1.78 percentage points relative to other industries. The second column shows a similarly large 2.12 percentage points decline in the abnormal returns of industries that export greater shares to China relative to other industries. This result is consistent with the idea that investors anticipated retaliations when U.S. tariffs were announced. In the third column, we further find that manufacturing sectors experienced a 1.30 percentage points decline in abnormal returns compared to other sectors, which can be explained by the U.S. manufacturing sector's heavy reliance on inputs from China. The first three columns in Panel B, in comparison, reveal that Chinese tariff announcements were associated with lower abnormal returns only for industries that export greater shares to China.

Over the last 30 years, the international trade literature has emphasized the substantial firm-level heterogeneity in import, export, and FDI behavior that cannot be captured by industry-level variables: heterogeneity we explore in the following four columns of Table 5. Consistent with this literature, we show in Panel A column (4) that firms that imported from China had abnormal returns 3.12 percentage points lower than those of other firms on days when the U.S. announced tariffs. This is a larger effect than the effect of being in the top quartile of China imported-input intensity at the industry level. Column (5) reveals a similarly large negative impact on the abnormal returns of firms that export to China, which again may reflect investors' anticipation of retaliatory tariffs in response to U.S. tariff announcements. In comparison, columns (4) and (5) in Panel B show that

lowing standard approaches, we assume that each industry imports an input in the same proportion as the aggregate economy.

Chinese announcements had a precisely estimated but smaller negative impact on the abnormal returns of firms that export to China but not on those of firms that import from China. These patterns are consistent with the industry-level patterns documented in the first two columns of the table: investors anticipated Chinese retaliation when the U.S. announced tariffs, but did not similarly anticipate U.S. retaliation when China announced tariffs.

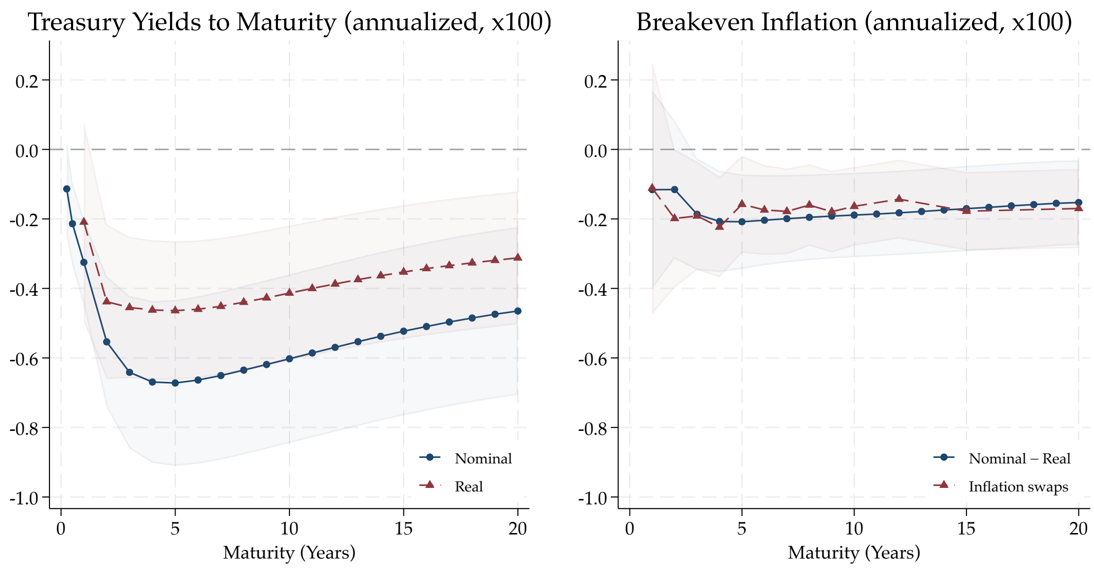
In the last two columns, we explore the impact of the trade war on other dimensions of firm heterogeneity. As we noted earlier, China retaliated against U.S. multinationals and exporters. In column (6), we examine the impact of the trade war on firms with high Chinese sales shares. Table 3 reveals that 42 percent of firms in our sample have positive revenues from China, whether through exports or affiliate sales, while only 4 percent export directly or indirectly. This suggests that a large fraction of firms with high revenue shares likely operate through affiliates in China. Firms in the top quartile of the Chinese revenue share distribution had significantly lower abnormal returns than other firms when the U.S. announced tariffs. The lower abnormal returns are consistent with Pinchis-Paulsen (2020), who finds that China retaliated against U.S. multinationals through means other than tariffs. Finally, more productive firms are more likely to engage in international trade, either as exporters or importers, or to be multinationals. All of these factors mean that they are also more likely to be affected by U.S. tariffs and Chinese retaliation. In the last column of the table, we regress firm abnormal returns on a dummy variable that equals 1 if the firm is in the top quartile of the employment distribution. We find that larger firms experienced significantly more negative abnormal returns than small firms, consistent with the fact that they are more likely to import from, export to, or sell in China.

2.4 Response Across Asset Classes

We now examine how tariff announcements affected asset classes beyond equities. These responses help understand how tariff announcements changed discount rates. They will be key inputs in estimating the welfare effect implied by by asset price responses.

The Effect on Nominal Yields We first estimate the effect of announcements on the nominal yield curve. We measure the daily (annualized) yield to maturity on 3- and 6-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 4 shows the cumulative daily changes in these yields across all trade-war announcements (and we report substantially more detail across days and financial instruments in Appendix B.4). 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 10 basis points (bps) for 3-month maturities, 60 bps for 4-year maturities, and 40 bps 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 4: Effect of Tariff Announcements on the Yield Curve and Breakeven Inflation



Note: Each panel shows the cumulated daily change in the indicated rates or yields, in percentage points, over all days with a tariff announcement, after controlling for surprises in macroeconomic releases. Shaded areas denote 95% confidence intervals. The left panel plots changes in the nominal and real yield curves. Nominal yields at the 3- and 6-month maturities are from FRED; nominal yields at 1- to 20-year maturities and real yields at 2- to 20-year maturities are from Gürkaynak et al. (2007). The one-year real yield is measured as the one-year nominal yield minus the one-year inflation swap rate. The right panel reports the change in breakeven inflation, measured as the difference between nominal and real yields and using inflation swap rates from Bloomberg (USSWIT).

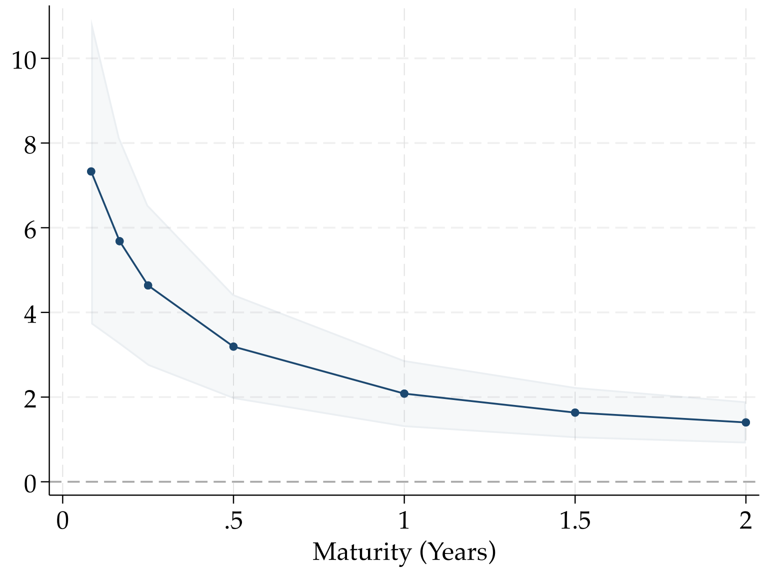
The Effect on Real Yields and Breakeven Inflation Changes in nominal yields could reflect changes in real Treasury yields or in expected inflation (or the inflation risk premium). To isolate these two components, we also plot in the left panel of Figure 4 (in red) the effect of tariff announcements on 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 between the nominal and real yield curves yields the breakeven inflation rate, which captures expected inflation plus the inflation risk premium. The right panel of Figure 4 plots this breakeven inflation rate across maturities. We also plot breakeven inflation measured using inflation swap rates from Bloomberg, which provide a market-based measure of expected inflation that does not rely on TIPS liquidity. Both measures tell a consistent story: tariff announcements decreased breakeven inflation by roughly 10 to 20 basis points across maturities. This is surprising since tariffs are commonly seen as inflationary. In a different setting, Schmitt-Grohé and Uribe (2025) similarly find little historical support for this conventional view. Two potential channels can rationalize this deflationary response. First, tariffs may act as a contractionary demand shock that raises the probability of a recession (Auclert et al. (2025)). Second, by raising government revenue, tariffs may improve the fiscal outlook and lower expected inflation (Gómez-Cram et al. (2025)).

The Effect on SVIX 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), who introduces the SVIX index. The squared SVIX, denoted SVIX_t^2, is defined as the risk-neutral expectation of the squared market return, computed from the prices of out-of-the-money call and put options on the S&P 500 index—similar in construction to the well-known VIX index. The key theoretical result in Martin (2017) is that SVIX_t^2 provides a lower bound on the expected excess return on the market. Moreover, he argues that this bound is tight, so that SVIX_t^2 can be used as a proxy for the equity premium. We estimate the Equity-Premium Bound (EPB) from the one-month to the two-year horizon using data from OptionMetrics and refer to it as EPB in the rest of the paper.

Figure 5 shows that tariff announcements also had a large and significant positive effect on the annualized EPB. The effect of announcements on the EPB declines rapidly with maturity: while announcements increase the EPB at the 1-month horizon by 7 percentage points, they increase it by only 1 percentage point at the 2-year horizon. Empirically, this reflects that trade announcements dramatically increase the prices of short-maturity out-of-the-money call or put options, but have more muted effects on long-maturity options.

Robustness In Table 1, we reported stock-market returns event-by-event. In the same spirit, Appendix Table B.6 reports the change in nominal yields, real yields, and the equity-premium bound event-by-event. This shows that our results are not driven by an outlier event: almost all announcements tend to decrease yields and increase the equity premium bound. As with stock-market returns, Appendix Figure B.2 reports the dynamic effect of announcements on these variables over a ten-day window. The appendix figure

Figure 5: Effect of Tariff Announcements on the Equity-Premium Bound



Note: The figure reports the cumulated daily change in the equity-premium bound, in percentage points, over all days with a tariff announcement, after controlling for surprises in macroeconomic releases. The equity-premium bound is constructed using the methodology of Martin (2017) on data from OptionMetrics. Shaded areas correspond to the 95% confidence interval.

shows that the change in these variables is concentrated on the announcement days, indicating that the market neither under- nor overreacted on those days.

3 Model

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 translates into firms' cash flow 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 for the movements in wages. We then show how, under additional assumptions on tariff-induced ERP changes, the cash-flow welfare effect can be decomposed into static price, dynamic price, and residual TFP components. Second, in Section 3.2, we embed these policy-induced movements in cash flows into a dynamic model of consumer behavior to express the consumption-equivalent welfare effect of the policy in terms of the PDV of these cash-flow movements.

3.1 Producers

The production structure is based on the Jones (1975) specific factors model, extended along two dimensions. First, we assume that fixed factors are firm-specific instead of industry-specific.[9] Second, we extend it from a static one-period model into a dynamic infinite-horizon model. In our model, time is discrete and indexed by t, and there is a set of firms in the economy indexed by i. At each time t, firm i produces according to a constant-returns-to-scale technology,[10] which combines three types of inputs: a firm-specific fixed factor V_i, a quantity of labor L_{it} hired in a competitive labor market, and a set of J differentiated intermediate inputs (m_{jit}), where $j \in \{1, ..., J\}$. Firms maximize profits taking the output price p_{it}, wages, and input prices as given.[11] 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 i's unit cost of production at time t by $c_i(w_t, \pi_{it}, q_{1t}, ..., q_{Jt}, A_{it})$, where the arguments correspond to the wage (w_t), the shadow price of the firm's fixed factor (π_{it}), the prices of a set of intermediate inputs ($q_{1t}, ..., q_{Jt}$), and a Hicks-neutral productivity parameter A_{it}.[12] Since every firm potentially has a different cost function, we allow for arbitrary firm heterogeneity in productivity. Shephard's Lemma tells us that the unit-input requirements are given by the derivative of the cost function; that is, $a_{Lit} = \frac{\partial c_i}{\partial w_t}$, $a_{Vit} = \frac{\partial c_i}{\partial \pi_{it}}$, and $a_{jit} = \frac{\partial c_i}{\partial q_{jt}}$, where $a_{Lit}, a_{Vit}, a_{jit}$ denote the unit-input requirements for labor, fixed factor, and intermediate input j, respectively. In equilibrium, a firm's marginal

[9]The firm-specific fixed factor in our model captures any input that is fixed in the short-to-medium run and earns a residual rent equal to revenue net of variable costs. In practice, this corresponds to three broad categories of firm assets. Intangible capital—including patents, proprietary technology, brand equity, and trade secrets—is firm-specific almost by definition. Specialized physical capital, such as steel mills, refineries, or purpose-built logistics infrastructure, behaves like a specific factor because its salvage value outside its current use is low, even though it appears on the balance sheet. Finally, organizational capital—the accumulated routines, management practices, and institutional knowledge embedded in a firm—is perhaps the most important specific factor for modern listed firms.

[10]Our setup naturally handles decreasing returns to scale, since a decreasing-returns technology can always be rewritten as a constant-returns technology with a fixed firm-specific factor. The setup does not, however, cover increasing returns to scale. In that case, specific-factor rents and cash flows to firm owners are no longer the same object: sustaining an equilibrium requires some departure from competitive pricing, so observed cash flows combine specific-factor rents and markup profits. Market valuations would then no longer be a sufficient statistic for the welfare-relevant component of firm value unless we separately identified the markup component.

[11]One could motivate this setup by assuming Bertrand competition in which each domestic firm faces foreign exporters selling at a price $p_i^* + \tau_i$, where p_i^* is the international price of the good and τ_i is the output tariff facing firm i's foreign competitors.

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

cost is equal to its output price,

$$a_{Lit}w_t + a_{Vit}\pi_{it} + \sum_j a_{jit}q_{jt} = p_{it}. \tag{1}$$

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

$$\sum_i a_{Lit}y_{it} = L, \text{ and} \tag{2}$$

$$a_{Vit}y_{it} = V_i, \tag{3}$$

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

To model the impact of a policy change, we start with a "baseline" equilibrium in which all product and input prices, as well as firm productivity, are constant over time. We treat a policy shock as a policy that shifts prices and productivity away from the baseline equilibrium in each period. Since, in the baseline equilibrium, aggregate employment (L), each firm's specific factor (V_i), prices, and productivity are fixed over time, we know that the wage and firm-level employment are also fixed over time; that is, $w_t = w$ and $L_{it} = L_i$. 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 C.4 that we can easily modify the setup to allow for baseline productivity growth without changing any of our propositions.

We model a tariff change as causing a set of log-change deviations in output prices, input prices, and, potentially, TFP ($\hat{p}_{it}, \hat{q}_{jt}, \hat{A}_{it}$) in the period t relative to the baseline values ($p_{it} = p_{i0}$, $q_{jt} = q_{j0}$, and $A_{it} = A_{i0}$). Because the amount of each firm's specific asset is fixed ($\hat{V}_i = 0$), log changes in the shadow price of the specific factor equal the log change in firm cash flow (i.e., $\hat{\pi}_{it} = \widehat{\pi_{it}V_i}$), where hats over variables indicate log changes in these variables from their baseline values in period t. Thus, we will henceforth refer to $\hat{\pi}_{it}$ as the log change in the firm's cash flow in period t due to the policy change.

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

$$\hat{a}_{Vit} - \hat{a}_{Lit} = \sigma\left(\hat{w}_t - \hat{\pi}_{it}\right). \tag{4}$$

We are now ready to prove our first proposition, which links changes in cash flows to wages.

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

$$\hat{w}_t = \sum_i \frac{L_i}{L}\hat{\pi}_{it},$$

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

Proof. See Appendix C.1 □

The intuition behind the first equation in Proposition 1 is that the full-employment condition implies that changes in factor prices cannot increase the aggregate demand for labor. However, the aggregate demand for labor will only remain constant if the changes in relative wages ($\hat{w}_t - \hat{\pi}_{it}$) 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 ($\sum_i \frac{L_{it}}{L}\hat{\pi}_{it}$). The second equation follows immediately from this equation and the fact that the amount of the specific factor is fixed, so the left-hand side of equation (4) is just $-\hat{L}_{it}$.[13]

Proposition 1 is based on the structure of Jones (1975) but differs in several respects. First, Jones was concerned about mapping tariff-induced changes in product prices to 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 a single elasticity of substitution between labor and the specific factor, we simplify the expressions in his canonical model and can construct a sufficient statistic for computing wage and employment changes using only information on changes in cash flow.[14] Wages move

[13] We relax the assumption of fixed factors in Appendix C.6.

[14] By contrast, implementing the Jones approach would require knowledge of 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 $\sigma = 1$ (cf., 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.

one-for-one with the employment-weighted average of log changes in cash flow.[15]

3.2 Households

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:

$$I_t = w_t L + \sum_i \pi_{it} V_i + TR_t.$$

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:

$$\hat{C}_t = \frac{wL}{C}\hat{w}_t + \sum_i \frac{\pi_i V_i}{C}\hat{\pi}_{it} + \frac{TR}{C}\widehat{TR}_t. \tag{5}$$

The policy change can be thought of as affecting an infinite sequence of changes in wage, cash flow, and tariff revenue: $\hat{w}_t$, $\hat{\pi}_{it}$, and $\widehat{TR}_t$ 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. Equation (5) highlights the three channels through which trade policy can affect welfare in most models—it can affect real wage income, real firm profitability, or real tariff revenues. This formulation is standard in the trade literature and flexible enough to apply to both monopolistic competition and neoclassical models of how tariffs affect welfare. For example, the monopolistic competition model of Ossa (2014) presents an expression (see his equation 14) for how tariffs affect welfare. The welfare impact of a tariff in his setup depends on the tariff's effects on the same three terms that we have in our paper. In contrast, neoclassical models impose a zero-profit condition in equilibrium that rules out the possibility that protection can raise firm profits. Therefore, the impact of tariffs is restricted to how much they move real wages and how much tariff revenue they generate.[16]

[15] 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.

[16] For example, in neoclassical models as well as canonical monopolistic competition models, countries can gain from protection because it raises real wages and generates higher tariff revenues (the first and third

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 percent change in consumption (in every state and every period) that would compensate the agent for the effect of the policy change. We now characterize this consumption-equivalent welfare effect for a representative agent with log utility over consumption.

Proposition 2. *For an agent with log utility, the consumption-equivalent welfare effect of the deviation path $(\hat{C}_t)_{t=0}^{\infty}$ is*

$$\mathcal{C} = \sum_{t=0}^{\infty}(1-\rho)\rho^t \mathrm{E}_0\left[\hat{C}_t\right], \tag{6}$$

where $\rho \equiv 1 - C_t/W_t$ denotes one minus the consumption-to-wealth ratio (where wealth W_t is the present discounted value of future consumption; see Appendix C.2).

Proof. See Appendix C.2. □

This proposition says that the consumption-equivalent welfare effect $\mathcal{C}$ is simply the weighted average of the expected log deviation in consumption at all horizons — note that the weights $(1-\rho)\rho^t$ decay exponentially at rate ρ and sum up to one across all horizons. The parameter ρ, which in equilibrium equals the agent's subjective discount factor, governs how future consumption is weighted relative to today's consumption. This expression captures two important channels through which tariffs can impact welfare. First, and most obviously, tariffs may decrease or increase the average level of consumption, which would move welfare proportionally. Second, even if average consumption is fixed, tariffs may increase the variance of consumption, thereby decreasing welfare by lowering the average of log consumption. In the formula, this second channel is captured by the fact that the summand reflects the average deviation in log consumption at each horizon, rather than the deviation in the log of average consumption.[17]

terms on the right-hand side of equation (5)). These models are not useful for thinking about the impact of tariffs on stock prices because their assumption of zero firm profits in equilibrium rules out *a priori* the possibility that protection can benefit or harm firms. As a result, we follow Grossman and Levinsohn (1989) and analyze the impact of tariff policy on asset prices through the lens of the specific factors model, which allows for all three channels.

[17]In Appendix C.5, we derive a more general expression for the consumption-equivalent welfare effect $\mathcal{C}$ for an agent with Epstein-Zin preferences, with arbitrary relative risk aversion and elasticity of intertemporal substitution. Relative to the log utility case, the consumption-equivalent welfare effect gains an additional term that depends on the product between (i) the impact of tariffs on the higher-order cumulants of future log consumption, equivalently of cumulative log consumption growth from time 0 to horizon t

3.3 Linking Welfare to Cash Flows, Firm Values, and Discount Rates

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 now show how to express the impact of tariffs on consumption-equivalent welfare ($\mathcal{C}$) in terms of the PDV of deviations in firm values and discount rates. We begin by decomposing the welfare effect into the shares attributable to each source of household income. Substituting equation (5) into equation (6), we obtain an expression for the welfare effect in terms of the discounted value of policy-induced changes in wages, cash-flows, and tariff revenues:

$$\mathcal{C} = \sum_{t=0}^{\infty}(1-\rho)\rho^t \mathrm{E}_0\left[\frac{wL}{C}\hat{w}_t + \sum_i \frac{\pi_i V_i}{C}\hat{\pi}_{it} + \frac{TR}{C}\widehat{TR}_t\right].$$

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

$$\mathcal{C} = \underbrace{\sum_i \frac{wL_i + \pi_i V_i}{C}\left(\sum_{t=0}^{\infty}(1-\rho)\rho^t \mathrm{E}_0[\hat{\pi}_{it}]\right)}_{\text{Deviation in firm cash-flows } \mathcal{C}_\pi} + \underbrace{\frac{TR}{C}\left(\sum_{t=0}^{\infty}(1-\rho)\rho^t \mathrm{E}_0\left[\widehat{TR}_t\right]\right)}_{\text{Deviation in tariff revenues } \mathcal{C}_{TR}}. \tag{7}$$

This equation expresses the welfare effect as the sum of two terms: the PDV of the deviation in firm cash flows and the PDV of the deviation in tariff revenues. Importantly, welfare is determined by the expected deviation in log (or relative) cash flows. For example, consider a firm in a world with no uncertainty, whose cash flow, π_{it}, equals one in all periods, so expected cash flows equal one by construction. In this case, $\mathrm{E}_0[\hat{\pi}_{it}] = 0$. Now suppose that uncertainty rises so that its cash flow equals 1.5 with probability 0.5 and 0.5 with probability 0.5. Expected cash flows are still equal to one, but we would now have $\mathrm{E}_0[\hat{\pi}_{it}] = \frac{1}{2}\ln 1.5 + \frac{1}{2}\ln 0.5 \approx -0.14$, so welfare would fall. Equation (7) tells us that this greater uncertainty would lower welfare because our assumption of log utility (used in the derivation of $\mathcal{C}$ in Proposition 2) has the property that increased consumption uncertainty lowers welfare.

and (ii) the distance between the agent's relative risk aversion and one. In particular, if agents are more risk averse than log utility (i.e., if the coefficient of relative risk aversion satisfies $\gamma > 1$), and if tariffs increase the even cumulants of log consumption (like variance) or decrease odd cumulants (like skewness), then our baseline welfare effect (the one given in Proposition 2) will underestimate the full welfare loss.

