

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 to 2019—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 consumption-equivalent welfare effect of tariffs. Our estimates suggest 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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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 to 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 effect 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 to 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 announcement dates was 11.5%—a 4.2 trillion dollar loss in firm equity value—while the Chinese stock market fell even more, by 17.5%. These aggregate declines were broad: the full distribution of firm returns shifted to the left on announcement days, with the median firm losing over 1% of its value on Chinese announcement days alone. We show that the same asset-pricing patterns recur during the 2025 to 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 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, Rognlie, and Straub \(2025\)](#)), or improved fiscal revenues ([Gómez-Cram, Kung, and Lustig \(2025\)](#)). 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, that is, 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 an adjustment for revisions to future 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 3.8% in our baseline specifi-

cation and use the model to understand why this point estimate is much larger than the welfare losses 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. Even after allowing for the largest plausible dynamic price effects, most of the gap remains: markets expected declines in firm cash flows that measured price effects cannot account for. Our model attributes this residual to expected changes in TFP, but it may also reflect other effects of tariffs, such as supply-chain costs, or other future policies that investors inferred from the announcements.

Related Literature Our work is closely linked to the literature on stock-market event studies related to trade policy announcements ([Hartigan, Perry, and Kamma \(1986\)](#); [Grossman and Levinsohn \(1989\)](#); [Breinlich \(2014\)](#); [Fisman, Hamao, and Wang \(2014\)](#); [Moser and Rose \(2014\)](#); [Breinlich et al. \(2018\)](#); [Crowley, Meng, and Song \(2019b\)](#); [Huang et al. \(2023\)](#); [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 \(2013\)](#); [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, and we allow for this channel to be operative as well.¹ Our work is also related to the macro literature evaluating the impact of trade on income that has found evidence of large impacts of trade on productivity, income, and growth (cf., [Frankel](#)

¹For example, [Amity 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.

and Romer (1999); Alcalá and Ciccone (2004); Feyrer (2019); Wacziarg and Welch (2008); Waugh (2019)). Although our work also finds large effects of trade on welfare, which our model attributes largely to expected productivity losses, 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, Bloom, and Davis (2016); Pierce and Schott (2016); Handley and Limão (2017); Caldara et al. (2020); 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, Redding, and Weinstein (2020); Fajgelbaum et al. (2020); Flaaen, Hortaçsu, and Tintelnot (2020); Amiti, Redding, and Weinstein (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, Lettau, and Ludvigson (2025); Atkeson, Heathcote, and Perri (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.

Section I presents the stylized facts. Section II develops the model linking asset prices to welfare. Section III describes the estimation and reports the welfare results. Section IV interprets and validates these results. Section V concludes.

I. 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, and that markets fully incorporated each announcement within a single trading day. 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. Sections [I.A](#) and [I.B](#) document the first fact, Section [I.C](#) the second and third, and Section [I.D](#) the fourth.

A. *The Tariff Announcements*

Over the course of the 2018 to 2019 trade war, the U.S. implemented tariffs in waves. The average tariff rate on all U.S. imports rose by approximately 3.5 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. We chose announcements of new tariff waves, and not just threats. Our choice of announcement dates has the advantage of being comprehensive and objective, in that we do not use actions or statements that do not correspond to observable changes in tariffs.²

Table [I](#) presents the eleven tariff-announcement dates, comprising six U.S. tariff and five Chinese tariff-retaliation announcements. 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 announcement date (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 announcement date (March 1, 2018) is the announcement of steel and aluminum tariffs, which were also broadly applied and imposed

²The tariffs announced by both sides remained in place throughout our sample period, with some minor exceptions. On the U.S. side, no tariffs that were actually implemented were reduced during 2018 to 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% retaliatory tariff on U.S. 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 U.S. postponing its own planned escalation from 10 to 25% on \$200 billion of Chinese goods. Substantial reductions by either side came only later, under the Phase 1 agreement of February 2020, when the U.S. reduced some of the September 2019 tariffs from 15 to 7.5%, 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 I: Stock-Market Returns on Tariff-Announcement Days

Date	Country	Description	Log Return (x100)	
			US	CHN
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	−0.8
22mar2018 ^{†‡}	US	U.S. imposes \$60B in annual tariffs on China	−2.4	−2.9
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 U.S. 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	−13.7
Cumulative	CHN		−6.5	−10.2
Cumulative	All		−11.5	−17.5

Note: The table reports log returns (multiplied by 100) for the U.S. value-weighted market portfolio from CRSP and the China Securities Index 300 on each tariff announcement day. The date is the first day U.S. markets could trade on the announcement. [†] indicates U.S. or Chinese announcements made 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. [‡] indicates two announcements whose first Chinese trading day is the same; the cumulative Chinese returns count this day once. Country indicates whether the U.S. or China announced the tariff action.