The first term in equation (7) 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 M_{it} be the total value of firm i at time t (i.e., the market value of its equity plus its debt). The return of owning firm i between t and $t+1$ is defined as:

$$R_{i,t+1} \equiv \frac{M_{i,t+1}}{M_{i,t} - \pi_{i,t} V_i}.$$

Assuming the no-bubble condition $\lim_{t \to \infty} R_{it}^{-1} M_{it} = 0$, we can express a firm's value as the discounted value of its future cash-flows:[18]

$$M_{i0} = \mathrm{E}_0 \left[\sum_{t=0}^{\infty} \frac{\pi_{it} V_i}{R_{i1} \ldots R_{it}} \right]. \tag{8}$$

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

Proposition 3. *Around a baseline path in which the ratio of cash flow to firm value, $\pi_{it} V_i / M_{it}$, is equal to the constant consumption-to-wealth ratio, C_t / W_t, we have:*

$$\hat{M}_{i0} = \sum_{t=0}^{\infty} (1-\rho) \rho^t \mathrm{E}_0 \left[\hat{\pi}_{it} \right] - \sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{it} \right].$$

Proof. See Appendix C.3. □

This proposition, which is an application of the Campbell and Shiller (1988) decomposition to our economy, states that an increase in a firm's value can reflect either an increase in the expected future cash flows earned by firm owners or a decrease in the discount rate applied to these future cash flows.[19] We can solve for the PDV of the deviation in firm cash flows—the first term on the right—in terms of the deviation in firm value ($\hat{M}_{i0}$) plus the PDV of the deviation in firm discount rates ($\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{it} \right]$). In other words, if we observe a decline in firm value ($\hat{M}_{i0}$) on the day of a policy announcement and add the change in discount rates on that day ($\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{it} \right]$), the total gives the movement in expected cash flow. While equation (7) tells us that tariff-induced movements in prices and uncertainty only matter for welfare insofar as they affect cash flow (and tariff revenues),

[18] The definition of returns implies $M_{i0} = \pi_{i0} V_i + \frac{M_{i1}}{R_{i1}} = \pi_{i0} V_i + \frac{\pi_{i1} V_i}{R_{i1}} + \frac{M_{i2}}{R_{i1} R_{i2}}$. Iterating forward gives the result.

[19] 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.

Proposition 3 tells us that if we want to measure these expected cash-flow movements using data on firm values, we also need to make an adjustment for how the announcements affect discount rates. For example, if tariff-induced uncertainty has no impact on cash flows but raises discount rates by, say raising the equity premium and making investors reluctant to hold stocks, this will cause $\sum_{t=1}^{\infty}\rho^t \mathrm{E}_0\left[\hat{R}_{it}\right]$ to rise and firm market values, $\hat{M}_{i0}$, to fall.

Combining this result with equation (7) allows us to write the aggregate welfare effect as follows

$$\mathcal{C} = \underbrace{\sum_i \frac{wL_i + \pi_i V_i}{C}\left(\hat{M}_{i0} + \sum_{t=1}^{\infty}\rho^t \mathrm{E}_0\left[\hat{R}_{it}\right]\right)}_{\text{Deviation in firm cash flows } \mathcal{C}_\pi} + \underbrace{\frac{TR}{C}\sum_{t=0}^{\infty}(1-\rho)\rho^t \mathrm{E}_0\left[\widehat{TR}_t\right]}_{\text{Deviation in tariff revenues } \mathcal{C}_{TR}}. \tag{9}$$

The first term is a weighted average of the log change in firm values adjusted for the change in their discount rates. This accounts for the fact that only deviations in firm cash flows (as opposed to deviations in discount rates) matter for welfare (see, for instance, Fagereng et al. (2025)). The second term accounts for deviations in tariff revenues. Equation (9) rewrites equation (7) in terms of variables we can estimate: the deviation in firm values associated with the tariff announcement and the deviation in firm discount rates. In other words, we measure the welfare movement due to tariff-induced cash-flow changes by using the drop in average firm values associated with tariff announcements, adjusted for the portion attributable to higher discount rates (due, say, to greater uncertainty).

3.4 Comparing Our Welfare Measure to Canonical Trade Models

This section relates our welfare measure to those generated by canonical trade models. The difference in the two procedures is most transparent in a comparison with the static specific factors model. Welfare in the static specific factors model depends on the "effective rate of protection" (ERP), which is a well-known measure of the impact of a vector of (possibly tariff induced) price changes on a firm:

$$\hat{p}^e_{it} \equiv \frac{\hat{p}_{it} - \sum_j \omega_{jit}\hat{q}_{jt}}{1 - \sum_j \omega_{jit}}, \tag{10}$$

where ω_{jit} denotes the expenditure shares of firm i on input j as a share of total revenue (similarly, we will denote ω_{Lit} and ω_{Vit} the expenditure shares on labor and the fixed factor). The numerator in this definition is the change in the firm's output price less a weighted average of all of the input prices, while the denominator is the share of value added in sales. A standard approach to compute the effective rate of protection is to write

$\hat{p}_{it}$ and $\hat{q}_{jt}$ as functions of the tariffs (i.e., $\hat{p}_{it} = \hat{p}_{it}(\boldsymbol{\tau_t})$ and $\hat{q}_{jt} = \hat{q}_{jt}(\boldsymbol{\tau_t})$), where $\boldsymbol{\tau_t}$ denotes the tariff vector.[20]

If we denote the log change in ERP predicted by a static trade model by $\hat{p}^e_{i0}$, we can write the welfare effect we measure as a function of the change in ERP, future price movements, and productivity ($\hat{A}_{it}$) as given in the following proposition.

Proposition 4. *The expected welfare effect due to changes in expected firm cash flows can be written as the sum of a static price effect, a dynamic price effect, and a TFP effect:*

$$\begin{aligned} \mathcal{C}_\pi = & \underbrace{\sum_i \frac{wL_i + \pi_i V_i}{C} \hat{p}^e_{i0}}_{\textit{Static Price Effect}} \\ & + \underbrace{\sum_i \frac{wL_i + \pi_i V_i}{C} \sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{p}^e_{it} - \hat{p}^e_{it-1} \right]}_{\textit{Dynamic Price Effect}} \\ & + \underbrace{\sum_i \frac{wL_i + \pi_i V_i}{C} \sum_{t=0}^{\infty} (1-\rho)\rho^t \mathrm{E}_0 \left[\frac{\hat{A}_{it}}{1 - \sum_j \omega_{ji}} \right]}_{\textit{TFP Effect}} . \end{aligned} \tag{11}$$

Proof. See Appendix E.2. □

The static price effect tells us how much a given vector of tariff changes would affect welfare if the initial tariffs caused the same percentage change in the ERP from the baseline level in each future period and had no impact on productivity. A value-added-weighted average of these ERP movements gives the first component of the welfare impact, which is what a conventional specific factors model would obtain. The dynamic price effect captures welfare losses due to future growth in the ERP deviations. For example, if tariffs caused changes in ERP through some dynamic pricing process, greater uncertainty about future prices, or through an escalation of the trade war, this would be captured in the dynamic price effect. Weighting these future ERP changes by firm value added and the appropriate discount factor provides a mapping from this expected growth in future prices into welfare. Finally, the TFP effect captures how a tariff announcement affects welfare by affecting TFP now and in the future. Note that this TFP effect should be interpreted as a residual component: it captures any effect of tariffs on cash flows that is not accounted for by the direct tariff-exposure channel. It may therefore reflect not only

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

productivity changes, but also changes in markups, supply-chain fixed costs, geopolitical risk, competitive conditions, and innovation incentives in exposed industries. In this sense, it is a model-implied TFP component rather than a direct measure of physical productivity.

Equation (11) makes clear the difference between measuring welfare using a comparative static exercise and our approach. In comparative static exercises, $\hat{p}^e_{i0}$ is measured by estimating how tariffs change the ERP assuming that these tariffs do not affect expected future TFP and that all future changes in ERP equal the initial change ($\hat{p}^e_{it} = \hat{p}^e_{i0}$). Our approach, which is based on estimating the cash-flow effect directly, allows us to relax the assumptions that the TFP and dynamic price effects are zero and capture the full effect of a tariff increase. Later in Section 5.1, we quantify the relative importance of each of these components for the overall welfare effect we estimate.

4 Estimation

The previous section provided an expression for the aggregate welfare effect in terms of the change in firm values, adjusted for changes in firm discount rates and in future tariff revenues. Section 4.1 shows how to use asset-price movements to estimate the deviation in firm cash flows (i.e., firm values adjusted for changes in discount rates). Section 4.2 validates these estimates by comparing the VAR-implied path of discount rates to reduced-form evidence from the term structure. Section 4.3 discusses how to aggregate the firm-level estimates to the economy level. Section 4.4 discusses the estimation of tariff revenues. Section 4.5 presents the results for our estimated welfare effect.

4.1 Estimating the Deviation in Firm Cashflows

We rely on Proposition 3 to express the deviation in firm cash flows as the deviation in firm market value adjusted for future changes in discount rates:

$$\widehat{\Pi}_i \equiv \underbrace{\sum_{t=0}^{\infty}(1-\rho)\rho^t \mathrm{E}_0\left[\hat{\pi}_{it}\right]}_{\text{Deviation in firm cashflows}} = \underbrace{\hat{M}_{i0}}_{\text{Deviation in firm value}} + \underbrace{\sum_{t=1}^{\infty}\rho^t \mathrm{E}_0\left[\hat{R}_{it}\right]}_{\text{Deviation in firm discount rate}}. \tag{12}$$

4.1.1 Estimating the Deviation in Firm Values $\hat{M}_{i0}$

We estimate the change in each firm's value due to announcement k as its log return on the first day the markets could trade the new information ("high-frequency identification"). Formally, we identify the effect of tariff announcement k on the market value of equity of a firm i as the coefficient $\theta_{i,k}$ in the following regression:

$$\ln R_{it}^{E} = \alpha_i + \sum_{k=1}^{K} \theta_{i,k} D_{kt} + \sum_{d=1}^{D} \gamma_{i,d} ES_{d,t} + \epsilon_{i,t}, \tag{13}$$

where $\ln R_{it}^{E}$ is firm i's daily log equity return; the event coefficients $\theta_{i,k}$ are our empirical estimates of the announcement-induced change in firm equity value for each event k; K is the number of tariff-announcement events; D_{kt} is an indicator variable equal to one if day t is in the window of announcement k; and $ES_{d,t}$ corresponds to the surprise in economic release series $d \in \{1, ..., D\}$. We estimate this regression using all trading days between 2017 and 2019, separately for each firm i.

Since we observe equity returns but need total firm value changes, we must adjust for leverage. We construct the effect of announcement k on the overall market value of firm i as

$$\hat{M}_{i0} = \sum_{k=1}^{K} \kappa_i \theta_{i,k}, \tag{14}$$

where κ_i denotes the ratio of firm i's market value of equity to its market value of assets.[21] 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.

4.1.2 Estimating the Deviation in Firm Discount Rates

We now turn to the estimation of the deviation in firm discount rates, which enters the first term in the deviation in aggregate welfare in equation (9). The challenge in computing this term is in obtaining an expression for the change in discount rates induced by the policy $\left(\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{it}\right]\right)$. 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 i in period t ($\hat{R}_{it}$) corresponds to a weighted average of the deviation of the interest rate on its debt ($\hat{R}_{it}^{D}$) and the deviation in the expected return of its equity ($\hat{R}_{it}^{E}$):

[21] Because our estimation methodology does not impose a constraint that each tariff announcement has an identical effect on stock prices, we allow some announcements to have larger or smaller effects. Imposing a structure on the relationship between the content of an announcement and the magnitude of the market response is difficult because the announcements are heterogeneous in which countries, firms, and products were targeted, the magnitude of the increase, whether third countries could supply the product, whether existing tariffs were already prohibitive, and whether they would cause retaliation. This heterogeneity makes it impossible, in general, to summarize the tariff announcements with a scalar size variable.

$$\mathrm{E}_0\left[\hat{R}_{it}\right] = (1-\kappa_i)\mathrm{E}_0\left[\hat{R}^D_{it}\right] + \kappa_i \mathrm{E}_0\left[\hat{R}^E_{it}\right], \tag{15}$$

where κ_i still denotes the ratio of the market value of equity to the market value of assets for firm i (assumed to be constant over time).

To make progress, we make two simplifying assumptions. First, we assume that the interest rate on firm debt moves one-for-one with the risk-free rate. Second, following the Capital Asset Pricing Model (CAPM), we assume that the expected return on firm equity equals the risk-free rate plus the firm's market beta times the equity premium:

$$\mathrm{E}_0\left[\hat{R}^D_{it}\right] = \hat{R}_{f,t}; \quad \text{and} \quad \mathrm{E}_0\left[\hat{R}^E_{it}\right] = \hat{R}_{f,t} + \beta_{i,MKT}\left(\hat{R}_{MKT,t} - \hat{R}_{f,t}\right), \tag{16}$$

where $\hat{R}_{f,t}$ denotes the log deviation in the risk-free rate, $\hat{R}_{MKT,t}$ denotes the log deviation in the expected stock-market return, and $\beta_{i,MKT}$, 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 i discount rate:

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

This equation expresses the deviation in firm i 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_i) and its equity-market beta ($\beta_{i,MKT}$), which jointly capture the firm's overall exposure to changes in equity premia. This decomposition reduces the problem of estimating firm-specific deviations in discount rates to the estimation of two aggregate quantities: the path of future risk-free rates and the path of future excess stock-market returns. An important implication is that, for the aggregate welfare effect, any misspecification in firm-level discount rates (e.g., deviations from the CAPM) is immaterial as long as it averages out across firms. The only reason this cancellation is not exact in our setting is that we aggregate using employment-based weights rather than market-value weights; in practice, this distinction has a negligible effect on our estimates.

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 that the deviation in future risk-free rates and future excess stock-market returns defined in equation (17) can be obtained as the first two elements of the vector $\rho\boldsymbol{B}(\boldsymbol{I} - \rho\boldsymbol{B})^{-1}d\boldsymbol{x}_0$.[22]

In summary, 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 first describe the variables in the VAR and then discuss the estimation of each quantity in turn (see Appendix D.1 for more details). For our baseline results, we consider the VAR system in equation (18) where the vector $\boldsymbol{x}_t$ contains seven variables:

$$\boldsymbol{x}_t = \Big(\ln R_{f,t}, \underbrace{\ln R_{MKT,t} - \ln R_{f,t}}_{\ln R_{EMKT}}, \mathrm{TS}_t, \mathrm{EPB}_t, \mathrm{VS}_t, \mathrm{CS}_t, \ln PD_t\Big).$$

Our choice of variables is similar to Campbell and Vuolteenaho (2004). 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 (the difference between the log book-to-market ratios of small value and small growth stocks), the credit spread CS_t (the difference in the yield of BAA and 3-month T-Bill), and the log price-dividend ratio

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

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

A similar derivation holds for the deviation in future excess stock-market returns. Since $\boldsymbol{x}_0$ includes the 3-month T-bill yield, one could alternatively include the contemporaneous short-rate movement in the risk-free-rate component. Including the contemporaneous short-rate movement changes the risk-free component by about 0.0003 and leaves the reported welfare estimates unchanged at the displayed precision.

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

$$\Delta \boldsymbol{x}_t = \boldsymbol{\alpha} + \sum_{k=1}^{K} \boldsymbol{\theta}_k D_{kt} + \sum_{d=1}^{D} \boldsymbol{\gamma}_d ES_{d,t} + \boldsymbol{\epsilon}_t, \tag{19}$$

where D_{kt} is an indicator variable equal to one if day t is in the window of announcement k, and $ES_{d,t}$ corresponds to the surprise in the economic series d. Table 6 reports the results of the estimation. As discussed in Section 2, the stock-market drops around the announcement days, the risk-free rate decreases, slightly at the 3-month horizon and more strongly at the 10-year horizon, while the equity premium increases. Moreover, the value spread also increases, which implies that the equity value of growth firms (firms with low book-to-market ratio) declined less than the one of value firms in response to the announcements.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\log R_f$	$\log R_{EMKT}$	TS	EPB	VS	CS	$\log PD$
Announcement	-0.0003*	-0.1253***	-0.0047***	0.0464***	0.0955***	-0.0005*	-0.1269***
	(0.0002)	(0.0256)	(0.0014)	(0.0097)	(0.0292)	(0.0003)	(0.0298)
N	753	753	753	753	753	753	753

Note: The table reports the sum of $\boldsymbol{\theta}_k$ in the regression (19), i.e., the change in the variable listed in the column header that can be attributed to the tariff announcement. The sample includes all trading days from 2017 to 2019. Standard errors are in parentheses.

We then estimate the VAR matrix $\boldsymbol{B}$ by regressing each variable in the VAR on its value one quarter (63 trading days) earlier. We opt for a quarterly frequency as we are interested in measuring the long-term impacts of changes in the vector $\boldsymbol{x}_0$ on future risk-free rates and excess stock-market returns. However, to increase statistical power, we use overlapping daily observations—that is, we regress $\boldsymbol{x}_{t+63}$ on $\boldsymbol{x}_t$ for every trading day t, rather than only at quarter-ends. We use Newey-West standard errors with a bandwidth of 63 days to account for the resulting overlap in observations.[23] Appendix Table D.1 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, and intuitively, the equity-premium bound predicts higher expected excess returns $\ln R_{EMKT}$. The R^2 of this regression is approximately 15 percent (at a quarterly horizon), suggesting that our VAR captures a large amount of excess return predictability.

Table 7 combines the estimates for $d\boldsymbol{x}_0$ (Table 6) and the estimate for $\boldsymbol{B}$ (Appendix Table D.1) to compute the deviation in future risk-free rates and future excess stock-market returns as the first two elements of the vector $\rho\boldsymbol{B}(\boldsymbol{I}-\rho\boldsymbol{B})^{-1}d\boldsymbol{x}_0$. We find that the deviation in future risk-free rates due to tariff announcements is approximately 0.2 percentage points (first column) while the deviation in future excess stock returns is approximately 3.9 percentage points (second column). These estimates imply that the overall drop in the aggregate stock-market return due to changes in the required return on equity is 4.1 percentage points (third column). 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 one third of the decline in the aggregate stock-market value around tariff announcements. Note that the relative importance of discount-rate shocks on announcement days is consistent with the rule of thumb that discount rate shocks account for approximately half of the variance of stock market returns (see, for instance, Campbell (2003)).

Table 7: Estimated Changes in Future Discount Rates

Deviation in Future Risk-free Rates	Deviation in Future Excess Returns	Total
$\sum_{t=1}^{\infty}\rho^t \mathrm{E}_0\left[\hat{R}_{f,t}\right]$	$\sum_{t=1}^{\infty}\rho^t \mathrm{E}_0\left[\hat{R}_{MKT,t}-\hat{R}_{f,t}\right]$	$\sum_{t=1}^{\infty}\rho^t \mathrm{E}_0\left[\hat{R}_{MKT,t}\right]$
0.002	0.039	0.041
(0.010)	(0.044)	(0.044)

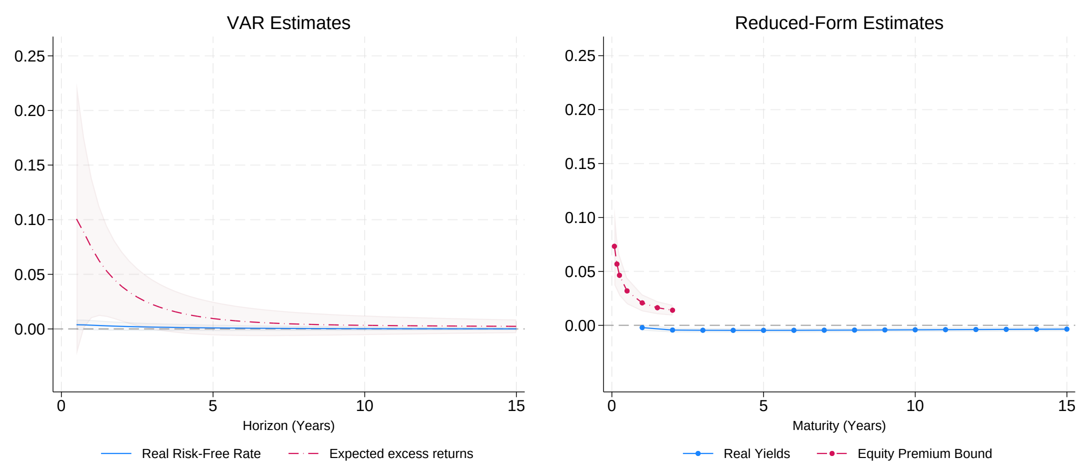
Note: The table reports the deviation in risk-free rate, $\boldsymbol{e}_1'\rho\boldsymbol{B}(\boldsymbol{I}-\rho\boldsymbol{B})^{-1}d\boldsymbol{x}_0$, and the deviation in the equity premium, $\boldsymbol{e}_2'\rho\boldsymbol{B}(\boldsymbol{I}-\rho\boldsymbol{B})^{-1}d\boldsymbol{x}_0$. Note that the matrix $\boldsymbol{B}$ is reported in Appendix Table D.1 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. Standard errors in parentheses, computed using the delta method, taking into account both the uncertainty in the estimation of $d\boldsymbol{x}_0$ (as reported in Table 6) and the uncertainty in the estimation of the matrix $\boldsymbol{B}$ (as reported in Appendix Table D.1).

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

4.2 Validating our Estimates of Discount Rates

We assess the plausibility of the estimates coming from the VAR by comparing the VAR's estimates for movements in the real risk-free rate and equity premium with the observed changes in the term structure of real yields and the equity-premium bounds measured in Section 2. We consider a number of additional external validity checks in Sections 5.2, 5.3, and 5.4. The left panel of Figure 6 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 6 reproduces the change in the term structure of real Treasury yields and in the equity-premium bound around announcement days obtained in Section 2. These two figures give similar results regarding the evolution of discount rates following tariff announcements: the real risk-free rate decreases, especially at longer horizons, while the expected excess stock-market return sharply increases, especially at short horizons. Thus, the VAR is consistent with our earlier reduced-form evidence, presented in Section 2, on the evolution of discount rates.[24]

Figure 6: 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, $(4/T)\sum_{t=1}^{T}\mathrm{E}_0[\hat{R}_{f,t}] = (4/T)\sum_{t=1}^{T}\boldsymbol{e}_1'\boldsymbol{B}^t d\boldsymbol{x}_0$ and $(4/T)\sum_{t=1}^{T}\mathrm{E}_0[\hat{R}_{MKT,t} - \hat{R}_{f,t}] = (4/T)\sum_{t=1}^{T}\boldsymbol{e}_2'\boldsymbol{B}^t d\boldsymbol{x}_0$. 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 TIPS yields were reported earlier in Figure 4 and the equity-premium bounds in Figure 5).

[24]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.

4.3 Reweighting the Compustat-CRSP Sample

The aggregate cash-flow effect is obtained by aggregating the firm deviation in cash flows using total factor payments $(wL_i + \pi_i V_i)/C$ as weights. 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 and service-sector firms, so we need to weight firms to approximate the distribution of employment size and sectors in the U.S. economy.

To construct these weights, we map the Compustat-CRSP sample to the overall economy. We do so in three steps (see Appendix D.3 for details). First, we classify Compustat firms into 18 sectors (2-digit NAICS) and four employment-size bins (below 500, 501–5,000, 5,001–20,000, and over 20,000 employees), and compute an employment-weighted average of the deviation in firm cash flows within each sector-bin cell. Second, we aggregate across employment bins within each sector, using the share of total U.S. employment in each cell (from the Statistics of U.S. Businesses) as weights. Third, we aggregate across sectors using sectoral value added divided by C (total U.S. value added plus tariff revenue) as weights, based on BEA data.

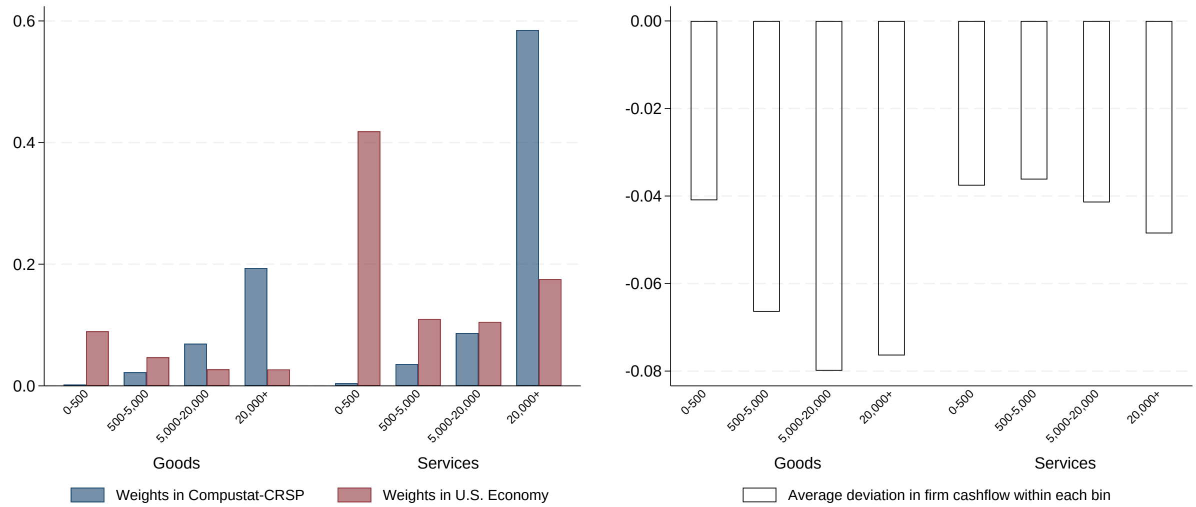
The left panel in Figure 7 compares our constructed weights with the relative employment share of cells within the CRSP-Compustat sample. Our weighting procedure assigns greater weight to small firms and services than the CRSP-Compustat sample. The right panel of Figure 7 plots the average deviation in firm cash flow within these cells (cumulated across all announcement days). One can see that the declines in asset values tend to be smaller for smaller and service firms than for other firms, consistent with these firms being 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 cash flows relative to the value-weighted CRSP-Compustat return.

We find that tariff announcements caused aggregate firm values to fall 7.0 percent (see Table 8). This drop is just over half the decline in the aggregate stock-market return reported in Table 1. The difference between the two numbers is due to 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 smaller drops in asset values, so our weighting procedure tends to dampen the overall effect of announcements on asset values (Figure 7).

4.4 Estimating the Deviation in Tariff Revenues

The last term for the welfare effect of the policy is the deviation in tariff revenues. To avoid introducing additional estimates into the procedure, we bound the impact of tariff

Figure 7: Weights and Deviation in Firm Cash Flows 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.

revenues on our estimation. We have yearly U.S. tariff rates for each product h (HS10) and exporting country c. Let $\Omega^{US}_{h,2019}$ be the set of countries that export product h to the U.S. in 2019 and Ω^{US}_{2019} the set of products the U.S. imported in 2019.

We can construct an upper bound on the revenue 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:

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

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 upper bound for the increase in tariff revenues, but note that because TR/C in equation (9) is small, there is little scope for different assumptions about the movement in tariff revenues to affect the results.

4.5 Aggregate Welfare Results

We now compute the aggregate welfare effect of the tariff announcements, which is the sum of the three components in equation (9), across all announcement days: the deviation in firm values, the deviation in firm discount rates, and the deviation in tariff revenues. We report the impact of the tariff announcements on welfare in Table 8. In our baseline specification, we find that the deviation in firm value is -7.0 percent, while the deviation in firm future discount rates is 2.5 percent; as a result, the implied deviation in firm future cash flows is -4.5 percent ($= -7.0 + 2.5$). 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 -3.9 percent.

Table 8: Welfare Effect of Tariff Announcements

	Components			Total	
	Firm values	Firm discount rates	Tariff Revenues		
Baseline	-0.070	0.025	0.006	-0.039	(0.026)
Robustness w.r.t. firm sample					
Enforcing balanced panel	-0.072	0.028	0.006	-0.038	(0.029)
Drop firms w/ specific ann.	-0.069	0.025	0.006	-0.038	(0.026)
Robustness w.r.t. firm weights					
Zero effect on fin. firms	-0.066	0.024	0.006	-0.036	(0.025)
Zero effect for firms < 500 emp.	-0.036	0.013	0.006	-0.017	(0.014)
Robustness w.r.t. tariff revenues					
Using Fajgelbaum et al. (2020)	-0.070	0.025	0.002	-0.043	(0.026)
Robustness w.r.t. ann. window					
3-day window	-0.058	0.040	0.006	-0.012	(0.027)
Robustness w.r.t. VAR variables					
Without TS	-0.070	0.035	0.006	-0.028	(0.024)
Without EPB	-0.070	0.032	0.006	-0.032	(0.030)
Without VS	-0.070	0.055	0.006	-0.008	(0.016)
Without CS	-0.070	0.039	0.006	-0.025	(0.022)
Without $\log PD$	-0.070	-0.009	0.006	-0.072	(0.034)
Adding Covid Period	-0.070	0.021	0.006	-0.043	(0.029)
Robustness w.r.t. discount rate model					
3-FFM instead of CAPM	-0.070	0.026	0.006	-0.038	(0.024)
Corp. yields instead of risk-free	-0.070	0.024	0.006	-0.040	(0.026)

Note: The table reports the welfare effect of trade announcements, as well as its two components defined in equation (9): the aggregate deviation in firm cash flows, and the effect on tariff revenues. The last column reports the standard errors in parentheses, which are obtained using the delta method (see Appendix Section D.4 for details).

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

Firm Sample We first show that our estimates remain unchanged when we restrict the sample to a balanced set 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 unchanged when we exclude firms with firm-specific announcements in the same window as one of our tariff announcements (as reported in Capital IQ).

Firm Weights Next, we explore the robustness of our results to our weighting scheme using two alternative procedures reported in Table 8.

First, we estimate the welfare effect assuming that firms in the financial sector are unaffected by tariffs. This reflects two concerns: first, it reflects that our model applies more naturally to nonfinancial firms, and second, adding the deviation for financial firms may lead to double-counting, as these firms hold claims on nonfinancial firms. Assuming tariffs have no impact on financial firms has little impact on the results.

Second, we compute the welfare effect under the extreme assumption that tariff announcements have no effect on firms with fewer than 500 employees (i.e., we assume that deviations in firm values and discount rates are zero for all firms below this threshold). Despite this assumption, we still find a sizable welfare effect equal to -1.7 percent.

Tariff Revenues Our baseline choice of the maximum possible tariff revenue underestimates the welfare losses from the tariffs. We correct for this bias by using Fajgelbaum et al. (2020)'s estimates of tariff revenues instead of our upper bound. This more realistic estimate increases the welfare loss from 3.9 percent to 4.3 percent.

Event Window In the baseline results, we estimate deviations in firm values and discount rates using the responses of financial variables on the day of the tariff announcements. As a robustness check, we now explore using a longer three-day window. The estimated decline in firm values falls modestly from -7.0 to -5.8 percent, while the component due to changes in firm discount rates increases from 2.5 to 5 percent. Overall, the estimated welfare effect is smaller in magnitude using the three-day window.

We explore the sensitivity of our estimate of the component due to changes in discount rates in Appendix Table D.3. Compared to the estimates obtained using the one-day window (Table 6), the estimated changes in the VAR variables become much noisier using a three-day window. In particular, all changes in the VAR variables that are unrelated to stock-market returns lose statistical significance, consistent with the idea that the longer window picks up unrelated events. In other words, the change in the VAR variables over three days likely reflects unrelated macroeconomic noise rather than genuine tariff-induced changes in discount rates.

Overall, we believe the one-day window is more appropriate for our analysis and that the three-day results should be interpreted with caution. This is consistent with the high-frequency evidence in Figure B.1, which supports the choice of a one-day window (as opposed to a shorter or a longer window) for the reaction of stock prices.

VAR Variables To estimate firm-level discount rates, we specify a VAR with a set of variables that is very standard relative to the literature. We now check that our results are qualitatively not dependent on the exact choice of variables in the VAR. As a robustness check, we re-estimate the VAR after removing successively each one of the components of the vector $\boldsymbol{x}_t$. We report the results for the deviation in future risk-free rates and expected excess stock-market returns in Appendix Table D.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 with two exceptions. When we run a VAR excluding the price-dividend ratio, in which case the predicted change in discount rates is significantly lower. This reflects the importance of the price-dividend ratio as a predictor of future discount rates (Cochrane (2008)). In contrast, excluding the value spread leads to a larger predicted change in discount rates. The reason is that tariff announcements disproportionately lowered the stock prices of value firms relative to growth firms, increasing the value spread. Since a higher value spread predicts lower future discount rates on average, including the value spread leads the VAR to attribute less of the aggregate firm-level return decline to discount-rate news.

VAR Estimation Period Our baseline VAR is estimated using data through December 2019, i.e., before the onset of the COVID-19 pandemic. The COVID period introduced extreme and unprecedented dynamics in the VAR state variables—near-zero interest rates with high persistence, a collapse in the term spread, and historic highs in the price-dividend ratio—that could distort the estimated law of motion of the VAR. As a robustness check, we re-estimate the VAR including data through 2022. As reported in Table 8, this specification yields a welfare estimate that is very similar to our baseline (-4.3 percent vs. -3.9 percent), suggesting that our results are not sensitive to the inclusion of the COVID period.

Factor Model In the baseline results, we assumed that firm debt rates move one-for-one with the risk-free rate and that the CAPM governs expected equity returns. 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 on 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. The welfare estimate remains virtually unchanged.

Second, we assume that the log deviation in the interest rate paid on firm debt is equal to the log deviation in the yields of BAA bonds rather than the risk-free rate on debt. As reported in Table 8, we find that our measure of welfare hardly changes; that is, our VAR implies relatively small deviations in credit spreads following announcement shocks. See Appendix D.5 for more details.

5 Interpretation and Validation of Welfare Results

In this section, we validate and interpret our aggregate welfare results. First, we use the structure of our model to decompose the aggregate welfare effect into static price effects, dynamic price effects, and TFP effects. Second, we test whether announcement-day stock price movements persist over longer horizons, as they should if they reflect durable changes in firm values rather than short-lived overreaction. Third, we examine whether our cash-flow estimates predict realized cash-flow and other outcomes. Fourth, we examine whether the asset pricing patterns documented during the 2018-2019 trade war extend to the more recent trade policy events in 2025-26.

5.1 Decomposition of Aggregate Welfare

We conduct a back-of-the-envelope calculation to understand the quantitative differences between conventional measures of the cost of the trade war and those we obtain in this paper. We use equation (11) to decompose our baseline number for the welfare effects of asset prices through firm cash flows into the static price effect, the dynamic price effect, and the TFP effect. First, as we explain in detail in Appendix E.3, we can estimate the static price effect ($\hat{p}^{e}_{i0}$) by applying tariff pass-through estimates during the 2018-19 trade war from Fajgelbaum et al. (2020) and Amiti et al. (2019). Specifically, we use these estimates to compute the static impact of the tariff on the effective rates of protection, then aggregate these to determine what our welfare estimates would have been if markets had thought that the applied tariffs would cause a permanent change in ERP, with no impact on TFP. Depending on how one models the way in which U.S. firms adjust their pricing in response to tariffs, we estimate that the static effect of the tariffs would have lowered U.S. welfare by 0.17 to 0.3 percent (see Appendix E.3 for details). These estimates are remarkably similar to those obtained by Amiti et al. (2019) and Fajgelbaum et al. (2020) who estimate welfare losses of around 0.3 percent. The similarity of the results establishes that the specific factors model, which forms the basis of our setup, delivers standard results if one assumes that tariff wars will not affect TFP or have any time-varying impact on prices.

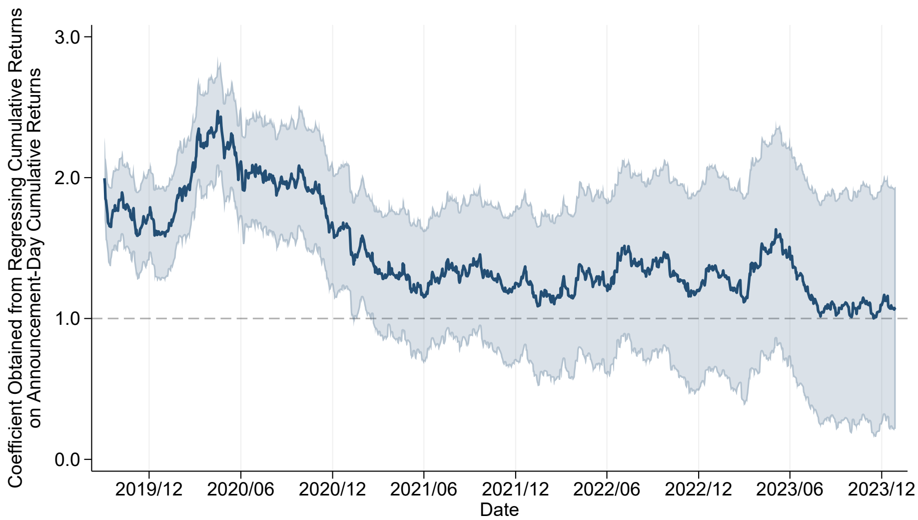
We can also use the structure of our model to bound the magnitudes of the last two terms (the dynamic price and TFP effects). The lower bound of the dynamic price effect can be estimated by assuming that the U.S. levied its "maximum " tariffs with probability 1. In the 2024 presidential campaign, President Trump discussed levying tariffs of 60 percent on China and 20 percent on all other countries—a larger average increase than that of the 1930 Smoot-Hawley tariff (see Irwin (2017))—which we take as the likely maximum expected U.S. threat point. If markets were certain that these tariffs would be implemented at the outset of the 2018-19 trade war, we calculate that the dynamic price effect would have lowered U.S. welfare by 0.82 to 1.84 percentage points depending on the assumptions made about tariff passthrough into domestic prices (see Appendix E.3.1 for details). Subtracting the largest possible losses due to the price effects still leaves a large welfare loss due to the change in expected TFP: -1.76 $(= -3.9 + 0.3 + 1.84)$. In other words, our baseline estimates imply that markets anticipated the tariffs would cause a welfare loss much larger than static estimates suggest, due to expected declines in TFP. Note that this TFP effect should be understood as a residual: it captures any effect of tariffs on cash flows that does not come from direct tariff exposure. It can include mechanisms outside the model, such as effects of tariffs on markups, supply-chain fixed costs, geopolitical risk, competition, and innovation in exposed industries.

5.2 Testing for persistent effects

One concern with using announcement-day stock returns to assess tariff announcements is that markets may have overreacted to the tariff news. To examine this concern, we ask whether firms that performed relatively worse on announcement days saw ex-post revision in asset returns; that is, whether the initial cross-sectional response faded over time. To test this, we regress each firm's cumulative return over the 2018-2023 period on its cumulative return during announcement days alone. If announcement effects are not undone by subsequent events, the coefficient should be 1, i.e., announcement day moves predict, on average, where firm values end up. If instead the effects mean-revert as U.S.-China tensions resolve, the coefficient should revert to zero.

We present the results from this exercise in Figure 8. The figure shows that the coefficient begins at approximately 2 at the end of the announcement sample and converges to approximately 1 by the end of the first Trump administration, where it remains for the rest of the sample period. Thus, if anything, the initial cross-sectional response is amplified in the short run before settling near one. The long-run coefficient of 1 indicates that the cross-sectional differences in returns induced by tariff announcements are fully preserved in the data over a multi-year horizon, with no evidence of mean reversion. This is inconsistent with the view that announcement-day returns reflect sentiment-driven overreaction. Rather, they appear to capture genuine and lasting changes in firm prospects.

Figure 8: Long-Run Effects of Tariff Announcements on Firm Returns



Note: This figure plots the time series of slope coefficients from a sequence of cross-sectional regressions, together with a 95 percent confidence band. For each calendar date t from September 2019 through December 2023, we regress firm-level cumulative log returns since January 2018 on the firm-level log returns summed across all trade-policy announcement days.

5.3 Cash-Flow Validation

Given the persistence of the shocks, a reasonable follow-on question is whether our use of equation (12) to obtain estimates of $\hat{\Pi}_i$ tells us anything about realized cash flows. We build on the methodology of Greenland et al. (2024), who, as part of their own validation exercise, examined whether firms that experienced worse cumulated abnormal returns on tariff-announcement dates also experienced worse future real outcomes. In our case, however, we ask whether our estimates of expected cash flows—the primitive object of interest in our theory—predict realized future accounting cash flows. Finding such a relationship need not be guaranteed for several reasons. Empirically, the effects of the trade war may have taken many years to appear in accounting data, or unanticipated future shocks may have been correlated with those during the trade war, leading us to find no relationship even if one exists. Alternatively, even absent any data limitations, our theory may miss features of the economy that prevent a clean mapping between $\hat{\Pi}_i$ and realized cash flows. The existence of such a relationship would nonetheless build confidence that our procedure captures aspects of expectations about future cash-flow movements.

We test whether our estimated expected cash flow changes (derived from the event-study stock price reactions) predict *realized* changes in firm-level outcomes after the trade war by estimating panel regressions of the form:

$$\ln(Y_{i,t}) = \alpha_i + \delta_t + \beta\hat{\Pi}_i \times \text{Post}_t + \gamma'\mathbf{X}_i \times \text{Post}_t + \varepsilon_{i,t} \tag{20}$$

where $Y_{i,t}$ is an observable outcome (i.e., accounting cash flows, profits, sales, employment, labor productivity (sales per worker), or investment); Post_t is a dummy that equals one in 2019 and later years; $\hat{\Pi}_i$ is the firm's estimated expected cash flow deviation; $\mathbf{X}_i$ is a vector of pre-trade-war firm characteristics used in Greenland et al. (2024). The sample spans 2013 to 2024. The parameter β tells us whether deviations in expected cash flows at the time of tariff announcements are associated with higher or lower $Y_{i,t}$. For example, if the dependent variable is accounting cash flows, and $\beta = 1$, this would mean that cash flows in the five years after the end of the trade war would on average move one for one with estimated expected cash flow deviations.

We cannot simply regress $Y_{i,t}$ on $\hat{\Pi}_i$ because $\hat{\Pi}_i$ is the sum of two terms: the easy-to-measure deviation in firm value ($\hat{M}_{i0}$) and the deviation in the firm discount rate, obtained from the VAR, which is likely estimated with substantial error. We define an instrument, Z_i, as

$$Z_i \equiv \hat{M}_{i0} - \kappa_i\beta_{i,MKT}\sum_{k=1}^{K}\theta_{MKT,k}, \tag{21}$$

where $\theta_{MKT,k}$ is the market return (relative to the risk-free rate) on announcement day k, and $\beta_{i,MKT}$ is estimated on the pre-trade-war year of 2017, so that the beta estimates are not contaminated by the announcement-period returns. The first term in Z_i is identical to the first term in the definition of $\hat{\Pi}_i$, which makes the instrument relevant. By construction, Z_i strips out all market-level variation from the cumulative announcement-day return, scaled by leverage (κ_i). It therefore captures only the firm-specific, idiosyncratic component of the price response (adjusted for capital structure), which, as we show in Appendix D.2, is orthogonal to the measurement error in the VAR. Thus, the instrument is valid because it also satisfies the exclusion restriction.

Table 9 presents the results from testing whether $\hat{\Pi}_i$ predicts the evolution of cash flows and other firm outcomes. The first stage *F*-statistics exceed 5,000, indicating that our instrument has power. In column 1, we report the results of regressing cash flow, defined as operating income after depreciation plus interest and related expenses, against $\hat{\Pi}_i$ and obtain a coefficient of 1.26, which is not statistically different from 1.[25] In other words, we can reject the hypothesis that $\hat{\Pi}_i$ is uncorrelated with future accounting cash flow

[25] Although we do not report the OLS estimates in the table, they are the same sign as the IV estimates, but smaller in magnitude. This result is consistent with our interpretation of IV as being needed to correct classical measurement error.

Table 9: Relationship between Expected Changes in Cash Flows and Future Observables

Panel A: Second Stage						
	(1) $\ln(\text{CF}_{it})$	(2) $\ln(\text{Prof}_{it})$	(3) $\ln(\text{Sales}_{it})$	(4) $\ln(L_{it})$	(5) $\ln(\text{Sales}_{it}/L_{it})$	(6) $\ln(\text{Inv}_{it})$
Post $\times$ $\widehat{\Pi}_i$	1.26***	1.15***	0.95***	0.70***	0.25*	0.91***
	(0.35)	(0.42)	(0.21)	(0.22)	(0.13)	(0.24)
First-stage F-stat	5610.92	5610.92	5610.92	5603.14	5603.14	5418.89
Panel B: First Stage						
Post $\times$ Z_i	1.06***	1.06***	1.06***	1.06***	1.06***	1.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Within-R2	0.832	0.832	0.832	0.832	0.832	0.848
Observations	14463	14463	14463	14447	14447	12736

Note: Data is at the firm-annual level for the period 2013 to 2024, from Compustat and CRSP. CF_{it} is the observed cash flow, defined as operating income after depreciation plus interest and related expenses. Profit is defined as operating income after depreciation less interest and related expenses. We remove firm-year observations with nonpositive profits. Labor productivity is measured as sales per worker. $\widehat{\Pi}_i$ is our estimate of the expected present discounted value of deviations in firm cash flow, cumulated across all event days using one-day windows. Z_i is defined in equation (21). Post is a dummy variable that equals one for years 2019–2024. Inv_{it} ("investment") is the sum of physical and intangible investment, where physical investment is the capital expenditure and intangible investment is calculated as xrd + (0.3*sga) following Peters and Taylor (2017) (Section 3 and Appendix B). xrd is R&D expenses; sga is selling, general, and administrative expense (xsga) less R&D expense (xrd) and in-process R&D expenses (rdip). 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. Standard errors clustered by firm are in parentheses. The Kleibergen-Paap first-stage F statistics are reported. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

and cannot reject the hypothesis that cash flow estimates from financial markets move on average one-to-one with realized cash flows in the first five years after the trade war. According to Proposition 1, firms that have higher cash flows should expand employment and sales. We test this prediction in columns (3) and (4), which show that we observe this pattern in the data as well: a one-unit lower predicted cash-flow deviation is associated with a 0.95 log-point decrease in sales but only a 0.70 log-point decrease in employment.