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 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 announcements are listed in Table I in date order, with more details and links to each announcement provided in Appendix A.A.

B. Aggregate Stock Market Response

Stock markets reacted consistently to these tariff announcements. Table I 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 announcement dates except one U.S. announcement date and one Chinese announcement date, with a total drop of 11.5% across all announcements.³ These announcements had an even larger effect on the China Securities Index 300, which reacted with about one and a half times the severity, declining a total of 17.5 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.

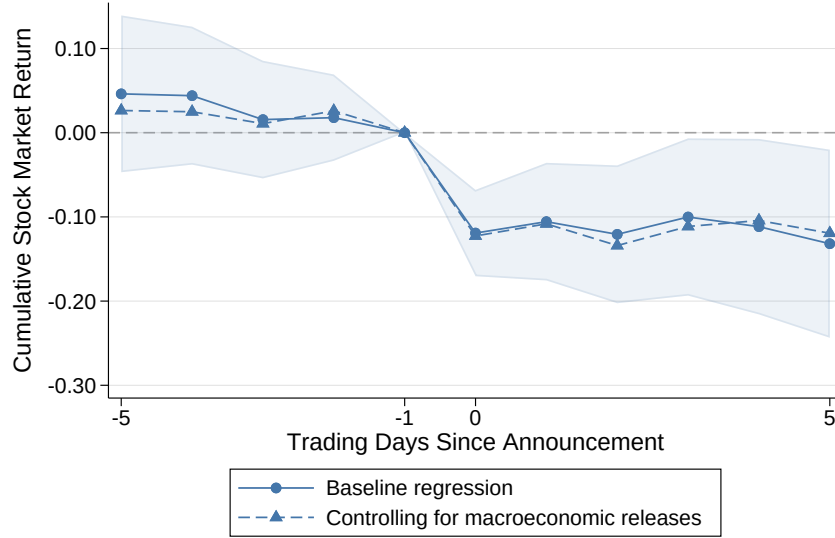
We also analyze intraday stock returns in Appendix A.B and find no evidence that prices moved systematically in the days before or after announcements. We typically see prices move sharply at the time of each announcement, though there is sometimes evidence that the market began or ended its move a few 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 announcement days, 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 I showed, there were

³We 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.

significant cumulative declines of over 10% on the announcement days.⁴ These falls were persistent, as the market did not recover in the following five trading days. In Section IV.A, we show that this persistence extends well beyond the announcement window: cross-sectional differences in announcement-day returns are preserved in firm valuations over a multi-year horizon.

Figure 1: The Dynamics of Stock-Market Returns around Tariff Announcements



Note: This figure plots the cumulative log stock-market return relative to the close on 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 $s > -1$ (each point is measured relative to the close on the day before the announcement). The dashed line reports the results of the same procedure controlling for economic surprises, that is, $\ln R_{MKT,t} = \alpha + \sum_{s=-4}^5 \theta_s D_{s,t} + \sum_{d=1}^D \gamma_d ES_{d,t} + \epsilon_t$ 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, together with the four monetary policy shocks of [Lewiss \(2025\)](#). Shaded areas correspond to the 95% 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.

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 an-

⁴Because 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 to 2019, aggregate their log returns, and repeat one million times. Only 0.005% of draws produced a lower cumulative return, strongly rejecting the hypothesis that the negative stock-market response on tariff-announcement days arose by chance.

nouncements occurred on our announcement days, we also report cumulative stock market returns around tariff announcements, after controlling for the set of macroeconomic release surprises from Bloomberg and the monetary policy shocks from Lewis (2025). 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 announcement 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 2016 to 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 30-minute window after each tweet (when the tweet occurs during extended trading hours, 4:00 AM to 8:00 PM EST) or in the close-to-open return (when it occurs outside extended trading hours). Appendix Table AIV reports these results. The cumulative market effect of escalation tweets that fall outside our announcement windows is small (-0.47% over 30-minute windows and 0.20% in close-to-open windows), which is negligible relative to the -11.5% 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.