Columns (5) and (6) report the results for labor productivity (sales per worker) and investment. Column (5) shows that a one-unit lower predicted cash-flow deviation is associated with a 0.25 log-point decrease in labor productivity. While our theory allows for firm-level changes in TFP, the empirical outcome here measures labor productivity as sales per worker rather than TFP, so the decline could also reflect changes in prices, capital intensity, or other factors. Finally, column (6) shows that firms with larger predicted cash-flow declines also reduce investment. Our baseline model assumes that the firm-specific factor is fixed, but in Appendix C.6 we show that if firms can respond to tariffs by investing less, lower investment amplifies the negative welfare effect of tariffs relative to our estimate based on future cash-flow changes alone.[26]

5.4 External Validity: Trade Policy Announcements in President Trump's Second Term

Although we lack the data to construct cash flow estimates for the more recent trade war, we can examine whether the asset-pricing patterns we documented for the 2018–2019 trade war extend to the more recent period. Our sample runs from January 2025 through February 2026, the latest event for which the required data are available. Interpreting the results requires some context. The U.S. administration justified tariffs in the 2018-2019 trade war under well-established laws—Section 301 of the Trade Act of 1974 and Section 232 of the Trade Expansion Act of 1962—and the announced tariffs were implemented without significant loopholes and have remained in place to this day. In contrast, the Trump Administration's use of the International Emergency Economic Powers Act

[26]Because investment is chosen optimally, tariff-induced changes in the firm-specific factor have no direct first-order effect on firm value. The additional term in Appendix C.6 arises instead because endogenous investment changes labor demand and wages, and therefore changes the mapping from market-implied firm-value responses to aggregate welfare. This result does not contradict Le Chatelier's principle, which states that allowing an additional margin of adjustment weakly reduces the welfare impact of a given policy shock. Le Chatelier compares two economies hit by the same underlying shock: one in which firms have the extra adjustment margin, and one in which they do not. Our exercise is different: we take the announcement-day stock-price response as given and ask how that same market response maps into welfare under different models of firm adjustment. With an investment margin, the same market response is associated with lower investment and labor demand, which puts additional downward pressure on wages. The welfare effect can therefore be more negative.

(IEEPA) in the recent period was viewed as legally questionable.[27] The frequency and extreme variability of tariff rate announcements in the second trade war further complicated investors' ability to form beliefs about where tariff rates would ultimately settle. Nevertheless, as we show below, the asset pricing patterns from the first trade war are broadly replicated in the second.

Table 10: Stock-Market Changes on 2025-2026 Tariff Announcement Days

Trading Date	Tariff Change	Description	Market Return (x100)
22jan2025	Increase	U.S. to impose 10% tariff on Chinese imports	0.4
04feb2025	Mixed	China imposes 10–15% tariffs on some U.S. energy and industrial goods U.S. paused 25% tariff on Mexico and Canada for 30 days	0.8
27feb2025	Increase	U.S. announces an additional 10% tariff on Chinese imports and 25% tariffs on imports from Canada and Mexico	-1.5
04mar2025	Increase	China imposes 10–15% tariffs on U.S. agricultural goods	-1.2
03apr2025	Increase	U.S. Liberation Day tariffs (34% on China)	-4.9
04apr2025	Increase	China retaliates with 34% tariff on U.S. goods	-5.9
09apr2025	Mixed	U.S. raises reciprocal tariffs on China by 84% China retaliates with 84% tariff U.S. suspends Liberation tariffs on all countries U.S. increases tariff on China to 125%	8.7
11apr2025	Increase	China raises reciprocal tariffs from 84% to 125%	1.8
12may2025	Decrease	U.S. and China tariff truce	3.0
11aug2025	Decrease	U.S. and China extend the tariff truce for 90 days	-0.2
27oct2025	Decrease	U.S. and China strike deal over rare earths and tariffs	1.0
20feb2026	Mixed	U.S. Supreme Court ruled IEEPA tariffs illegal U.S. imposes 10% global tariff on all countries under Section 122	0.6
Cumulative	Increase		-11.4
Cumulative	Decrease		3.8
Cumulative	Mixed		10.1

Note: This table reports value-weighted U.S. stock-market returns on trade policy announcement days between January 2025 and February 2026. Columns report the trading date on which returns are measured, the direction of the tariff change, with "Mixed" indicating multiple announcements on the same day comprising tariff increases and decreases; and a description of the event, and the value-weighted market return. Cumulative Tariff Increases aggregates the returns of trading days on which only a tariff increase was announced. The cumulative decrease row aggregates the returns of trading days on which a tariff decrease, pause, or truce was announced, and the final row cumulates the returns on event dates where a mixture of increases and decreases occurred.

In Table 10, we present twelve events involving China, including both positive and negative announcements. Most are specifically targeted at China, though we also include major broad-based events, like the "Liberation Day" tariffs, which imposed very high rates on all countries including China; we exclude events solely targeting non-China

[27]For example, betting markets such as Kalshi and Polymarket put the probability that the Supreme Court would rule against using IEEPA as justification for the tariffs at around 50 percent as early as September 2025.

countries or particular industries, such as steel tariffs. The event dates for the 2025–26 trade war are more difficult to identify cleanly than those from the 2018–19 period, as in some cases multiple events occurred on the same day—sometimes moving in opposite directions. The second column indicates whether each event date consisted of an announced increase in tariffs, a decrease (or pause), or a mix of both.

The first event in 2025 was on January 22, when the U.S. announced it was considering an additional 10 percent tariff on Chinese imports because of China's role in the U.S. fentanyl crisis. The additional U.S. tariff was later implemented on February 4, with China retaliating the same day with tariffs of 10–15% on energy and industrial U.S. exports. In both cases, equity market returns were positive, explained by other announcements on the same days. For the first event, the offsetting announcement was not trade-related — there was an AI investment announcement of $500 billion. For the second event, it was trade-related but not targeting China — a 30-day pause on the 25% tariff on goods from Mexico and Canada (announced after trading hours on the previous day). Unsurprisingly, this news dwarfed China's retaliation, which targeted only a small subset of U.S. exports. The next two events did produce negative market reactions of more than one percentage point: on February 27, the U.S. announced another 10% tariff on China, and on March 4, China retaliated with 10–15% tariffs on agricultural goods rather than energy and industrial exports.

Liberation Day tariffs were announced on April 2, 2025, after markets had closed, producing a decline in equity returns of close to five percent on the following day. Although markets were expecting some tariffs, the sheer scale surprised markets. The tariffs, officially called "reciprocal tariffs," imposed a minimum 10% baseline rate on all countries, with higher country-specific rates for those with large trade deficits with the U.S.—ranging up to 49% for some countries. China was hit particularly hard, facing an additional 34 percent reciprocal tariff on top of the existing 20% fentanyl tariff, bringing the total tariff on Chinese goods to 54 percent. The following day, April 4, China retaliated by imposing 34 percent tariffs on all U.S. exports and restricting exports of rare earth metals to the U.S., producing a further decline in equity returns of 5.9 percent.

On April 8, 2025, after markets had closed, the U.S. raised its reciprocal tariffs on China from 34% to 84%. The following day, April 9, China retaliated by announcing an 84% tariff on all U.S. exports. Also on April 9, the U.S. announced it was raising its reciprocal tariff on China further to 125%, bringing the total tariff on Chinese goods to 145% when combined with the existing fentanyl tariff. At the same time, the U.S. announced that Liberation Day tariffs on all countries other than China would be paused for 90 days, pending bilateral negotiations. This was thus a mixed event, combining further escalation with China and a significant de-escalation for the rest of the world. Despite the escalation with China, the pause dominated market sentiment, and equity returns jumped 8.7 percent.

Given the number of announcements surrounding the Liberation Day tariffs and the resulting market volatility, it is difficult to attribute each market movement precisely. On April 11, 2025, before markets opened, the trade war was further escalated with China announcing its tariff on U.S. goods would increase to 125%. The S&P opened down 0.5%, but later in the day comments from the White House indicating that President Trump was optimistic that China would seek a deal pushed the S&P to close 1.8% higher. On May 12, the market jumped 3.0 percent on the announcement of a 90-day tariff truce, with both countries reducing their reciprocal tariffs from 125% to 10%, bringing the effective U.S. tariff rate on Chinese goods to 30% once the fentanyl tariff is included. The extension of that truce for a further 90 days on August 11 barely registered, likely because markets had already priced in the extension. A further de-escalation came on Sunday October 26, when Treasury Secretary Bessent announced that the threat of 100% tariffs on China was off the table, with the return rising 1.0 percent the following day.

The final events reported in Table 10 occur in 2026. On February 20, the Supreme Court ruled the tariffs imposed under IEEPA were illegal. President Trump immediately responded by introducing a new 10% "global" tariff on all countries under Section 122 of the Trade Act of 1974, which allows tariffs of up to 15% for 150 days. The Supreme Court ruling dominated market sentiment, with the market closing 0.6% higher.

Despite the complexity of the announcements in 2025-2026, Table 10 demonstrates that the cumulative effects of the 2025–2026 trade war are remarkably similar to those of the earlier one. Overall, markets fell by 11.4 percentage points following major announcements of tariff increases, nearly identical in magnitude to the 11.5-percentage-point decline during the 2018–2019 trade war. Equity returns fell 6.1 percent on U.S. announcement days and a further 5.4 percent on Chinese announcement days. On event dates consisting solely of announced tariff decreases or pauses, aggregate returns increased 3.8 percent. Events involving multiple simultaneous announcements, pauses, or reversals were, on average, associated with large positive equity returns, mostly driven by the suspension of all Liberation Day tariffs on countries other than China. The cumulative rise on those event dates was 10.1 percent.

These tariff announcements also had an impact on yields in predictable ways. We report the impact of the 2025–26 tariff announcements on yields in Appendix Table E.1 in the online appendix, which we compare with the 2018–19 results in Appendix Table B.6. For announcements that increased tariffs, we see mixed effects on nominal yields (negative for U.S. announcements and positive for Chinese announcements) and big, positive effects on the equity premium bound, consistent with the patterns documented in the 2018–19 trade war. In contrast, trade war announcements that included a reduction in tariffs or a truce lowered the EPB and raised nominal and real yields, on average, consistent with lower expected future trade-war costs. Thus, the asset-pricing patterns from the first trade war are broadly consistent with those we document in the second.

6 Conclusion

This paper develops a methodology for assessing the welfare effects of economic policy using the reaction of financial markets to policy announcements, and applies it to the U.S.-China trade war of 2018–2019. We document four stylized facts that motivate our approach: tariff announcements produced large, broad, and persistent declines in stock prices; firms directly exposed to China through trade suffered relatively worse returns; these cross-sectional return differences predicted subsequent declines in real outcomes; and announcements triggered a flight to safety, depressing real yields while raising equity-risk premia. Using an infinite-horizon specific factors model, we show that the change in firm cash flows is a sufficient statistic for identifying expected movements in wages, employment, and welfare, and we validate this approach by showing that market-implied cash-flow changes predict realized accounting outcomes in the years following the trade war.

Our welfare estimates are large relative to conventional measures based on static models. The reason is that static analyses constrain tariffs to have no effect on TFP and no bearing on the likelihood of future price changes, whereas our approach imposes neither restriction and instead lets financial markets reveal what investors actually expected. Seen through the lens of our model, the bulk of the gap between our estimates and static ones can be accounted for by an anticipated decline in TFP, providing empirical support for dynamic models that feature trade-related productivity spillovers and for political-economy models that embed the risk of future tariff escalation into the costs of starting a trade war.

Our methodology is not specific to trade policy. Because it requires only that announcements be unanticipated and that asset prices reflect investors' expectations of future cash flows, it can be applied to any setting in which a discrete, unexpected event generates measurable financial market reactions. We hope this approach will prove useful for evaluating the welfare consequences of a broader class of policy interventions, and that the links our theory develops between cash flows, employment, productivity, and prices will help future researchers better understand the mechanisms at work.

References

Alcalá, F. and A. Ciccone (2004). Trade and productivity. *Quarterly Journal of Economics 119*(2), 613–646.

Amiti, M. and J. Konings (2007). Trade liberalization, intermediate inputs, and productivity: Evidence from Indonesia. *American Economic Review 97*(5), 1611–1638.

Amiti, M., S. J. Redding, and D. E. Weinstein (2019). The impact of the 2018 tariffs on prices and welfare. *Journal of Economic Perspectives 33*(4), 187–210.

Amiti, M., S. J. Redding, and D. E. Weinstein (2020). Who's paying for the U.S. tariffs? A longer-term perspective. In *AEA Papers and Proceedings*, Volume 110, pp. 541–46.

Atkeson, A., J. Heathcote, and F. Perri (2024). There is no excess volatility puzzle. Working Paper 32481, National Bureau of Economic Research.

Auclert, A., M. Rognlie, and L. Straub (2025). The macroeconomics of tariff shocks. Working Paper 33726, National Bureau of Economic Research.

Baker, S. R., N. Bloom, and S. J. Davis (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics 131*(4), 1593–1636.

Bernanke, B. S. and K. N. Kuttner (2005). What explains the stock market's reaction to federal reserve policy? *The Journal of finance 60*(3), 1221–1257.

Bown, C. P. (2020). US–China Phase One Tracker: China's Purchases of US Exports. Piie chart, Peterson Institute for International Economics.

Brandt, L., J. Van Biesebroeck, L. Wang, and Y. Zhang (2017). WTO accession and performance of chinese manufacturing firms. *American Economic Review 107*(9), 2784–2820.

Brandt, L., J. Van Biesebroeck, L. Wang, and Y. Zhang (2019). WTO accession and performance of chinese manufacturing firms: Corrigendum. *American Economic Review 109*(4), 1616–21.

Breinlich, H. (2014). Heterogeneous firm-level responses to trade liberalization: A test using stock price reactions. *Journal of International Economics 93*(2), 270–285.

Breinlich, H., E. Leromain, D. Novy, T. Sampson, and A. Usman (2018). The economic effects of brexit: Evidence from the stock market. *Fiscal Studies 39*(4), 581–623.

Caldara, D., M. Iacoviello, P. Molligo, A. Prestipino, and A. Raffo (2019). The economic effects of trade policy uncertainty. *Journal of Monetary Economics forthcoming*.

Campbell, J. Y. (2003). Consumption-based asset pricing. *Handbook of the Economics of*

Finance 1, 803–887.

Campbell, J. Y. and R. J. Shiller (1988). The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies 1*(3), 195–228. Campbell, John Y. Shiller, Robert J. 1465-7368.

Campbell, J. Y. and T. Vuolteenaho (2004). Bad beta, good beta. *American Economic Review 94*(5), 1249–1275. Campbell, JY Vuolteenaho, T.

Cavallo, A., G. Gopinath, B. Neiman, and J. Tang (2021). Tariff pass-through at the border and at the store: Evidence from us trade policy. *American Economic Review: Insights 3*(1), 19–34.

Cochrane, J. H. (2008). The dog that did not bark: A defense of return predictability. *The Review of Financial Studies 21*(4), 1533–1575.

Corden, W. M. (1966). The structure of a tariff system and the effective protective rate. *Journal of Political Economy 74*(3), 221–237.

Crowley, M. A., N. Meng, and H. Song (2019). Policy shocks and stock market returns: Evidence from chinese solar panels. *Journal of the Japanese and International Economies 51*, 148–169.

Dix-Carneiro, R. and B. K. Kovak (2017). Trade liberalization and regional dynamics. *American Economic Review 107*(10), 2908–46.

Fagereng, A., M. Gomez, É. Gouin-Bonenfant, M. Holm, B. Moll, and G. Natvik (2025). Asset-price redistribution. *Journal of Political Economy 133*(11), 3494–3549.

Fajgelbaum, P. D., P. K. Goldberg, P. J. Kennedy, and A. K. Khandelwal (2020). The return to protectionism. *Quarterly Journal of Economics 135*(1), 1–55.

Feyrer, J. (2019). Trade and income-exploiting time series in geography. *American Economic Journal: Applied Economics 11*(4), 1–35.

Fisman, R., Y. Hamao, and Y. Wang (2014). Nationalism and economic exchange: Evidence from shocks to Sino-Japanese relations. *The Review of Financial Studies 27*(9), 2626–2660.

Flaaen, A., A. Hortaçsu, and F. Tintelnot (2020, July). The production relocation and price effects of us trade policy: The case of washing machines. *American Economic Review 110*(7), 2103–27.

Frankel, J. A. and D. H. Romer (1999). Does trade cause growth? *American economic review 89*(3), 379–399.

Gómez-Cram, R., H. Kung, and H. Lustig (2025). Can U.S. Treasury markets add and subtract? NBER Working Paper 33604, National Bureau of Economic Research.

Gorodnichenko, Y. and M. Weber (2016). Are sticky prices costly? evidence from the stock market. *Journal of Monetary Economics 79*, 43–68.

Greenland, A., M. Ion, J. Lopresti, and P. Schott (2024). Using equity market reactions to infer exposure to trade liberalization. *forthcoming in the Journal of International Economics*.

Greenwald, D. L., M. Lettau, and S. C. Ludvigson (2023, June). How the Wealth Was Won: Factor Shares as Market Fundamentals. *Journal of Political Economy 131*(3), 705–761.

Grossman, G. M. and J. A. Levinsohn (1989). Import competition and the stock-market return to capital. *American Economic Review 79*(5), 1065–1087.

Gürkaynak, R. S., B. Sack, and J. H. Wright (2007). The us treasury yield curve: 1961 to the present. *Journal of monetary Economics 54*(8), 2291–2304.

Gürkaynak, R. S., B. Sack, and J. H. Wright (2010, January). The tips yield curve and inflation compensation. *American Economic Journal: Macroeconomics 2*(1), 70–92.

Handley, K. and N. Limão (2017). Policy uncertainty, trade, and welfare: Theory and evidence for China and the United States. *American Economic Review 107*(9), 2731–2783.

Hanson, S. G. and J. C. Stein (2015). Monetary policy and long-term real rates. *Journal of Financial Economics 115*(3), 429–448.

Hartigan, J. C., P. R. Perry, and S. Kamma (1986). The value of administered protection: a capital market approach. *The Review of Economics and Statistics*, 610–617.

Hébert, B. and J. Schreger (2017). The costs of sovereign default: Evidence from argentina. *American Economic Review 107*(10), 3119–3145.

Huang, Y., C. Lin, S. Liu, and H. Tang (2023). Trade networks and firm value: Evidence from the U.S.-China trade war. *Journal of International Economics 145*.

Irwin, D. A. (2017). *Peddling Protectionism: Smoot-Hawley and the Great Depression*. Princeton, NJ: Princeton University Press.

Jones, R. W. (1975). Income distribution and effective protection in a multicommodity trade model. *Journal of Economic Theory 11*(1), 1–15.

Knoblach, M. and F. Stöckl (2020). What determines the elasticity of substitution between capital and labor? a literature review. *Journal of Economic Surveys 34*(4), 847–875.

Knox, B. and A. Vissing-Jorgensen (2022). A stock return decomposition using observables.

Kovak, B. K. (2013). Regional effects of trade reform: What is the correct measure of liberalization? *American Economic Review 103*(5), 1960–76.

Lewis, D. J., C. Makridis, and K. Mertens (2019). Do monetary policy announcements shift household expectations? *FRB of New York Staff Report* (897).

Lewis, D. J. l. (2020). Announcement-specific decompositions of unconventional monetary policy shocks and their macroeconomic effects. *FRB of New York Staff Report* (891).

Martin, I. (2017). What is the expected return on the market? *The Quarterly Journal of Economics 132*(1), 367–433.

Martin, I. W. (2013). Consumption-based asset pricing with higher cumulants. *Review of Economic Studies 80*(2), 745–773.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *econometrica 71*(6), 1695–1725.

Moser, C. and A. K. Rose (2014). Who benefits from regional trade agreements? the view from the stock market. *European Economic Review 68*, 31–47.

Nakamura, E. and J. Steinsson (2018). High-frequency identification of monetary non-neutrality: the information effect. *Quarterly Journal of Economics*, 1283–1330.

Ossa, R. (2014). Trade wars and trade talks with data. *American Economic Review 104*(12), 4104–4146.

Peters, R. H. and L. A. Taylor (2017). Intangible capital and the investment-q relation. *Journal of Financial Economics 123*, 251–272.

Pierce, J. R. and P. K. Schott (2016). The surprisingly swift decline of US manufacturing employment. *American Economic Review 106*(7), 1632–1662.

Pinchis-Paulsen, M. (2020). Retooling sanctions: China's challenge to the liberal international order. *Chicago Journal of International Law 21*(2), 331–382.

Schmitt-Grohé, S. and M. Uribe (2025). The effects of transitory and permanent u.s. import tariff shocks. Working Paper 33997, National Bureau of Economic Research.

Topalova, P. (2010). Factor immobility and regional impacts of trade liberalization: Evidence on poverty from india. *American Economic Journal: Applied Economics 2*(4), 1–41.

Topalova, P. and A. Khandelwal (2011). Trade liberalization and firm productivity: The case of india. *Review of economics and statistics 93*(3), 995–1009.

Wacziarg, R. and K. H. Welch (2008). Trade liberalization and growth: New evidence. *The World Bank Economic Review 22*(2), 187–231.

Waugh, M. E. (2019). The Consumption Response to Trade Shocks: Evidence from the US-China Trade War. Working Paper 26353, National Bureau of Economic Research.

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

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Contents

A Summary of Data Sources

Table A.1: Summary of Data Sources

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

Variable	Construction
China Revenue Share	*Source: FactSet Geographic Revenue Exposure (2017)* These data report revenue shares from major markets (including China) for 3,134 firms (identified by PERMNO). If we cannot match a firm to this dataset, we try to match using tickers. If we cannot match a firm using either PERMNO or the ticker to one in the Datamyne dataset, we assume that its China revenue share is zero. More details are provided in Section B.5.
China Importer/ Exporter	*Source: Datamyne dataset of the value and quantity of exports to and imports from China (via sea) by U.S. firms in 2017, Supply chain data from Capital IQ* We combine the Datamyne dataset with supply chain data to determine whether each firm imported from or exported to China (via sea) in 2017 either directly or through a subsidiary/supplier. Refer to Section B.5 for details on variable construction.

Variable	Construction
Economic Surprise Variables (ES_t)	*Source: Daniel Lewis based on Lewis et al. (2019)* The difference between a macroeconomic data release value and the Bloomberg median of economists' forecast on the previous day. The 65 series we use to construct our economic surprise variables are ISM manufacturing, ISM non-manufacturing, ISM prices, construction spending, durable goods new orders, factory orders, initial jobless claims, ADP payroll employment, non-farm payrolls, unemployment rate, total job openings, consumer credit, non-farm productivity, unit labor costs, retail sales, retail sales less auto, federal budget balance, trade balance, import price index, building permits, housing starts, industrial production, capacity utilization, business inventories, Michigan consumer sentiment, PPI core, PPI, CPI core, CPI, Empire State manufacturing index, Philadelphia Fed BOS, GDP (advance estimate), GDP (second estimate), GDP price index, personal income, personal spending, PCE price index, core PCE price index, wholesale inventories, new home sales, CB consumer confidence, leading economic index, employment cost index, Wards total vehicle sales, continuing claims retail sales ex auto and gas, NAHB housing market index, change in manufacturing payrolls, MNI Chicago, PMI pending home sales, Richmond Fed manufacturing index, Dallas Fed manufacturing index, existing home sales, Chicago Fed national activity index, capital goods (non-defense ex air), NFIB small business optimal index, Cap goods ship. ex air, KC Fed manufacturing activity, Markit U.S. manufacturing purchasing managers index, Case-Shiller home price index, and Markit U.S. services purchasing managers index, federal funds shock, forward guidance shock, asset purchase shock, and the Federal Reserve information shock.

Variable	Construction
Equity-Premium Bound (EPB_t)	*Source: OptionMetrics, dataset with prices of actively traded option on the S&P 500 (ticker SPX)* We follow Martin (2017) method for constructing EPB_t.
Firm	*Source: CRSP-Compustat Annual Merged Dataset (2017)* A firm is defined by its Compustat Global Company Key or GVKEY. In our sample, the GVKEY codes map one-to-one to the unique identifier and permanent identifier to security or PERMNO in CRSP. As such, we are able to use PERMNO (**`permno`**) and GVKEY (**`gvkey`**) interchangeably across datasets.
Firm Employment L_i	*Source: CRSP-Compustat Annual Merged Dataset (2017)* The employment variable in Compustat [**`emp`**] includes the following items: all part-time and seasonal employees; and all employees of consolidated subsidiaries, both domestic and foreign. The employment variable excludes consultants, contract workers, and employees of unconsolidated subsidiaries.
Firm Equity Returns ($\ln R^E_{it}$)	*Source: CRSP U.S. Stock Database* We define log firm returns as the *log* of one *plus* net returns [**`ret`**]; $\ln(1 + \textbf{ret})$.

Variable	Construction
Labor and Specific Factor Shares (θ_{Li} and θ_{Vi})	*Source: Compustat and BEA Input-Output table* Firm cash flow as a share of revenue is calculated by dividing accounting cash flows with gross sales [**`sale`**] in 2017, obtained from Compustat. We use the BEA's 450-by-450 industry (6-digit NAICS) IO table in 2012 to construct labor and materials shares of revenue. In Section B.5, we describe how we combine all of these shares to construct the labor and specific factor shares of value added (θ_{Lf} and θ_{Vf}).
Ratio Between Market Value of Equity and Market Value of Assets κ_i	*Source: CRSP-Compustat Annual Merged Dataset (2017)* κ_i is defined as the ratio between the market value of equity and the market value of total assets (equity + debt). The market value of equity (or market capitalization) is defined below. The market value of assets is the sum of the market value of equity and the value of debt, constructed as total assets [**`at`**] *minus* stockholder equity [**`seq`**] *minus* cash and short-term investments [**`che`**]; **`at`** − **`seq`** − **`che`**. If cash and short-term investments is missing, we replace it with zero. Finally, we winsorize κ_i to be between 0.1 and 1.0.
Market Value of Equity	*Source: CRSP-Compustat Annual Merged Dataset (2017)* We use the 2017 market value of equity of a firm [**`mkval`**]. When this variable is unavailable we use the *product of* annual price close (fiscal) [**`prcc_f`**] *and* common shares outstanding [**`csho`**]; **`prcc_f`** × **`csho`**.
Profit	*Source: CRSP-Compustat Annual Merged Dataset (2017)* Profit is "operating income after depreciation" [**`oiadp`**] *minus* "interest and related expense (total)" [**`xint`**]; **`oiadp`** − **`xint`**.

Variable	Construction
Property, Plant, and Equipment (PPE) per worker	*Source: CRSP-Compustat Annual Merged Dataset (2017)* PPE per worker is property, plant, and equipment (gross total) [**`ppegt`**] *divided by* employees [**`emp`**]; **`ppegt`**/**`emp`**.
Nominal Yields	**1. Maturity: 3, 6, and 12 months***Source: Board of Governors of the Federal Reserve System, {3-Month, 6-Month, 1-Year} Treasury Bill Secondary Market Rate, Discount Basis; retrieved from FRED, Federal Reserve Bank of St. Louis* We obtain the nominal yields with the following maturities from FRED: 3-Month [**`DTB3`**], 6-Month [**`DTB6`**], and 12-Month [**`DTB1YR`**]. **2. Maturity: all remaining maturities up to 30 years***Source: daily US yield curve data up to 2019 dataset from Gürkaynak et al. (2007); dataset retrieved from Refet Gurkaynak's website* The US yield curve dataset was published alongside Gürkaynak et al. (2007) and is updated regularly. At the time of writing, the dataset reports nominal and real yields up until October 25, 2019, at different maturities ranging from one to thirty years. Nominal yields in the paper refers to "Zero-Coupon Yield (Continuously Compounded)" [**`SVNY`**xx].

Variable	Construction
Real Yields	*Source: daily US TIPS curve data up to 2019 dataset from Gürkaynak et al. (2010); dataset retrieved from Refet Gurkaynak's website* The US yield curve dataset was published alongside Gürkaynak et al. (2010) and is updated regularly (data up to 10/25/2019). Real yields are "TIPS Yield Zero Coupon (Continuously Compounded)" [**TIPSY***xx*].
Inflation Swap Rates	*Source: Bloomberg (USSWIT)* We obtain U.S. dollar inflation swap rates at maturities of 1 to 10 years from Bloomberg (ticker USSWIT). These are zero-coupon swaps that pay the realized CPI inflation over the contract period. The swap rate provides a market-based measure of breakeven inflation that, unlike the difference between nominal and TIPS yields, is not affected by TIPS liquidity premia.
Tobin's Q	*Source: CRSP-Compustat Annual Merged Dataset (2017)* Tobin's Q is market capitalization *plus* book value of total assets [**at**] *minus* book value of common equity [**ceq**], *all divided* by the book value of total assets [**at**].
U.S. Import Value	*Source: U.S. Census Bureau* We obtain 2017 U.S. import values for each good (HTS10) and exporting country from the U.S. Census Bureau.

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

Variable	Construction
VAR State Variables	*Source: FRED, CRSP, Fama-French Data Library, Moody's* The VAR includes seven state variables. (1) The log real risk-free rate: the annualized yield of 3-month T-Bills [**`DTB3`** from FRED] minus the smoothed average of CPI inflation [**`CPIAUCSL`** from FRED] in the previous twelve months, divided by four. (2) The log excess stock-market return: the log value-weighted CRSP market return minus the annualized yield of 3-month T-Bills. (3) The term spread: the difference in the yield-to-maturity of ten-year Treasuries (from the nominal yield curve of Gurkaynak et al., documented above) and the annualized yield of 3-month T-Bills. (4) The equity-premium bound from OptionMetrics (see above). (5) The value spread: the difference between the log book-to-market ratios of small value and small growth stocks, constructed using data from the Fama-French Data Library. (6) The credit spread: the difference between Moody's Seasoned Baa Corporate Bond Yield [**`BAA`** from FRED] and the annualized yield of 3-month T-Bills. (7) The log price-dividend ratio: the ratio between the value of the CRSP value-weighted market portfolio and the dividends distributed in the previous year. In some specifications, the VAR is augmented with the SMB and HML factor returns from the Fama-French Data Library.

Variable	Construction
Firm-Level Market Betas	*Source: CRSP U.S. Stock Database* Firm-level market betas ($\beta_{i,MKT}$) are estimated from OLS regressions of daily excess firm returns on excess market returns using CRSP data over the year 2017. We require firms to be traded on more than 120 days in 2017. In the Fama-French 3-factor specification, we additionally estimate $\beta_{i,SMB}$ and $\beta_{i,HML}$ from regressions on the three Fama-French factors.
SPY ETF Intraday Prices	*Source: NYSE Trade and Quote (TAQ) Database* We obtain intraday trade prices of the SPY ETF from TAQ. To minimize microstructure noise, we take the median trade price within each second. We then suppress bounceback observations—defined as instances where a return exceeding 0.1% in absolute value is immediately followed by a return of opposite sign also exceeding 0.1% in absolute value—by removing the intermediate observation. The plotted series is the resulting cleaned one-second SPY price series.

B Appendix for Section 2 (Stylized Facts)

B.1 Event Dates

The following tables present the event dates (i.e., the date of the first news report of each increase in tariffs) for the 2018–2019 and 2025–2026 announcements, the date that new tariffs were implemented, the country imposing the tariffs, and the news link of each event. The earliest event date was identified via Factiva and Google Search.

B.2 Intraday Stock Returns

To sharpen the test for pre-announcement leakage, we complement the daily analysis with intraday prices of the SPY exchange-traded fund (which tracks the S&P 500 index).

Table B.1: Details on Event Dates, 2018–2019

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

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

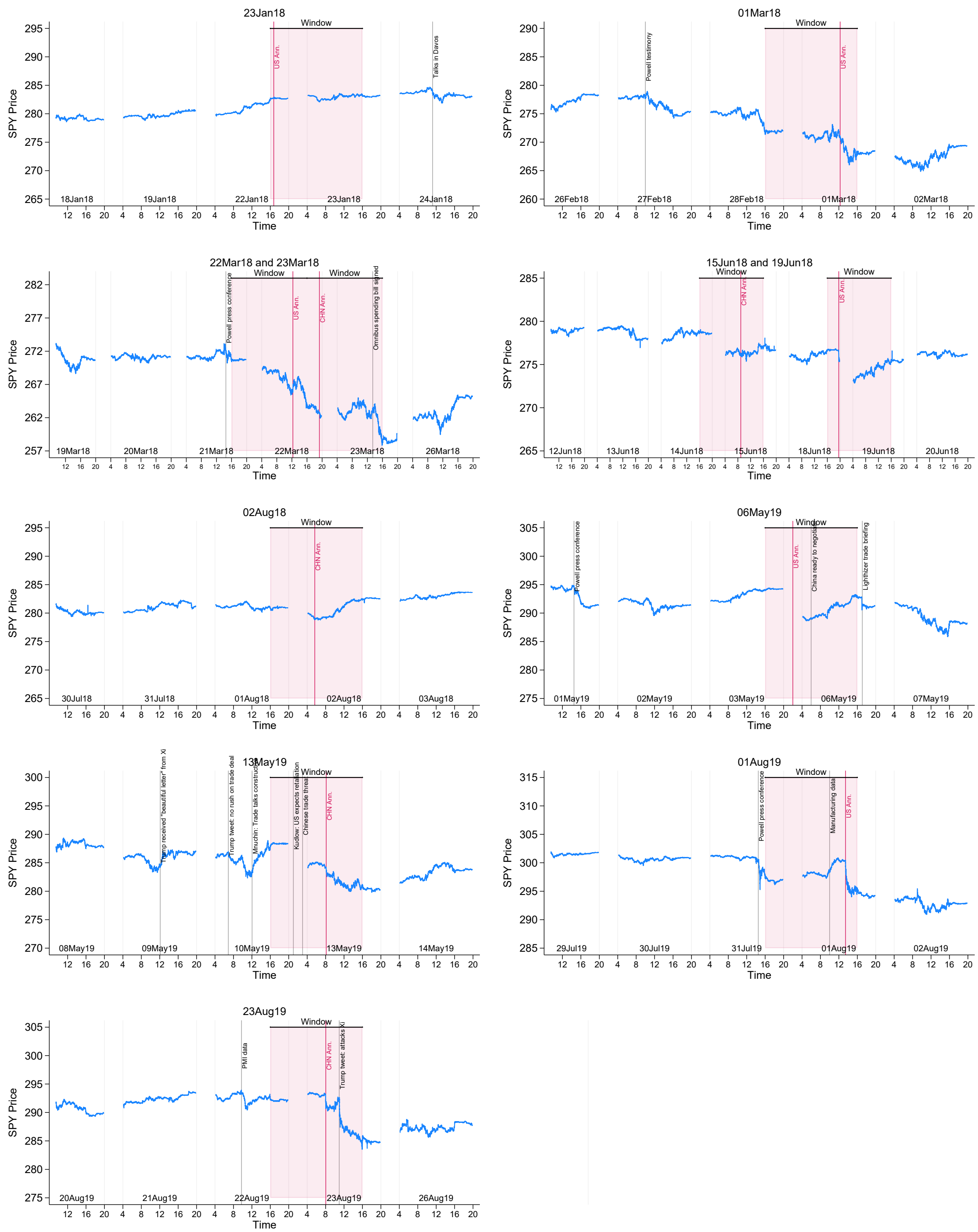
Table B.2: Details on Event Dates, 2025–2026

Event Date	Implementation Date	Country	News Link
22jan2025*	04feb2025	U.S.	NYT
04feb2025	10feb2025	China	NBC News
27feb2025	04mar2025	U.S.	Barron's
04mar2025	10mar2025	China	Bloomberg
03apr2025*	05apr2025	U.S.	Bloomberg
04apr2025	10apr2025	China	Bloomberg
09apr2025*	09apr2025	U.S.	Reuters
09apr2025	10apr2025	China	Bloomberg
09apr2025	09apr2025	U.S.	Bloomberg
11apr2025	12apr2025	China	CNBC
12may2025	14may2025	U.S. & China	Bloomberg
11aug2025	12aug2025	U.S. & China	Reuters
27oct2025**	27oct2025	U.S. & China	Reuters
20feb2026	20feb2026	U.S.	CNBC
20feb2026	24feb2026	U.S.	CNBC

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

To minimize microstructure noise, we take the median trade price within each second and suppress bounceback observations—instances where a return exceeding 0.1% in absolute value is immediately followed by a return of opposite sign also exceeding 0.1%—by removing the intermediate observation.

Figure B.1: Intraday Stock Returns around Tariff Announcements



Note: Each panel plots the intraday price of the SPY ETF in a narrow window around the time of the tariff announcement (marked by the vertical line). The sample covers all eleven tariff-announcement events listed in Table 1.

Figure B.1 plots SPY prices over several trading days around each announcement, with the announcement times marked with dashed red vertical lines. Table B.3 catalogs all notable intraday price movements visible in the figure. Every large move inside an announcement window coincides with the corresponding tariff announcement. The few notable moves outside announcement windows—such as the drop on February 27, 2018 (Powell's congressional testimony), March 19, 2018 (the Cambridge Analytica scandal), or July 31, 2019 (hawkish FOMC rate cut)—are attributable to non-trade news. We typically see prices move sharply at the time of each announcement, though there is sometimes evidence that the market began or ended its move a few hours before or after an announcement. However, the data make clear that markets processed the information about tariff announcements within a trading day.

Table B.3: Notable Intraday Price Movements in Figure B.1

Figure Panel	Date	Approx. Return	Likely Cause
Moves inside announcement windows			
23Jan18	23Jan18	$+2\%$	Solar/washing machine tariffs
01Mar18	01Mar18	-2%	Steel/aluminum tariffs
22–23Mar18	22Mar18	-2%	US $60B tariffs on China
	23Mar18	-3.5%	China retaliates on 128 products
15–19Jun18	15Jun18	-2%	China retaliates on $50B
	19Jun18	-1.5%	US announces tariffs on $200B
02Aug18	02Aug18	≈ 0	China retaliates on $60B
06May19	06May19	-3.5%	Trump tweet: raise tariffs to 25%
13May19	13May19	-3%	China retaliates on $60B
01Aug19	01Aug19	-2%	Trump tweet: 10% on $300B
23Aug19	23Aug19	-4%	China retaliates; Trump escalates
Moves outside announcement windows			
01Mar18	27Feb18	-3.5%	Powell congressional testimony
22–23Mar18	19Mar18	-2.5%	Cambridge Analytica scandal
	21Mar18	$+2\%$	FOMC meeting
	26Mar18	$+3.5\%$	Reports of US-China negotiations
15–19Jun18	13Jun18	-1%	FOMC rate hike
02Aug18	01Aug18	-2%	FOMC statement / trade escalation reports
13May19	10May19	$-2\%/+2\%$	25% tariff takes effect; talks resume
01Aug19	31Jul19	-1.5%	FOMC hawkish rate cut

Notes: This table lists all notable intraday price movements visible in Figure B.1. "Approx. Return" reports the approximate intraday return read from the figure.

B.3 Stock-Market Reaction During Other Events

Our baseline analysis focuses on 11 tariff-announcement days identified by concrete policy actions. A natural concern is that trade-policy news may have moved markets on days outside our announcement windows as well, which may bias our estimates. To investigate this, we examine two types of events that go beyond our chosen dates.

First, we examined trade-related presidential tweets. We collected all tweets by President Trump during 2016-2019 from the Trump Twitter Archive that mention trade and can be interpreted as threats of escalation, and that fall *outside* our announcement windows. We then measure stock market reactions in a one-hour window around each tweet (when the tweet occurs during trading hours) or in the close-to-open return (when it occurs outside trading hours). Table B.4 reports these results. The cumulative market effect of these escalation tweets outside our announcement windows is small (-0.47% over 1-hour windows), suggesting that tweets not tied to concrete policy actions had little market impact.

Table B.4: Stock-Market Reaction to Trade-Related Presidential Tweets on Tariffs and China

Date	Summary	Log Return (x100)	
		1h-window	Close-to-open
Panel A: Outside Announcement Windows			
03dec16 06:40	Threatens 35% border tax on firms that offshore		0.61
02mar18 05:49	Trade wars are good and easy to win	-0.05	
02mar18 08:01	Reciprocal taxes coming; $800B trade deficit	0.01	
05mar18 06:47	Steel/aluminum tariffs until fair NAFTA signed	-0.06	
24jun18 16:12	Remove trade barriers or face more than reciprocity		-0.40
04dec18 09:22	China talks started; 90-day deadline; I am Tariff Man	-0.23	
04dec18 19:19	Real deal with China or major tariffs	-0.17	
30jul19 06:38	China worst year in 27; not buying ag as promised	0.02	
Cumulative		-0.47	0.20
Panel B: Inside Announcement Windows			
01mar18 06:53	Steel & aluminum hurt by decades of unfair trade	0.22	
22mar18 14:39	Pledges all lawful tools against unfair trade	-0.34*	
06may19 06:46	US losing $500-800B/yr on trade; not anymore	0.09	
13may19 06:08	China pays tariffs not US consumers; firms leaving China	-0.08	
01aug19 13:25	China reneged; new 10% tariff on remaining $300B	-1.72***	
23aug19 10:57	Orders firms home from China; raises tariffs further	-1.45***	
23aug19 17:00	Raises tariffs to 30% on $250B after China retaliates	-0.10	
Cumulative		-3.38***	

Note: This table reports S&P 500 log returns (x100) around Trump tweets mentioning trade that can be interpreted as a threat of escalation. Panel A covers tweets outside announcement windows; Panel B covers tweets inside announcement windows. Returns are measured over a 1-hour window (when the tweet occurs during trading hours) or as close-to-open returns (when the tweet occurs outside trading hours). Stars indicate statistical significance relative to the unconditional distribution of returns over similar windows. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Second, we examine whether other U.S. government actions targeting China—but unrelated to tariffs—also moved the stock market. These include executive orders and other policy actions directed at Chinese firms or the Chinese government (e.g., sanctions, export controls, investment restrictions). Table B.5 reports the stock-market return on each of these days. Non-tariff actions did not have a material impact on stock markets, confirming that the negative returns we observe on our event days are specifically related to the expected economic impact of the tariff announcements.

Table B.5: Stock-Market Returns on Announcement Days of Executive Orders and Actions Targeting China

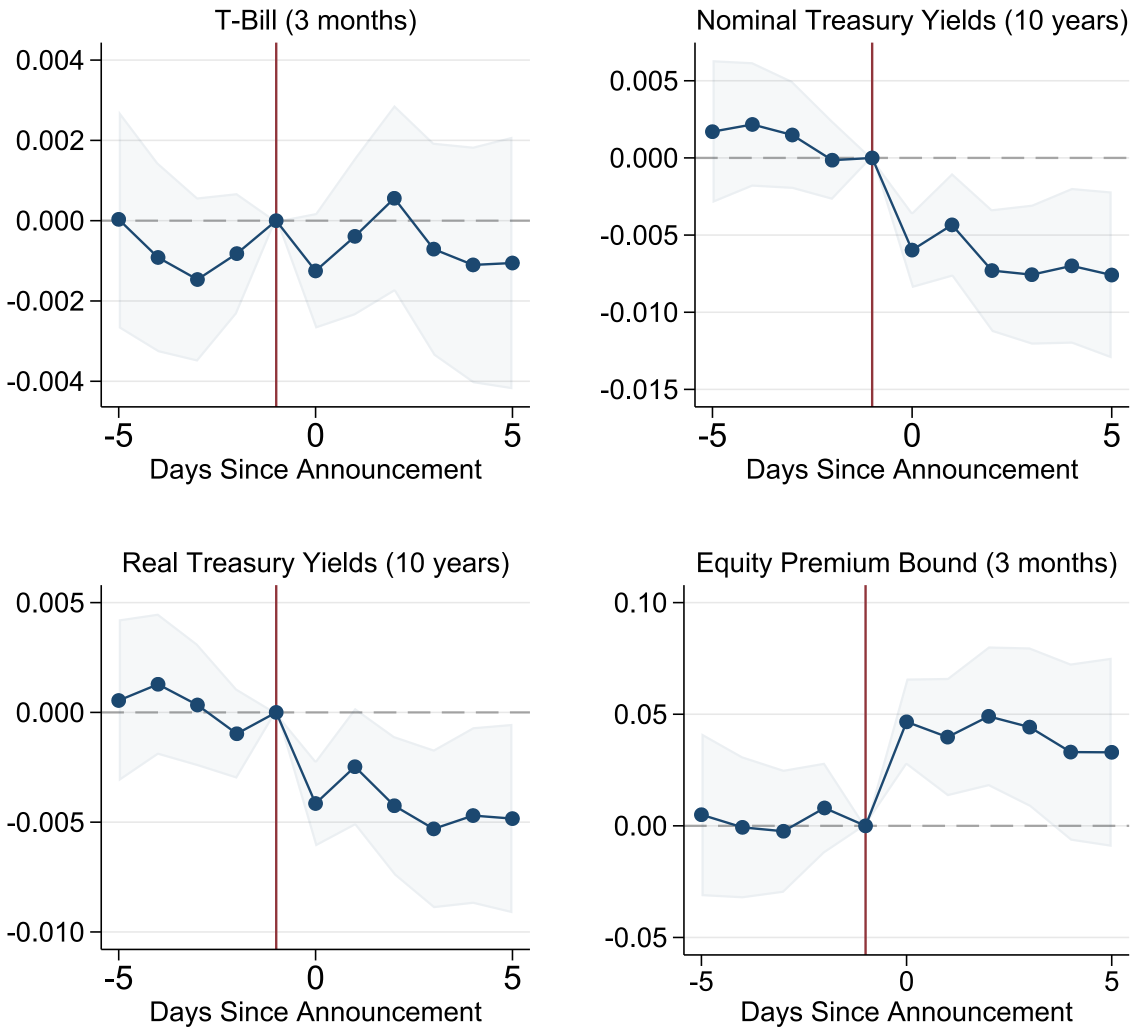
Event Date	Description	$\ln R_{MKT,t}$ (x100)
17jul2017	Treasury sanctions Chinese companies for proliferation activities in support of a key designated Iranian defense entity	0.0
20dec2017	U.S. sanctions human rights abusers and corrupt actors	-0.0
27apr2018	Treasury identifies Chinese trafficker as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

Note: This table reports the stock-market return on days when the U.S. government took non-tariff actions targeting China, including executive orders, sanctions, export controls, and investment restrictions. The first and last columns report the date and description of each event. The second column reports the log stock-market return on each day. $\ln R_{MKT,t}$ is the log of one plus the proportional change of the value-weighted market portfolio return from CRSP.

B.4 Returns of Other Asset Classes Pre and Post Announcement Days

In Figure 1, we reported the dynamic effect of announcements on stock-market returns over a five-day window. In the same spirit, Figure B.2 reports the dynamic effect of announcements on the changes in nominal yields, real yields, and the equity-premium bound over a five-day window. This figure shows that the changes in these variables are concentrated on the days of the announcements, which supports the notion that a one-day window is long enough to capture the overall effect of announcements.

Figure B.2: The Dynamics of Discount Rates around Tariff Announcements



Note: This figure plots the cumulative change in each variable from the day before the announcement. Formally, we estimate the following regression on all trading days between 2017 and 2019:

$$\Delta Y_t = \alpha + \sum_{s=-4}^{5} \beta_s D_{s,t} + \sum_{d=1}^{D} \gamma_d \times ES_{d,t} + \epsilon_t,$$

where $D_{s,t} = 1$ if day t is s days after an announcement; $D_{s,t} = 0$ otherwise, and $ES_{d,t}$ denotes the surprise in macroeconomic releases. We then plot the cumulative change in Y_t from the eve of the announcement to horizon s as $11 \sum_{k=s+1}^{-1} \hat{\beta}_k$ if $s < -1$ and $11 \sum_{k=0}^{s} \hat{\beta}_k$ if $s > -1$. Shaded areas correspond to the 95 percent confidence interval computed using robust standard errors.

Table B.6: Change in Other Asset Prices on Tariff-Announcement Days

Event Date	Country	T-Bill (x100)	Nom. 10y Yield (x100)	Real 10y. Yield (x100)	Breakeven infl. (x100)	EPB (x100)
23jan2018	US	-0.01	-0.03	-0.03	-0.01	0.02
01mar2018	US	-0.03	-0.06	-0.04	-0.02	0.47
22mar2018	US	-0.02	-0.07	-0.05	-0.02	0.95
23mar2018	CHN	0.02	-0.00	0.00	-0.01	0.59
15jun2018	CHN	0.00	-0.01	-0.02	0.01	0.00
19jun2018	US	0.00	-0.03	-0.03	-0.01	0.15
02aug2018	CHN	-0.01	-0.02	-0.01	-0.01	-0.09
06may2019	US	0.01	-0.03	-0.03	-0.00	0.31
13may2019	CHN	-0.02	-0.07	-0.04	-0.03	0.76
01aug2019	US	-0.01	-0.13	-0.05	-0.08	0.37
23aug2019	CHN	-0.03	-0.09	-0.08	-0.01	0.92
Cumulative	US	-0.06	-0.35	-0.22	-0.13	2.28
Cumulative	CHN	-0.04	-0.19	-0.14	-0.05	2.19
Cumulative	All	-0.10	-0.54	-0.36	-0.18	4.47

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

B.5 Construction of China-Exposure Variables

We consider three ways in which firms were exposed to China: importing, exporting, and foreign sales (either through exporting or subsidiaries). It is important to capture indirect imports that are ultimately purchased by U.S. firms because many firms do not import directly from China but instead obtain Chinese inputs through their subsidiaries or the U.S. subsidiaries of foreign firms. In order to identify the supply chains, we use DUNS numbers from Dun & Bradstreet to merge importers from Datamyne with a list of firms and their subsidiaries from Capital IQ. We use a firm-name match to link firms, subsidiaries, and their suppliers that are reported in Datamyne, Compustat, Bloomberg, and FactSet and identify which firms are trading with China directly or indirectly through their network of suppliers. After matching firms with identical names in two or more datasets, we manually compared firms with similar names to identify whether they are matches.

The Datamyne data used to identify U.S. firms that import from China or export to China have a number of limitations. First, the product level reported is more aggregated than that in the Harmonized Tariff System 8-digit level at which U.S. tariffs are set. While some of the Datamyne data are at the Harmonized System (HS) 6-digit level, much of it is at the far more aggregated HS2-digit level, making it impossible to know what share of a firm's trade was affected by tariffs. We, therefore, use a binary exposure measure. Our "China Import " dummy is one if the firm or its supply network imported from China in 2017 and zero otherwise. We also construct a "China Export " dummy analogously for exports. Second, the Datamyne data only cover seaborne trade. The U.S. Census data reveal that in 2017, 62 percent of all imports from China and 58 percent of exports to China were conducted by sea. So although we capture over half of the value of U.S.-China trade, the China import and export dummies are likely to miss some U.S. firms that trade with China. On the export side, any exporters that are not reflected in the export dummy are included in the China revenue share variable.

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

Table B.7: Summary Statistics on Exposure Variables

	N	Mean	SD	Min	p25	p50	p75	p90	p95	Max
China Imported Input Intensity	2437	0.01	0.02	0.00	0.00	0.01	0.02	0.03	0.04	0.18
China Export Share	2437	0.01	0.02	0.00	0.00	0.00	0.02	0.03	0.06	0.30
Manufacturing Industry	2437	0.40	0.49	0.00	0.00	0.00	1.00	1.00	1.00	1.00
China Importer	2437	0.31	0.46	0.00	0.00	0.00	1.00	1.00	1.00	1.00
China Exporter	2437	0.04	0.20	0.00	0.00	0.00	0.00	0.00	0.00	1.00
China Revenue Share	2437	0.03	0.07	0.00	0.00	0.00	0.02	0.07	0.13	0.97
Size (Employment)	2437	14001.03	60761.74	1.00	414.00	2100.00	8700.00	29060.00	58000.00	2.30e+06

B.6 Calculation of Abnormal Returns

We provide further details on the calculation of abnormal returns. We begin by estimating the following CAPM using data on daily returns in 2017:

$$R_{it} - R_{f,t} = \alpha_i + \beta_{i,MKT}\left[R_{MKT,t} - R_{f,t}\right] + \epsilon_{it}.$$

where R_{it} is the return on the stock price of firm i on day t, $R_{f,t}$ is the risk-free rate on day t, and $R_{MKT,t}$ is the market return on day t. We then define the abnormal return for firm

i on day t as

$$AR_{it} = R_{it} - R_{f,t} - \left(\hat{\alpha}_i + \hat{\beta}_{i,MKT}\left[R_{MKT,t} - R_{f,t}\right]\right).$$

C Appendix for Section 3 (Model)

C.1 Proof of Proposition 1

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

$$\hat{w}_t = \sum_i \frac{L_i}{L}\hat{\pi}_{it},$$

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

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

$$\hat{y}_{it} = -\hat{a}_{Vit}, \tag{C1}$$

and

$$\sum_i \frac{L_i}{L}\left(\hat{a}_{Lit} - \hat{a}_{Vit}\right) = \hat{L}, \tag{C2}$$

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

$$-\sum_i \frac{L_i}{L}\sigma\left(\hat{w}_t - \hat{\pi}_{it}\right) = \hat{L}, \tag{C3}$$

or

$$\hat{w}_t = \sum_i \frac{L_i}{L}\hat{\pi}_{it} - \frac{\hat{L}}{\sigma} \tag{C4}$$

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

$$\hat{w}_t = \sum_i \frac{L_i}{L}\hat{\pi}_{it}. \tag{C5}$$

Substituting equation (C1) into equation (4) yields

$$-\hat{y}_{it} - \hat{a}_{Lit} = \sigma\left(\hat{w}_t - \hat{\pi}_{it}\right) \tag{C6}$$

or

$$\hat{L}_{it} = \sigma\left(\hat{\pi}_{it} - \hat{w}_t\right) = \sigma\left(\hat{\pi}_{it} - \sum_{i'} \frac{L_{i'}}{L} \hat{\pi}_{i't}\right). \tag{C7}$$

□

C.2 Proof of Proposition 2

Proposition. 2 *For an agent with log utility, the consumption-equivalent welfare effect of the deviation path* $(\hat{C}_t)_{t=0}^{\infty}$ *is*

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

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

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

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

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

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

To conclude the proof, note that, with log-utility, the consumption-to-wealth ratio is equal to $1-\beta$, and so we have $\rho = \beta$. The reason we use the notation ρ rather than β is that ρ is the relevant discount factor in the more general case of Epstein-Zin utilities (see Section C.5). □

C.3 Proof of Proposition 3

Proposition. 3 *Around a baseline path in which the ratio of cash flow to firm value, $\pi_{it}V_i/M_{it}$, is equal to the constant consumption-to-wealth ratio, C_t/W_t, we have:*

$$\hat{M}_{i0} = \sum_{t=0}^{\infty}(1-\rho)\rho^t \mathrm{E}_0\left[\hat{\pi}_{it}\right] - \sum_{t=1}^{\infty}\rho^t \mathrm{E}_0\left[\hat{R}_{it}\right]$$

Proof. Differentiating the PDV relationship (8) gives

$$\begin{aligned}
\hat{M}_{i0} &= \frac{1}{M_{i0}}\mathrm{E}_0\left[\sum_{t=0}^{\infty}\frac{\pi_{it}V_i}{R_{i1}\ldots R_{it}}\left(\hat{\pi}_{it}-\sum_{s=1}^{t}\hat{R}_{is}\right)\right] \\
&= \frac{1}{M_{i0}}\mathrm{E}_0\left[\sum_{t=0}^{\infty}\frac{\pi_{it}V_i}{R_{i1}\ldots R_{it}}\hat{\pi}_{it}\right] - \frac{1}{M_{i0}}\sum_{t=1}^{\infty}\mathrm{E}_0\left[\left(\sum_{s=t}^{\infty}\frac{\pi_{is}V_i}{R_{i1}\ldots R_{is}}\right)\hat{R}_{it}\right] \\
&= \frac{1}{M_{i0}}\mathrm{E}_0\left[\sum_{t=0}^{\infty}\frac{\pi_{it}V_i}{R_{i1}\ldots R_{it}}\hat{\pi}_{it}\right] - \frac{1}{M_{i0}}\sum_{t=1}^{\infty}\mathrm{E}_0\left[\frac{1}{R_{i1}\ldots R_{it}}\mathrm{E}_t\left[\sum_{s=t}^{\infty}\frac{\pi_{is}V_i}{R_{it+1}\ldots R_{is}}\right]\hat{R}_{it}\right] \\
&= \sum_{t=0}^{\infty}\mathrm{E}_0\left[\frac{\pi_{it}V_i}{M_{it}}\frac{M_{it}/M_{i0}}{R_{i1}\ldots R_{it}}\hat{\pi}_{it}\right] - \sum_{t=1}^{\infty}\mathrm{E}_0\left[\frac{M_{it}/M_{i0}}{R_{i1}\ldots R_{it}}\hat{R}_{it}\right]
\end{aligned}$$

where the second line uses the fact that $M_{it} = \mathrm{E}_t\left[\sum_{s=t}^{\infty}\frac{\pi_{is}V_i}{R_{it+1}\ldots R_{is}}\right]$, following (8). We then use the assumption that on the baseline path $\pi_{it}V_i/M_{it}$ is constant and equal to C_t/W_t (if not, all of our equalities should be understood as being first-order approximations around this baseline path, as in Campbell and Shiller (1988)).[1] In particular, using the definition of ρ above, we can write $(M_{it}-\pi_{it}V_i)/M_{it} = \rho$, which implies:

$$R_{it+1} = \frac{M_{it+1}}{M_{it}-\pi_{it}V_i} = \frac{1}{\rho}\frac{M_{it+1}}{M_{it}}.$$

Plugging this into the previous equation gives:

$$\hat{M}_{i0} = \sum_{t=0}^{\infty}(1-\rho)\rho^t \mathrm{E}_0\left[\hat{\pi}_{it}\right] - \sum_{t=1}^{\infty}\rho^t \mathrm{E}_0\left[\hat{R}_{it}\right].$$

□

C.4 Extension for Baseline Growth

The baseline model that we analyze does not allow for growth, but we can easily change it to a model in which productivity rises by ϕ each period. We demonstrate that the only

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

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

$$y_{it} = h\left(\phi^t V_i, \phi^t L_{it}, m_{jit}\right),$$

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

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

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

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

$$\sum_i \frac{a_{Li0}}{\phi^t}\left(\phi^t y_{i0}\right) = L, \text{ and}$$

$$\frac{a_{Vi0}}{\phi^t}\left(\phi^t y_{i0}\right) = V_i.$$

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

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

$$a_{jit} = \frac{m_{jit}}{y_{it}} = \frac{a_{ji0} y_{it}}{y_{it}} = a_{ji0}.$$

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

$$a_{Lit} w_t + a_{Vit} \pi_{it} + \sum_j a_{jit} q_{jt} = p_{it}$$

$$\frac{a_{Li0}}{\phi^t} \left(\phi^t w_0 \right) + \frac{a_{Vi0}}{\phi^t} \left(\phi^t \pi_{i0} \right) + \sum_j a_{ji0} q_{jt} = p_{it}$$

$$a_{Li0} w_0 + a_{Vi0} \pi_{i0} + \sum_j a_{ji0} q_{jt} = p_{it}.$$

Since we know that these equations hold in period 0, we know that if $q_{jt} = q_{j0}$, then $p_{it} = p_{i0.}$ Intermediate input prices will not change if labor and specific factor productivity growth affects all firms equally because intermediate input usage, consumer demand, and supply will all grow at a rate of ϕ.

C.5 Extension for Epstein-Zin Preferences

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

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

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

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

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

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

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

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

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

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

Solving for $\mathcal{C}$ gives:

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

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

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

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

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

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

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

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

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

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

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

$$\Lambda_{t\to t+k} = \left(\beta^k \left(\frac{C_{t+k}}{C_t}\right)^{-1/\psi}\right)^{\theta} \left(R^{-1}_{W,t\to t+k}\right)^{1-\theta}, \tag{C8}$$

where $\theta \equiv (1-\gamma)/(1-1/\psi)$ and $R_{W,t+1} \equiv \frac{W_{t+1}}{W_t - C_t}$ denotes the return on the wealth portfolio between t and $t+1$ and $R_{W,t\to t+k} = R_{W,t+1} \ldots R_{W,t+k}$ denotes the cumulative return on the wealth portfolio between t and $t+k$. In the special case where $\psi = 1/\gamma$ (separable preferences), equation (C8) gives the familiar expression $\Lambda_{t\to t+k} = \beta^k \left(C_{t+k}/C_t\right)^{-\gamma}$.

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

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

where the last line uses the definition of $\rho \equiv 1 - C_t/W_t$. Combining with (C8) allows us to simplify the expression for the SDF along the baseline path:

$$\begin{aligned} \Lambda_{t\to t+k} &= \left(\beta^k \left(\frac{C_{t+k}}{C_t}\right)^{-1/\psi}\right)^{\theta} \left(\rho^k \frac{C_t}{C_{t+k}}\right)^{1-\theta} \\ &= \beta^{\theta k} \rho^{(1-\theta)k} \left(\frac{C_{t+k}}{C_t}\right)^{-\gamma}, \end{aligned} \tag{C9}$$

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

$$
\begin{aligned}
W_t &= \mathrm{E}_t\left[\sum_{k=0}^{\infty} \Lambda_{t\to t+k} C_{t+k}\right] \\
&= C_t \sum_{k=0}^{\infty} \beta^{\theta k} \rho^{(1-\theta)k} \mathrm{E}_t\left[\left(\frac{C_{t+k}}{C_t}\right)^{1-\gamma}\right] \\
&= C_t \sum_{k=0}^{\infty} \beta^{\theta k} \rho^{(1-\theta)k} \mathrm{E}_t\left[\left(\frac{C_{t+k}}{C_{t+k-1}}\right)^{1-\gamma} \left(\frac{C_{t+k-1}}{C_{t+k-2}}\right)^{1-\gamma} \cdots \left(\frac{C_{t+1}}{C_t}\right)^{1-\gamma}\right] \\
&= C_t \sum_{k=0}^{\infty} \beta^{\theta k} \rho^{(1-\theta)k} \mathrm{E}_t\left[\left(\frac{C_{t+k}}{C_{t+k-1}}\right)^{1-\gamma}\right] \mathrm{E}_t\left[\left(\frac{C_{t+k-1}}{C_{t+k-2}}\right)^{1-\gamma}\right] \cdots \mathrm{E}_t\left[\left(\frac{C_{t+1}}{C_t}\right)^{1-\gamma}\right] \\
&= C_t \sum_{k=0}^{\infty} \beta^{\theta k} \rho^{(1-\theta)k} \mathrm{E}_0\left[\left(\frac{C_1}{C_0}\right)^{1-\gamma}\right]^k \\
&= C_t \sum_{k=0}^{\infty} \left(\beta^{\theta} \rho^{1-\theta} \mathrm{E}_0\left[\left(\frac{C_1}{C_0}\right)^{1-\gamma}\right]\right)^k \\
&= C_t \frac{1}{1 - \beta^{\theta} \rho^{1-\theta} \mathrm{E}_0\left[\left(\frac{C_1}{C_0}\right)^{1-\gamma}\right]},
\end{aligned}
$$

where the fourth and fifth lines use the fact that consumption growth is independently and identically distributed across periods along the baseline path and the last line uses the formula for the infinite sum of a geometric sequence. Hence, we have proven that the wealth-to-consumption ratio W_t/C_t is constant along the baseline path.

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

$$
\begin{aligned}
\rho &= \beta^{\theta} \rho^{(1-\theta)} \mathrm{E}_0\left[\left(\frac{C_1}{C_0}\right)^{1-\gamma}\right] \\
\implies \rho &= \beta \mathrm{E}_0\left[\left(\frac{C_1}{C_0}\right)^{1-\gamma}\right]^{\frac{1}{\theta}}.
\end{aligned}
$$

Plugging this into (C9) gives a simplified expression for the SDF along the baseline path:

$$
\begin{aligned}
\Lambda_{0\to t} &= \beta^t \left(\frac{C_t}{C_0}\right)^{-\gamma} \mathrm{E}_0\left[\left(\frac{C_t}{C_0}\right)^{1-\gamma}\right]^{1/\theta - 1} \\
&= \rho^t \frac{\left(\frac{C_t}{C_0}\right)^{-\gamma}}{\mathrm{E}_0\left[\left(\frac{C_t}{C_0}\right)^{1-\gamma}\right]}.
\end{aligned}
$$

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

$$\mathcal{C} = \frac{\sum_{t=0}^{\infty} \mathrm{E}_0 \left[\rho^t \frac{\left(\frac{C_t}{C_0}\right)^{1-\gamma}}{\mathrm{E}_0\left[\left(\frac{C_t}{C_0}\right)^{1-\gamma}\right]} \hat{C}_t \right]}{\sum_{t=0}^{\infty} \mathrm{E}_0 \left[\rho^t \frac{\left(\frac{C_t}{C_0}\right)^{1-\gamma}}{\mathrm{E}_0\left[\left(\frac{C_t}{C_0}\right)^{1-\gamma}\right]} \right]}$$

$$= \sum_{t=0}^{\infty} (1-\rho)\rho^t \mathrm{E}_0 \left[\frac{\left(\frac{C_t}{C_0}\right)^{1-\gamma}}{\mathrm{E}_0\left[\left(\frac{C_t}{C_0}\right)^{1-\gamma}\right]} \hat{C}_t \right],$$

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

This proposition generalizes Proposition 2 stated in the main text, which corresponds to the special case of log utility $\gamma = \psi = 1$. With general Epstein-Zin preferences, the consumption-equivalent welfare effect $\mathcal{C}$ can be expressed as a time-discounted, weighted average of the deviations in log consumption. The first set of weights, $(1-\rho)\rho^t$, adjusts for the agent's discounting over time (they sum to one across time) while the weights $\frac{C_t^{1-\gamma}}{\mathrm{E}_0\left[C_t^{1-\gamma}\right]}$ represent the agent's discounting of different states of nature (they sum up to one across states of nature in a given period).

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

$$\mathcal{C} = \sum_{t=0}^{\infty} (1-\rho)\rho^t \mathrm{E}_0 \left[\hat{C}_t\right] + \sum_{t=1}^{\infty} (1-\rho)\rho^t \mathrm{cov}_0 \left(\frac{C_t^{1-\gamma}}{\mathrm{E}_0\left[C_t^{1-\gamma}\right]}, \hat{C}_t \right). \tag{C10}$$

The first term corresponds to the welfare effect for an agent with log utility (the one discussed in Proposition 2). The second term corresponds to the normalized covariance of $C_t^{1-\gamma}$ and changes in log consumption. This second term is zero if $\gamma = 1$ (e.g., log utility) or if deviations in log consumption are independent of the realization of consumption along the baseline path. The following corollary expresses this second term as the sum of deviations in the higher-order cumulants of log consumption.

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

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

First, note that one can rewrite the expression for welfare given in Proposition 2 as:

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

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

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

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

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

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

Proof.

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

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

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

C.6 Extension for Endogenous Factors

In the baseline model, the quantity of each firm's specific factor V_i and the aggregate supply of labor L are both fixed. In this section, we extend the model to allow both to respond endogenously to the policy—for example, because firms can adjust the specific factor through investment in tangible or intangible capital, and because households choose their labor supply optimally. We do not need to specify how these quantities are determined; we only require that they are chosen optimally. We show that this extension introduces an additional term in the welfare expression. If tariff announcements reduce investment in firm-specific factors, as the evidence below suggests, this term makes the welfare effect more negative than in the baseline.

Welfare effect. By the envelope theorem, the endogenous adjustments in V_{it} and L_t have no first-order effect on welfare. Intuitively, because these quantities were chosen optimally to begin with, marginal deviations have no first-order welfare impact—for example, a household that reduces labor supply earns less but enjoys more leisure, and these effects cancel at the margin. This means the welfare expression is unchanged:

$$\mathcal{C} = \sum_{t=0}^{\infty}(1-\rho)\rho^t \, \mathrm{E}_0\left[\frac{wL}{C}\hat{w}_t + \sum_i \frac{\pi_i V_i}{C}\hat{\pi}_{it} + \frac{TR}{C}\widehat{TR}_t\right]. \tag{C11}$$

Similarly, because the initial level of investment was optimal, tariff-induced changes in V_{it} have no first-order effect on firm value.

Deviation in wages. Proposition 1 must be generalized. When the quantity of the specific factor is endogenous, the full-employment condition becomes $a_{Vit}\, y_{it} = V_{it}$, and log-differentiating gives

$$\hat{y}_{it} = \hat{V}_{it} - \hat{a}_{Vit}. \tag{C12}$$

Similarly, the labor full-employment condition $\sum_i a_{Lit} y_{it} = L_t$ gives

$$\sum_i \frac{L_i}{L}\left(\hat{a}_{Lit} + \hat{y}_{it}\right) = \hat{L}_t. \tag{C13}$$

Substituting (C12) into (C13) and using the CES condition $\hat{a}_{Vit} - \hat{a}_{Lit} = \sigma(\hat{w}_t - \hat{\pi}_{it})$ yields

$$\hat{w}_t = \sum_i \frac{L_i}{L}\hat{\pi}_{it} + \frac{1}{\sigma}\left(\sum_i \frac{L_i}{L}\hat{V}_{it} - \hat{L}_t\right). \tag{C14}$$

Compared to the baseline expression $\hat{w}_t = \sum_i \frac{L_i}{L}\hat{\pi}_{it}$, there is a new term that captures the effect of changes in the specific factor and aggregate labor on wages: a reduction in V_{it} lowers labor demand in firm i, which depresses wages. Similarly, an increase in labor supply depresses wages.

Deviation in firm cash flows. Proposition 3 continues to hold, again by the envelope theorem.

$$\hat{M}_{i0} = \sum_{t=0}^{\infty}(1-\rho)\rho^t \, \mathrm{E}_0[\hat{\pi}_{it}] - \sum_{t=1}^{\infty}\rho^t \, \mathrm{E}_0\left[\hat{R}_{it}\right]. \tag{C15}$$

Result. Plugging the last two equations in the expression for the welfare effect now gives

$$\mathcal{C} = \underbrace{\sum_i \frac{wL_i + \pi_i V_i}{C}\left(\hat{M}_{i0} + \sum_{t=1}^{\infty}\rho^t \operatorname{E}_0\Big[\hat{R}_{it}\Big]\right) + \frac{TR}{C}\left(\sum_{t=0}^{\infty}(1-\rho)\rho^t \operatorname{E}_0\left[\widehat{TR}_t\right]\right)}_{\text{baseline}}$$
$$+ \frac{1}{\sigma}\underbrace{\frac{wL}{C}\sum_{t=0}^{\infty}(1-\rho)\rho^t \operatorname{E}_0\left[\sum_i \frac{L_i}{L}\hat{V}_{it} - \hat{L}_t\right]}_{\text{new adjustment for endogenous factors}}. \tag{C16}$$

The first term is identical to the baseline welfare expression and can be estimated from stock prices and the VAR as in Section 4. The second term is new and reflects the general equilibrium effect of endogenous factor adjustment on wages. Its coefficient, $\frac{1}{\sigma}\frac{wL}{C}$, is the labor share of consumption divided by the elasticity of substitution between labor and the specific factor.

Special case: upward-sloping labor supply. We now consider the special case in which the aggregate labor supply responds to wages according to

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

where $\tilde{\sigma} > 0$ denotes the elasticity of labor supply with respect to wages. Substituting into (C14) and solving for $\hat{w}_t$ gives

$$\hat{w}_t = \frac{\sigma}{\sigma + \tilde{\sigma}}\sum_i \frac{L_i}{L}\hat{\pi}_{it} + \frac{1}{\sigma + \tilde{\sigma}}\sum_i \frac{L_i}{L}\hat{V}_{it}. \tag{C17}$$

The denominator $\sigma + \tilde{\sigma}$ reflects the fact that an upward-sloping labor supply dampens the wage response: when wages fall, workers withdraw, reducing labor supply and partially offsetting the decline in wages. Substituting into the welfare expression and applying Proposition 3 gives

$$\mathcal{C} = \sum_i \frac{\frac{\sigma}{\sigma+\tilde{\sigma}}wL_i + \pi_i V_i}{C}\left(\hat{M}_{i0} + \sum_{t=1}^{\infty}\rho^t \operatorname{E}_0\Big[\hat{R}_{it}\Big]\right)$$
$$+ \frac{1}{\sigma + \tilde{\sigma}}\frac{wL}{C}\sum_{t=0}^{\infty}(1-\rho)\rho^t \operatorname{E}_0\left[\sum_i \frac{L_i}{L}\hat{V}_{it}\right] + \mathcal{C}_{TR}. \tag{C18}$$

When $\tilde{\sigma} = 0$ and $\hat{V}_{it} = 0$, this reduces to the baseline welfare expression.

D Appendix for Section 4 (Estimation)

D.1 Details on VAR estimation

We now describe more precisely how we construct the set of variables used in the VAR discussed in (18). The log risk-free rate $\ln R_f$, corresponds to the annualized yield of 3-month T-Bills (`DTB3` in FRED) minus the growth of the CPI price index (`CPIAUCSL` in FRED) in the previous year. The excess market return $\ln R_{EMKT}$ corresponds to the log return of CRSP value-weighted stock market minus the risk-free rate implied by the yield of 3-month T-Bills. The term spread TS is the annualized yield-to-maturity of ten-year treasuries (`SVENY10` in Gürkaynak et al. (2007)) minus the annualized yield of 3-month T-Bills. The equity-premium bound corresponds to the annualized equity premium for the 3-month horizon constructed using the methodology of Martin (2017), using data from OptionMetrics. The value spread, VS, is the log difference in log book-to-market value between the top 10 percent and the bottom 10 percent of firms ranked by book to market equity, constructed using data from the Fama-French Data Library. The credit spread, CS, is the difference between the yield of BAA bonds, from Moody's Seasoned Baa Corporate Bond Yield, and the log risk-free rate. The log price-dividend ratio, $\ln PD$, is the logarithm of a smoothed average price-dividend ratio, constructed as the current price of the value-weighted CRSP portfolio divided by dividends distributed over the past year. In some robustness tests, we also add the return of the small-minus-big portfolio SMB (i.e., a portfolio of long small firms and short big firms) and the return of the high-minus-low portfolio HML (i.e., a portfolio of long high book-to-market equity and short low book-to-market equity) from the Fama-French Data Library.

Table D.1 presents the results from the VAR estimation. The following tables present the effects of tariff announcements on VAR variables using various window lengths and robustness exercises for changes in future discount rates.

D.2 The Construction and Validity of the Instrument

D.2.1 The Measurement Problem

In Section 5.3 of the paper, we regress future firm-level outcomes on the deviation in firm cash flows $\hat{\Pi}_i$, which we construct from stock-price data using Proposition 3, which lets us express the deviation in firm cash flows as:

$$\hat{\Pi}_i \;\equiv\; \sum_{t=0}^{\infty}(1-\rho)\rho^t E_0[\hat{\pi}_{it}] \;=\; \hat{M}_{i0} \;+\; \sum_{t=1}^{\infty}\rho^t E_0\left[\hat{R}_{it}\right],$$

Table D.1: VAR Matrix $\boldsymbol{B}$

	(1) F.log R_f	(2) F.log R_{EMKT}	(3) F.TS	(4) F.EPB	(5) F.VS	(6) F.CS	(7) F.log PD
log R_f	0.77***	3.03	0.12	-0.09	-3.50	-0.06	6.49**
	(0.07)	(2.44)	(0.13)	(0.85)	(2.70)	(0.05)	(2.59)
log R_{EMKT}	-0.00	0.14	0.00	-0.04	-0.11	-0.00	0.12
	(0.00)	(0.09)	(0.01)	(0.03)	(0.13)	(0.00)	(0.09)
TS	0.07	2.94*	0.39***	-0.21	2.01	-0.08***	4.92***
	(0.05)	(1.59)	(0.13)	(0.34)	(2.76)	(0.03)	(1.64)
EPB	0.02**	0.61	-0.00	0.56***	0.52	0.00	0.88**
	(0.01)	(0.40)	(0.02)	(0.09)	(0.47)	(0.01)	(0.38)
VS	-0.00	0.01	-0.00*	-0.01	0.95***	-0.00	0.05**
	(0.00)	(0.02)	(0.00)	(0.01)	(0.04)	(0.00)	(0.02)
CS	-0.40**	-11.69*	1.81***	1.73	-14.74	1.15***	-16.58**
	(0.17)	(6.25)	(0.48)	(1.42)	(9.14)	(0.12)	(6.52)
log PD	-0.00	-0.17***	0.01*	0.03***	-0.01	0.00***	0.79***
	(0.00)	(0.04)	(0.00)	(0.01)	(0.07)	(0.00)	(0.04)
R^2	0.79	0.15	0.84	0.45	0.87	0.89	0.88
N	5,976	5,976	5,976	5,976	5,976	5,976	5,976

Note: The table reports the result of estimating the regression in equation (18): $\boldsymbol{x}_{t+63} = \boldsymbol{a} + \boldsymbol{B}\boldsymbol{x}_t + \boldsymbol{u}_{t+63}$ 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 January 1996 and December 2019. Standard errors are estimated using Newey-West robust standard errors with a bandwidth of 63 to account for overlapping observations.

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

	(1) log R_f	(2) log R_{EMKT}	(3) TS	(4) EPB	(5) VS	(6) CS	(7) log PD	(8) SMB	(9) HML
Announcement	-0.0003*	-0.1253***	-0.0047***	0.0464***	0.0955***	-0.0005*	-0.1269***	0.0171	-0.0409**
	(0.0002)	(0.0256)	(0.0014)	(0.0097)	(0.0292)	(0.0003)	(0.0298)	(0.0166)	(0.0191)
N	753	753	753	753	753	753	753	753	753

Note: The table reports the sum of β_k in the regression (19). The sample includes all trading days from 2017 to 2019. Standard errors in parentheses.

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

	(1) log R_f	(2) log R_{EMKT}	(3) TS	(4) EPB	(5) VS	(6) CS	(7) log PD	(8) SMB	(9) HML
Announcement	-0.0004	-0.1140**	-0.0032	0.0397**	0.0615	-0.0001	-0.1319***	0.0271	-0.0247
	(0.0003)	(0.0444)	(0.0023)	(0.0167)	(0.0501)	(0.0005)	(0.0511)	(0.0279)	(0.0325)
N	753	753	753	753	753	753	753	753	753

Note: The table reports the sum of β_k in the regression (19), using three-day windows around announcements. The sample includes all trading days from 2017 to 2019. Standard errors in parentheses.

where $\hat{M}_{i0}$ is the deviation in firm value (estimated from announcement-day equity returns adjusted for leverage), and $\sum_{t=1}^{\infty} \rho^t E_0[\hat{R}_{it}]$ is the deviation in future discount rates (estimated via the VAR described in Section 4.1).

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

Specification	Deviations in Discount Rates $\rho\boldsymbol{B}(I-\rho\boldsymbol{B})^{-1}d\boldsymbol{x}_0$				
	RF	MKT-RF	MKT	SMB	HML
	$\sum \rho^t \mathrm{E}_0\left[\hat{R}_{f,t}\right]$	$\sum \rho^t \mathrm{E}_0\left[\hat{R}_{EMKT,t}\right]$	$\sum \rho^t \mathrm{E}_0\left[\hat{R}_{MKT,t}\right]$	$\sum \rho^t \mathrm{E}_0\left[\hat{R}_{SMB,t}\right]$	$\sum \rho^t \mathrm{E}_0\left[\hat{R}_{HML,t}\right]$
Baseline	0.002	0.039	0.041		
	(0.010)	(0.044)	(0.044)		
Without TS	-0.001	0.061	0.060		
	(0.011)	(0.043)	(0.042)		
Without EPB	-0.000	0.055	0.055		
	(0.011)	(0.053)	(0.052)		
Without VS	0.008	0.080	0.088		
	(0.007)	(0.032)	(0.031)		
Without CS	-0.004	0.073	0.069		
	(0.010)	(0.042)	(0.040)		
Without $\log PD$	-0.001	-0.013	-0.014		
	(0.010)	(0.050)	(0.053)		
FF 3-Factor Model	0.006	0.028	0.034	0.006	0.030
	(0.010)	(0.045)	(0.043)	(0.029)	(0.039)
3-Days Window	0.001	0.065	0.067		
	(0.009)	(0.044)	(0.046)		
Adding Covid Period	-0.013	0.057	0.044		
	(0.019)	(0.043)	(0.045)		

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

Following equation (13) of the paper, we estimate the effect of tariff announcement k on the log equity return of firm i from the regression:

$$\ln R_{it}^E \;=\; \alpha_i \;+\; \sum_{k=1}^{K} \theta_{i,k} D_{kt} \;+\; \sum_{d=1}^{D} \gamma_{i,d}\, ES_{d,t} \;+\; \epsilon_{i,t},$$

where D_{kt} is an indicator equal to one if day t falls in the window of announcement k, and $ES_{d,t}$ is the surprise in macroeconomic release series d on day t. The deviation in firm value is then constructed as in equation (14) of the paper:

$$\hat{M}_{i0} \;=\; \sum_{k=1}^{K} \kappa_i\, \theta_{i,k},$$

where κ_i is the ratio of the market value of equity to the market value of assets, which adjusts for leverage. The sum $\sum_{k=1}^{K} \theta_{i,k}$ therefore aggregates the firm's equity return response across all K tariff announcement events, after controlling for contemporaneous macroeconomic surprises on each day.

In practice, the discount-rate component $\sum_{t=1}^{\infty} \rho^t E_0[\hat{R}_{it}]$ is estimated with error. Denoting the true discount-rate deviation as D_i^* and the estimated deviation as D_i, we write the measurement error as:

$$\eta_i \equiv D_i - D_i^*,$$

so that the observed cash-flow deviation satisfies:

$$\hat{\Pi}_i = \Pi_i^* + \eta_i, \tag{D1}$$

where $\Pi_i^* = \hat{M}_{i0} + D_i^*$ is the *true* deviation in firm cash flows. Because OLS regression of future outcomes on $\hat{\Pi}_i$ treats η_i as part of the error term, the resulting estimates will in general be biased toward zero (classical attenuation bias) if η_i is mean-zero and uncorrelated with Π_i^*, or biased in a less predictable direction if the measurement error is non-classical.

D.2.2 Defining the Instrumental Variable

The coefficients $\theta_{i,k}$ from regression (13) give the estimated return of firm i on announcement day k, already purged of the firm-level intercept $\hat{\alpha}_i$ and the macro surprise controls $\sum_d \gamma_{i,d} ES_{d,t}$ through the regression design. We define the cumulative abnormal return as the component of $\sum_{k=1}^{K} \theta_{i,k}$ that is orthogonal to the cumulative market return:

$$\Psi_i \equiv \sum_{k=1}^{K} \theta_{i,k} - \beta_{i,MKT} \sum_{k=1}^{K} \theta_{MKT,k}, \tag{D2}$$

where $\theta_{MKT,k}$ is the market return on announcement day k and $\beta_{i,MKT}$ is estimated on the pre-trade-war sample year of 2017, so that the beta estimates are not contaminated by the announcement-period returns. The instrument is then $Z_i \equiv \kappa_i \Psi_i$, which scales the idiosyncratic equity return by the equity-to-asset ratio κ_i, making the first term in Z_i identical to the firm value $\hat{M}_{i0}$.

We argue that Z_i is a valid instrument for $\hat{\Pi}_i$ on the basis of two conditions: relevance and the exclusion restriction.

D.2.3 Relevance

The instrument Z_i is correlated with $\hat{\Pi}_i$ through its relationship with $\hat{M}_{i0}$. From equations (14) and (D2), we can write:

$$\hat{M}_{i0} = \kappa_i \sum_{k=1}^{K} \theta_{i,k} = Z_i + \kappa_i \beta_{i,MKT} \sum_{k=1}^{K} \theta_{MKT,k}, \tag{D3}$$

so that Z_i enters $\hat{M}_{i0}$, and hence $\hat{\Pi}_i$, with coefficient exactly equal to one. The first-stage regression is therefore:

$$\hat{\Pi}_i \;=\; \alpha \;+\; \delta\, Z_i \;+\; \mathbf{X}_i'\phi \;+\; \nu_i. \tag{D4}$$

D.2.4 Exclusion Restriction

The exclusion restriction requires that Z_i affects future firm outcomes *only* through its effect on the true cash-flow deviation Π_i^*, and in particular that:

$$\text{Cov}(Z_i,\, \eta_i) \;=\; 0. \tag{D5}$$

The key observation is that the measurement error $\eta_i = D_i - D_i^*$ arises entirely from aggregate or factor-level sources. Specifically, the estimated discount-rate deviation is:

$$D_i \;=\; \sum_{t=1}^{\infty} \rho^t E_0\Big[\hat{R}_{f,t}\Big] \;+\; \kappa_i\, \beta_{i,MKT} \sum_{t=1}^{\infty} \rho^t E_0\Big[\hat{R}_{MKT,t} - \hat{R}_{f,t}\Big]\,, \tag{D6}$$

where the two infinite sums are computed as $\boldsymbol{e_1'}\rho\boldsymbol{B}(\boldsymbol{I} - \rho\boldsymbol{B})^{-1}\boldsymbol{dx_0}$ and $\boldsymbol{e_2'}\rho\boldsymbol{B}(\boldsymbol{I} - \rho\boldsymbol{B})^{-1}\boldsymbol{dx_0}$, respectively, using the VAR matrix $\boldsymbol{B}$ and the aggregate announcement surprise vector $\boldsymbol{dx_0}$. The measurement error η_i therefore has two sources:

1. **VAR specification error:** The finite-sample or misspecified VAR produces biased estimates of how aggregate variables $\hat{R}_{f,t}$ and $\hat{R}_{MKT,t}$ evolve after the announcement shock. This error is *common across all firms* and enters each D_i through the aggregate surprise vector $\boldsymbol{dx_0}$, which is driven by the market return $\sum_{k=1}^{K} \theta_{MKT,k}$ rather than by individual firm-level residuals.

2. **Factor model error:** The CAPM may not be the correct pricing model, so that the true firm discount rate loads on factors beyond the market return. This misspecification is again a function of aggregate factor realizations, not of idiosyncratic firm-level returns.

By construction, $Z_i = \kappa_i \Psi_i$ is based on the component of the cumulative announcement-day return that is orthogonal to the market return, scaled by leverage. Thus, Ψ_i captures the idiosyncratic component of the price response to the tariff announcements. The relevant exclusion restriction is therefore

$$\text{Cov}(Z_i, \eta_i) = \text{Cov}(\kappa_i \Psi_i, \eta_i) \approx 0.$$

To see the identifying assumption more clearly, suppose first that the measurement error in the firm-level discount-rate component is generated by an aggregate discount-rate error ε^{agg} that enters firm i's measured discount-rate component in proportion to its market beta. Then

$$\eta_i = \kappa_i \beta_{i,MKT} \varepsilon^{\text{agg}},$$

so that

$$\text{Cov}(Z_i, \eta_i) = \text{Cov}(\kappa_i \Psi_i,\ \kappa_i \beta_{i,MKT} \varepsilon^{\text{agg}}) = \varepsilon^{\text{agg}} \text{Cov}(\kappa_i \Psi_i,\ \kappa_i \beta_{i,MKT}) \,. \tag{D7}$$

Thus, the exclusion restriction does not follow mechanically from the fact that Ψ_i is orthogonal to the aggregate announcement-day return. Rather, it requires the cross-sectional orthogonality condition

$$\text{Cov}(\kappa_i \Psi_i,\ \kappa_i \beta_{i,MKT}) = 0,$$

and, more generally, analogous orthogonality between $\kappa_i \Psi_i$ and the firm-specific loadings through which aggregate discount-rate measurement errors enter D_i.

This condition is plausible in our setting because Ψ_i is constructed from the idiosyncratic component of the announcement-day stock-price response, after removing the market component, while $\beta_{i,MKT}$ and κ_i are predetermined firm characteristics measured before the trade-war announcements. The identifying assumption would fail only if firms with larger idiosyncratic tariff-related cash-flow news also systematically had larger pre-period market betas or leverage in a way not captured by the controls. In this sense, the instrument is valid under the assumption that the cross-sectional component of tariff-related cash-flow news is orthogonal to the firm-specific loadings that scale aggregate discount-rate measurement error. A further concern might arise if $\beta_{i,MKT}$ were estimated on the same sample as the announcement returns, since a mismeasured beta could introduce a common component between Z_i and the CAPM-based discount-rate error. We avoid this problem by estimating $\beta_{i,MKT}$ on the pre-trade-war sample year of 2017, well before any tariff announcements.

Finally, the exclusion restriction also requires that Z_i has no *direct* effect on future firm outcomes other than through the cash-flow channel. This is plausible given the tight one-day event windows we employ: it is unlikely that firms with high idiosyncratic announcement returns systematically received coincident firm-specific good news unrelated to tariffs.

D.3 Details on Reweighting the Compustat-CRSP Sample

We now detail how we reweigh the sample of firms in our Compustat-CRSP sample to approximate the distribution of firms in the U.S. across sectors and employment size. We start by dividing the set of firms in our sample into 18 industries (defined by their first

2-digit NAICS code) and four employment bins (0-500, 501-5,000, 5,001-20,000, 20,001+). For the 2-digit NAICS industries 11 (agriculture), 61 (education), 62 (health care), and 81 (other services), we only use two employment bins, below or above 20000, to ensure that there are enough firms within each bin. We denote X the firm level variable to aggregate across firms (e.g., the response of firm values or cash flows to tariff announcements).

We compute the average value of X in sector s and employment bin b for event k as:

$$X_{sb} \equiv \sum_{i \in \Omega_{sb}} \frac{L_i}{\sum_{i' \in \Omega_{sb}} L_{i'}} X_i,$$

where Ω_{sbk} denotes the set of firms in industry sector s and employment bin b. The average value of X in sector s is then given by

$$X_s \equiv \sum_{b \in \Omega_s^B} \frac{L_{sb}}{\sum_{b' \in \Omega_s^B} L_{sb'}} X_{sb},$$

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

$$X \equiv \sum_{s \in \Omega^S} \frac{VA_s}{C} X_s,$$

where Ω^S denotes the set of sectors, VA_s is the value added of sector s and C is total U.S. value added plus tariff revenue, based on BEA and tariff-revenue data. Note that the final expression can be thought of as a weighted average of X_i:

$$X = \sum w_i X_i \quad \text{where} \quad w_i \equiv \frac{VA_s}{C} \cdot \frac{L_{sb}}{\sum_{b' \in \Omega_s^B} L_{sb'}} \cdot \frac{L_i}{\sum_{i' \in \Omega_{sb}} L_{i'}}$$

D.4 Details on computing the standard errors of the welfare effect

The cash-flow component of the welfare effect can be written as

$$\mathcal{C}_\pi = \sum_i w_i \left(\hat{M}_i + \sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{it} \right] \right),$$

where w_i denotes the weight of firm i, $\hat{M}_i$ is the deviation in firm value, and the second term captures the firm-specific deviation in future discount rates. Replacing the two components by the estimates obtained in Section 4.1 yields

$$\mathcal{C}_\pi = \sum_i w_i \left(\kappa_i \hat{R}_{i0} + \sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{f,t} \right] + \kappa_i \beta_{i,MKT} \sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{MKT,t} - \hat{R}_{f,t} \right] \right),$$

Computing standard errors for this expression is complicated by two sources of dependence. First, the reaction of stock returns across firms $\hat{R}_{i,0}$ is correlated across firms because firms are exposed to common shocks. Second, the firm-level returns are also correlated with the estimation of future aggregate discount rates, since one element of the VAR is the reaction of the aggregate stock market return $\hat{R}_{MKT,0}$.

To address this, we decompose firm-level announcement returns using a CAPM assumption; that is, we assume that the factor structure between firm level returns is well approximated by $\hat{R}_{i0} = \beta_{i,MKT} \hat{R}_{MKT,0} + \hat{\epsilon}_{i0}$, where $\hat{\epsilon}_{i0}$ is an idiosyncratic component independent across firms. Substituting this decomposition into the previous equation yields

$$\mathcal{C}_\pi = \underbrace{\left(\sum_i w_i \kappa_i \beta_{i,MKT} \right)}_{\text{cross-sectional}} \underbrace{\left(\hat{R}_{MKT,0} + \sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{MKT,t} - \hat{R}_{f,t} \right] \right)}_{\text{aggregate}} + (\sum_i w_i) \underbrace{\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{f,t} \right]}_{\text{aggregate}} + \underbrace{\sum_i w_i \kappa_i \hat{\epsilon}_{i0}}_{\text{cross-sectional}},$$

which separates the welfare effect into cross-sectional quantities (which depend on individual firm characteristics) and aggregate quantities (which depend on market-level variables related to the aggregate VAR).

We then apply the delta method on this decomposition to obtain the standard error for $\mathcal{C}_\pi$. More precisely, we estimate the covariance matrix of the cross-sectional components $\sum_i w_i \kappa_i \beta_{i,MKT}$ and $\sum_i w_i \kappa_i \hat{\epsilon}_{i0}$ using heteroskedasticity-robust standard errors from cross-sectional regressions. We then separately obtain the covariance matrix of the aggregate quantities—the market return $\hat{R}_{MKT,0}$, the deviation in future excess returns $\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{MKT,t} - \hat{R}_{f,t} \right]$, and the deviation in future risk-free rates $\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{R}_{f,t} \right]$—from the VAR. We then combine the two covariance matrices assuming zero correlation between the two because the cross-sectional and aggregate components use independent sources of variation.

D.5 Robustness to Using a Factor Model for Firm Discount Rates

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

First, we use the Fama-French 3-factor model instead of the CAPM to estimate the discount rate on firm equity. This effectively allows the discount rate on 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

$$\begin{aligned}\mathrm{E}_0\left[\hat{R}^E_{it}\right] = \mathrm{E}_0\left[\hat{R}_{f,t}\right] + \beta_{i,MKT}\mathrm{E}_0\left[\hat{R}_{MKT,t} - \hat{R}_{f,t}\right] \\ + \beta_{i,SMB}\mathrm{E}_0\left[\hat{R}_{SMB,t}\right] + \beta_{i,HML}\mathrm{E}_0\left[\hat{R}_{HML,t}\right],\end{aligned}$$

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 betas ($\beta_{i,MKT}$, $\beta_{i,SMB}$, $\beta_{i,HML}$) are estimated as the slope coefficients in a multivariate regression of realized firm excess returns on the realized factor returns ($R_{MKT,t} - R_{f,t}$), $R_{SMB,t}$, and $R_{HML,t}$. Combining this equation with (15) implies the following equation for the deviation in firm discount rates:

$$\begin{aligned}\underbrace{\sum_{t=1}^{\infty}\rho^t\mathrm{E}_0\left[\hat{R}_{it}\right]}_{\substack{\text{Deviation in firm } i\\ \text{discount rates}}} = \underbrace{\sum_{t=1}^{\infty}\rho^t\mathrm{E}_0\left[\hat{R}_{f,t}\right]}_{\substack{\text{Deviation in future}\\ \text{risk-free rates}}} + \kappa_i\beta_{i,MKT}\underbrace{\sum_{t=1}^{\infty}\rho^t\mathrm{E}_0\left[\hat{R}_{MKT,t} - \hat{R}_{f,t}\right]}_{\substack{\text{Deviation in expected}\\ \text{excess MKT returns}}} \\ + \kappa_i\beta_{i,SMB}\underbrace{\sum_{t=1}^{\infty}\rho^t\mathrm{E}_0\left[\hat{R}_{SMB,t}\right]}_{\substack{\text{Deviation in expected}\\ \text{SMB returns}}} + \kappa_i\beta_{i,HML}\underbrace{\sum_{t=1}^{\infty}\rho^t\mathrm{E}_0\left[\hat{R}_{HML,t}\right]}_{\substack{\text{Deviation in expected}\\ \text{HML returns}}}.\end{aligned} \tag{D7}$$

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, expected excess stock-market returns, expected SMB returns, and expected HML returns. As reported in Table D.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 $\beta_{i,SMB} > 0$) and lower for big firms (firms with $\beta_{i,SMB} < 0$). 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 higher aggregate deviation in firm discount rates by 0.1 percentage points. As a result, the overall decline in welfare is mechanically reduced by 0.1 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

$$\mathrm{E}_0\left[\hat{R}^D_{it}\right] = \mathrm{E}_0\left[\hat{R}_{f,t}\right] + \mathrm{E}_0\left[\widehat{CS}_t\right],$$

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 implies relatively small deviations in credit spreads following announcement shocks.

Third, we re-estimate the VAR using data through December 2022 rather than December 2019. As reported in Table D.4, extending the sample to include the COVID period shifts the estimated deviation in future risk-free rates from +0.2 to -1.3 percentage points, and the deviation in expected excess market returns from 3.9 to 5.7 percentage points. These shifts reflect the fact that COVID-era dynamics—near-zero interest rates with high persistence and extreme price-dividend ratios—alter the estimated VAR coefficients. Nevertheless, the total deviation in market discount rates remains similar (4.1 vs. 4.4 percentage points), and the implied welfare effect is nearly unchanged (-4.3 vs. -3.9 percent, Table 8).

E Appendix for Section 5 (Interpretation)

E.1 Movements in Other Asset Prices on Major Tariff Announcement Days in 2025 and 2026

E.2 Proof of Proposition 4

Before we prove the proposition, we prove the following lemma which maps movements in prices and productivity into movements in cash flow:

Lemma 2. *The sum of log changes in the effective rates of protection ($\hat{p}^e_{it}$) and adjusted productivity $\left(\frac{\hat{A}_{it}}{1-\sum_j \omega_{jit}}\right)$ for a firm can be expressed as a linear function of the log changes in cash flows ($\hat{\pi}_{it}$):*

$$\hat{p}^e_{it} + \frac{\hat{A}_{it}}{1-\sum_j \omega_{jit}} = \left(\frac{\omega_{Vit}}{1-\sum_j \omega_{jit}}\right)\hat{\pi}_{it} + \left(\frac{\omega_{Lit}}{1-\sum_j \omega_{jit}}\right)\sum_{i'} \frac{L_{i't}}{L}\hat{\pi}_{i't}.$$

Moreover, the log changes in firm cash flows ($\hat{\pi}_{it}$) and wages ($\hat{w}_t$) can be expressed as linear func-

Table E.1: Discount Rate Changes on 2025-2026 Trade Policy Announcement Days

Trading Date	Tariff Change	Country	T-Bill (x100)	Nom. 10y Yield (x100)	Real 10y Yield (x100)	Breakeven Infl. (x100)	EPB (x100)
22jan2025	Increase	U.S.	0.00	0.03	0.01	0.01	0.05
04feb2025	Mixed	U.S. & China	0.00	-0.01	-0.02	0.00	-0.27
27feb2025	Increase	U.S.	0.00	0.04	0.04	-0.00	0.42
04mar2025	Increase	China	-0.01	0.06	0.06	0.00	0.24
03apr2025	Increase	U.S.	-0.01	-0.14	-0.10	-0.03	2.15
04apr2025	Increase	China	-0.03	-0.05	0.05	-0.10	4.07
09apr2025	Mixed	U.S. & China	0.05	0.08	0.03	0.05	-6.06
11apr2025	Increase	China	0.01	0.07	0.06	0.00	-1.16
12may2025	Decrease	U.S. & China	0.09	0.07	0.07	-0.00	-1.14
11aug2025	Decrease	U.S. & China	0.01	-0.01	-0.01	-0.00	0.10
27oct2025	Decrease	U.S. & China	-0.04	-0.01	-0.00	-0.01	.
20feb2026	Mixed	U.S.	-0.01	0.01	0.01	-0.00	.
Cumulative	Increase		-0.04	0.01	0.12	-0.11	5.78
Cumulative	Decrease		0.06	0.05	0.06	-0.01	-1.04
Cumulative	Mixed		0.04	0.08	0.02	0.06	-6.33

Notes: This table reports changes in discount rate components on trade policy announcement days between January 2025 and February 2026. Columns report the trading date on which the variables are measured, the country or countries making announcements, the change in the 3-month T-Bill rate, the change in the 10-year nominal Treasury yield, the change in the 10-year TIPS real yield, and the change in the equity premium bound (EPB) of Martin (2017). Note that the OptionMetrics we use to construct the EPB is not available for the last two events. Cumulative Tariff Increases aggregates the variables of trading days on which only a tariff increase was announced. Cumulative Tariff Decreases and Mixed Events aggregates the variables of trading days on which a tariff decrease and a mixture of events (increases and decreases) occurred.

tions of the log changes in effective rates of protection ($\hat{p}^e_{it}$) and productivity ($\hat{A}_{it}$):

$$\hat{w}_t = \sum_i \varphi_{it} \left(\hat{p}^e_{it} + \frac{\hat{A}_{it}}{1 - \sum_j \omega_{jit}} \right) \text{ and}$$

$$\hat{\pi}_{it} = \left(\frac{1 - \sum_j \omega_{jit}}{\omega_{Vit}} \right) \left(\hat{p}^e_{it} + \frac{\hat{A}_{it}}{1 - \sum_j \omega_{jit}} \right) - \left(\frac{\omega_{Lit}}{\omega_{Vit}} \right) \sum_{i'} \varphi_{i't} \left(\hat{p}^e_{i't} + \frac{\hat{A}_{i't}}{1 - \sum_j \omega_{ji't}} \right),$$

where $\varphi_{it} \equiv L_{it} \left(\frac{1 - \sum_j \omega_{jit}}{\omega_{Vit}} \right) / \sum_{i'} L_{i't} \left(\frac{1 - \sum_j \omega_{ji't}}{\omega_{Vi't}} \right)$.

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

$$\omega_{Lit}\hat{w}_t + \omega_{Vit}\hat{\pi}_{it} + \sum_j \omega_{jit}\hat{q}_{jt} - \hat{A}_{it} = \hat{p}_{it}, \tag{E1}$$

where we have made use of the fact that

$$\omega_{Lit}\hat{a}_{Lit} + \omega_{Vit}\hat{a}_{Vit} + \sum_j \omega_{jit}\hat{a}_{jit} = -\hat{A}_{it}.$$

Using the definition of effective rates of protection in equation (10) and Proposition (1), we can rearrange equation (E1) to arrive at the first equation in the proposition:

$$\hat{p}^e_{it} + \frac{\hat{A}_{it}}{1-\sum_j \omega_{jit}} = \left(\frac{\omega_{Vit}}{1-\sum_j \omega_{jit}}\right)\hat{\pi}_{it} + \left(\frac{\omega_{Lit}}{1-\sum_j \omega_{jit}}\right)\sum_{i'}\frac{L_{i't}}{L}\hat{\pi}_{i't}.$$

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

$$\begin{aligned}
\left(\frac{\omega_{Lit}}{\omega_{Vit}}\right)\hat{w}_t + \hat{\pi}_{it} &= \left(\frac{1-\sum_j \omega_{jit}}{\omega_{Vit}}\right)\left(\hat{p}^e_{it} + \frac{\hat{A}_{it}}{1-\sum_j \omega_{jit}}\right) \\
\left[\sum_i \frac{L_{it}}{L}\left(\frac{\omega_{Lit}}{\omega_{Vit}}\right)+1\right]\hat{w}_t &= \sum_i \frac{L_{it}}{L}\left(\frac{1-\sum_j \omega_{jit}}{\omega_{Vit}}\right)\left(\hat{p}^e_{it} + \frac{\hat{A}_{it}}{1-\sum_j \omega_{jit}}\right) \\
\left[\sum_i L_{it}\left(\frac{1-\sum_j \omega_{jit}}{\omega_{Vit}}\right)\right]\hat{w}_t &= \sum_i L_{it}\left(\frac{1-\sum_j \omega_{jit}}{\omega_{Vit}}\right)\left(\hat{p}^e_{it} + \frac{\hat{A}_{it}}{1-\sum_j \omega_{jit}}\right) \\
\hat{w}_t &= \sum_i \varphi_{it}\left(\hat{p}^e_{it} + \frac{\hat{A}_{it}}{1-\sum_j \omega_{jit}}\right),
\end{aligned}$$

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

$$\hat{\pi}_{it} = \left(\frac{1-\sum_j \omega_{jit}}{\omega_{Vit}}\right)\left(\hat{p}^e_{it} + \frac{\hat{A}_{it}}{1-\sum_j \omega_{jit}}\right) - \left(\frac{\omega_{Lit}}{\omega_{Vit}}\right)\sum_{i'}\varphi_{i't}\left(\hat{p}^e_{i't} + \frac{\hat{A}_{i't}}{1-\sum_j \omega_{ji't}}\right).$$

□

We are now ready to prove the proposition:

Proposition. 4 *The expected welfare effect arising from changes in expected firm cash flows can be written as the sum of a static price effect, a dynamic price effect, and a TFP effect:*

$$\begin{aligned}
\mathcal{C}_\pi = &\underbrace{\sum_i \frac{wL_i + \pi_i V_i}{C}\hat{p}^e_{i0}}_{\textit{Static Price Effect}} \\
&+ \underbrace{\sum_i \frac{wL_i + \pi_i V_i}{C}\sum_{t=1}^{\infty}\rho^t \mathrm{E}_0\left[\hat{p}^e_{it} - \hat{p}^e_{it-1}\right]}_{\textit{Dynamic Price Effect}} \\
&+ \underbrace{\sum_i \frac{wL_i + \pi_i V_i}{C}\sum_{t=0}^{\infty}(1-\rho)\rho^t \mathrm{E}_0\left[\frac{\hat{A}_{it}}{1-\sum_j \omega_{ji}}\right]}_{\textit{TFP Effect}}.
\end{aligned} \tag{E2}$$

Proof. The first term in the equation gives us the role that cash flow plays in determining welfare:

$$\mathcal{C}_\pi \equiv \sum_i \frac{wL_i + \pi_i V_i}{C} \left(\sum_{t=0}^{\infty} (1-\rho)\rho^t \mathrm{E}_0[\hat{\pi}_{it}] \right).$$

Define

$$X_{it} \equiv \hat{p}^e_{it} + \frac{\hat{A}_{it}}{1 - \sum_j \omega_{ji}}.$$

Then Lemma 2 can be written compactly as

$$\hat{\pi}_{it} = \frac{1 - \sum_j \omega_{ji}}{\omega_{Vi}} X_{it} - \frac{\omega_{Li}}{\omega_{Vi}} \sum_{i'} \varphi_{i'} X_{i't}.$$

Substituting this expression into $\mathcal{C}_\pi$ gives

$$\begin{aligned}
\mathcal{C}_\pi &= \sum_{t=0}^{\infty} (1-\rho)\rho^t \mathrm{E}_0 \left[\sum_i \frac{wL_i + \pi_i V_i}{C} \left\{ \frac{1 - \sum_j \omega_{ji}}{\omega_{Vi}} X_{it} - \frac{\omega_{Li}}{\omega_{Vi}} \sum_{i'} \varphi_{i'} X_{i't} \right\} \right] \\
&= \sum_{t=0}^{\infty} (1-\rho)\rho^t \mathrm{E}_0 \left[\sum_i \frac{wL_i + \pi_i V_i}{C} \frac{1 - \sum_j \omega_{ji}}{\omega_{Vi}} X_{it} - \left(\sum_i \frac{wL_i + \pi_i V_i}{C} \frac{\omega_{Li}}{\omega_{Vi}} \right) \sum_{i'} \varphi_{i'} X_{i't} \right].
\end{aligned}$$

Since

$$1 - \sum_j \omega_{ji} = \omega_{Li} + \omega_{Vi},$$

we have

$$\frac{wL_i + \pi_i V_i}{C} \frac{\omega_{Li}}{\omega_{Vi}} = \frac{wL_i}{C} \frac{1 - \sum_j \omega_{ji}}{\omega_{Vi}}.$$

Using the definition

$$\varphi_i \equiv \frac{L_i \left(\frac{1 - \sum_j \omega_{ji}}{\omega_{Vi}} \right)}{\sum_{i'} L_{i'} \left(\frac{1 - \sum_j \omega_{ji'}}{\omega_{Vi'}} \right)},$$

it follows that

$$\varphi_i \left(\sum_{i'} \frac{wL_{i'}}{C} \frac{1 - \sum_j \omega_{ji'}}{\omega_{Vi'}} \right) = \frac{wL_i}{C} \frac{1 - \sum_j \omega_{ji}}{\omega_{Vi}}.$$

Therefore, after relabeling indices, the expression for $\mathcal{C}_\pi$ becomes

$$\begin{aligned}
\mathcal{C}_\pi &= \sum_{t=0}^{\infty} (1-\rho)\rho^t \mathrm{E}_0 \left[\sum_i \left\{ \frac{wL_i + \pi_i V_i}{C} \frac{1 - \sum_j \omega_{ji}}{\omega_{Vi}} - \frac{wL_i}{C} \frac{1 - \sum_j \omega_{ji}}{\omega_{Vi}} \right\} X_{it} \right] \\
&= \sum_{t=0}^{\infty} (1-\rho)\rho^t \mathrm{E}_0 \left[\sum_i \frac{\pi_i V_i}{C} \frac{1 - \sum_j \omega_{ji}}{\omega_{Vi}} X_{it} \right].
\end{aligned}$$

Finally, since

$$\omega_{Vi} = \frac{\pi_i V_i}{p_i y_i}, \qquad 1 - \sum_j \omega_{ji} = \frac{wL_i + \pi_i V_i}{p_i y_i},$$

we have

$$\frac{\pi_i V_i}{C} \frac{1 - \sum_j \omega_{ji}}{\omega_{Vi}} = \frac{wL_i + \pi_i V_i}{C}.$$

Hence,

$$\mathcal{C}_\pi = \sum_i \frac{wL_i + \pi_i V_i}{C} \sum_{t=0}^{\infty} (1-\rho)\rho^t \mathrm{E}_0 \left[\hat{p}_{it}^e + \frac{\hat{A}_{it}}{1 - \sum_j \omega_{ji}} \right].$$

Equivalently,

$$\mathcal{C}_\pi = \sum_i \frac{wL_i + \pi_i V_i}{C} \sum_{t=0}^{\infty} (1-\rho)\rho^t \mathrm{E}_0[\hat{p}_{it}^e] + \sum_i \frac{wL_i + \pi_i V_i}{C} \sum_{t=0}^{\infty} (1-\rho)\rho^t \mathrm{E}_0 \left[\frac{\hat{A}_{it}}{1 - \sum_j \omega_{ji}} \right].$$

Using the identity

$$\sum_{t=0}^{\infty} (1-\rho)\rho^t \mathrm{E}_0[\hat{p}_{it}^e] = \hat{p}_{i0}^e + \sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{p}_{it}^e - \hat{p}_{i,t-1}^e \right],$$

we obtain

$$\begin{aligned} \mathcal{C}_\pi = & \sum_i \frac{wL_i + \pi_i V_i}{C} \hat{p}_{i0}^e \\ & + \sum_i \frac{wL_i + \pi_i V_i}{C} \left(\sum_{t=1}^{\infty} \rho^t \mathrm{E}_0 \left[\hat{p}_{it}^e - \hat{p}_{it-1}^e \right] \right) \\ & + \sum_i \frac{wL_i + \pi_i V_i}{C} \left(\sum_{t=0}^{\infty} (1-\rho)\rho^t \mathrm{E}_0 \left[\frac{\hat{A}_{it}}{1 - \sum_j \omega_{ji}} \right] \right). \end{aligned}$$

which gives the static price effect, the dynamic price effect, and the TFP effect. □

E.3 Measuring the Static and Dynamic Price Effects

In this section, we describe how we compute the effective rate of protection, in order to calculate the first two terms in (11).

Construction of Industry-level Tariffs

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

$$\hat{\tau}_\iota \equiv \sum_{h \in H_\iota} \sum_c \frac{mv_{hc,2017}}{\sum_{h' \in H_\iota} \sum_{c'} mv_{h'c',2017}} \Delta \ln(1 + \tau_{hc}), \tag{E3}$$

where H_ι is the set of HTS10 codes that map to NAICS 6-digit industry ι; $mv_{hc,2017}$ is the annual import value of goods in HTS10 code h imported from country c in 2017; and $\Delta \ln(1 + \tau_{hc}) = \ln(1 + \tau_{hc,2019Dec}) - \ln(1 + \tau_{hc,2017Dec})$ is the log-change in ad-valorem tariff rates from December 2017 to December 2019. Thus, the change in output tariff $\hat{\tau}_\iota$ captures the average change in tariff rates applied to imported goods produced in industry ι.

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

$$\hat{\tau}^a_\iota \equiv \sum_{h \in H_\iota} \sum_c \frac{mv_{hc,2017}}{\sum_{h' \in H_\iota} \sum_{c'} mv_{h'c',2017}} \Delta \ln(1 + \tau^a_{hc}), \tag{E4}$$

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

E.3.1 Effective Rates of Protection Calculation

We use equation (10) to estimate how U.S. import tariff changes map into firm-level ERP ($\hat{p}^e_{i0}$) in a static model. Since firm-level intermediate-input use data are not available, we use industry-level data, i.e., we assume that the shift in the ERP for all firms in industry ι is given by

$$\hat{p}^e_\iota \equiv \frac{\hat{p}^\tau_\iota - \sum_j \omega_{j\iota} \hat{q}^\tau_j}{1 - \sum_j \omega_{j\iota}}, \tag{E5}$$

where $\hat{p}^\tau_\iota$ are estimates of how U.S. import tariff changes affected prices of U.S. outputs in industry ι, and $\hat{q}^\tau_j$ are estimates of how U.S. import tariff changes affected input prices i. The $\omega_{j\iota}$'s denote the cost-share of intermediate input i used in the production of output in industry ι.[2] We assign industry-level changes in ERP to each firm based on the industry it produces, i.e., $\hat{p}^e_{i0} = \hat{p}^e_\iota \quad \forall i \in \iota$.

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

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

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

$$\hat{p}_\iota^{e1} = -\frac{\sum_j \omega_{j\iota} \lambda_j \hat{\tau}_j}{1 - \sum_j \omega_{ji}}. \tag{E6}$$

We use the 2017 IO table to identify all of the inputs i used to produce output ι. We set $\hat{q}_j^\tau$ equal to $\lambda_j \hat{\tau}_j$ in equation (E5), where λ_j is the share of imports of input j in total absorption of input j (where absorption is calculated as production less exports plus imports). We multiply the cost share of each intermediate input j used to produce output ι ($\omega_{j\iota}$) by λ_j so that the tariff change is only applied to imported inputs and not to domestic inputs. The price of the imported input increases by the full amount of the tariff $\hat{\tau}_j$ (calculated in equation (E3)). Note that the tariffs on inputs are at the BEA IO level, which is a little more aggregated than NAICS 6-digit. Using this calculation of ERP, we assign the same value to each firm within a NAICS 6-digit industry in our Compustat sample, and reweight the industries to reflect the distribution of firms in the aggregate economy as we did in our baseline welfare calculations and described in Section D.3.

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

$$\hat{p}_\iota^{e2} \equiv \frac{\gamma \lambda_\iota \hat{\tau}_\iota - \sum_j \omega_{j\iota} \left[\lambda_j \hat{\tau}_j + (1-\lambda_j)(\gamma \lambda_j \hat{\tau}_j)\right]}{1 - \sum_j \omega_{j\iota}}. \tag{E7}$$

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

Estimating the Static Price Effect: We use tariff changes between 2017 and 2019 to assign these industry-level changes in ERP to firms in our sample and then use the reweighing scheme in Section D.3. We use equation (E6) to obtain an estimate for the welfare impact equal to -0.3 of a percent for the static price effect in equation (11). Our upper bound estimate of the static price effect uses equation (E7) to compute the ERP, which equals -0.17%.

Estimating the Lower Bound of the Dynamic Price Effect: We assume that the worst case scenario for future ERP is a tariff scheme in which the U.S. applies additional tariff rates of 60 percentage points against China and 20 percentage points against all other countries. We denote these tariffs by $\hat{\tau}^a_\iota$. Using these hypothetical output tariffs to calculate the changes in ERP in equation (E6), the resulting future change in ERP is $\sum_i \frac{wL_i+\pi_i V_i}{C}\hat{p}^e_{i1} = -2.19$. The dynamic effect in equation (11) is then given by $\sum_i \frac{wL_i+\pi_i V_i}{C}\rho\left[\hat{p}^e_{i1} - \hat{p}^e_{i0}\right]$, which comes down to $0.975 \times (-2.19\% + 0.3\%)$. If we instead use equation (E7) to calculate the changes in ERP, the resulting effect on ERP is $\sum_i \frac{wL_i+\pi_i V_i}{C}\rho\hat{p}^e_{i1} = -1.01$ and the dynamic effect comes down to $0.975 \times (-1.01\% + 0.17\%)$.