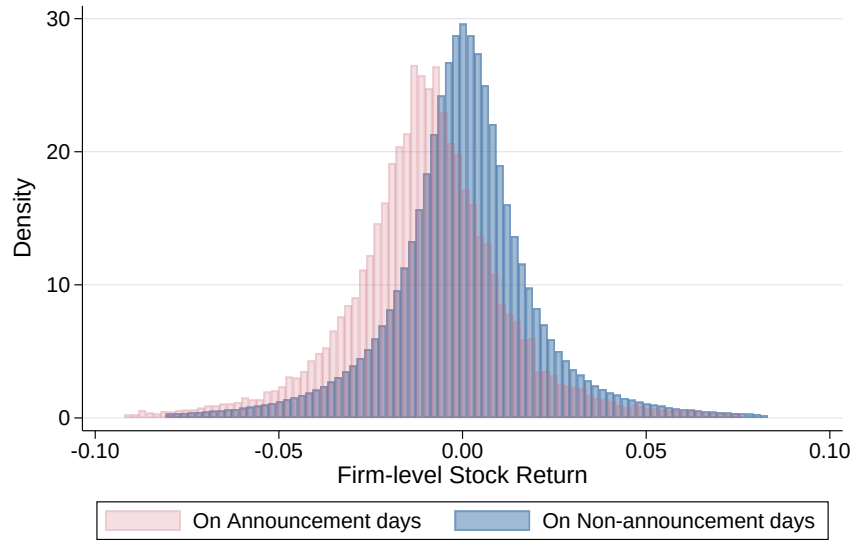
The difference between levying tariffs on China and non-tariff actions is also clearly visible when we examine stock price movements on days in 2017 to 2019 when the U.S. announced executive orders and actions targeting China that were unrelated to tariffs.⁵ We report the stock returns for each of these dates in Appendix Table AV. 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 in-

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

corporated in the U.S.⁶ 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 II 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 1.37% on Chinese announcement days and by only 0.67% 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 60% more than the ninetieth percentile.

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 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. We then plot the histogram of these residuals for each group, trimming observations outside of the 1st–99th percentile range.

⁶The 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) have 2017 *Compustat* data on employment, industry, and the market values of equity and debt (so that we can measure firm-level leverage). We exclude firms with zero employment and firms in public administration or unclassified establishments. We classify firms using *Compustat*'s historical NAICS code (`naics_h`) for fiscal year 2017, using the current header code (`naics`) when the historical code is missing. When a *Compustat* code has fewer than six digits, we use the six-digit *CRSP* code if its first two digits agree. This leaves 3,078 firms, which we refer to as our *Compustat-CRSP* sample.

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

	Mean	p10	p25	p50	p75	p90
U.S. announcements	−0.64* (0.34)	−0.75 (0.52)	−0.77* (0.40)	−0.67** (0.32)	−0.56** (0.25)	−0.50* (0.28)
China announcements	−1.36** (0.61)	−1.66** (0.77)	−1.54** (0.74)	−1.37** (0.62)	−1.14** (0.53)	−1.04* (0.54)
<i>N</i>	2,311,208	2,311,208	2,311,208	2,311,208	2,311,208	2,311,208

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. Standard errors are reported in parentheses. Standard errors for the mean (OLS) are clustered by day. Quantile-regression standard errors use 999 bootstrap replications that resample whole days within the U.S., China, and non-announcement groups and re-estimate the group mean adjustments in each replication.

C. 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 U.S.-imposed tariffs because their input prices will rise. Second, firms that compete with China in the U.S. market will likely benefit if the tariffs raise their Chinese competitors' tariff-inclusive prices. Third, Chinese retaliation may negatively affect U.S. exporters by raising the tariff-inclusive price of their output and therefore lowering the demand they face. In addition, because Chinese 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 ([Webster \(2022\)](#)), 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.⁷ Our empirical approach 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 \(2017\)](#)).

⁷We derive abnormal returns from a standard CAPM in Appendix [A.F](#).

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

	Mean
Firm imports from China	0.20
Firm or subsidiary imports from China	0.29
Firm, subsidiary, or supplier imports from China	0.31
Firm exports to China	0.03
Firm or subsidiary exports to China	0.04
Firm sells in China via exports or affiliate sales	0.41
Average share of revenue from Chinese exports or affiliate sales	0.03
Firm exposed to China through imports, exports, or affiliate sales	0.52

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 A.E for the construction of these variables. The sample is restricted to firms in the cross-section sample.

Our analysis focuses on our *Compustat-CRSP* sample, which we combine with *Capital IQ* and *FactSet* data to identify each firm’s network of subsidiaries, major suppliers, and affiliates. 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 A.E for details). In this section, we restrict attention to firms that have returns on every trading day of 2017 to 2019 and were checked in *Datamyne* (2,431 of the 3,078 firms in our *Compustat-CRSP* sample), which we call the cross-section sample. Table III shows that only 20% of the firms in our sample import directly from China, and only 3% export directly to China. However, if we take subsidiaries into account, these numbers rise to 29 and 4%, respectively. When we add imports by all firms in the supply chain, we find that 31% 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% 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 protection indicator that equals 1 if the tariff on the *output* of the industry increased, in Table IV. In the first column, where we present the total effect, cumulated across all U.S. announcements, 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. announcements, we find that the positive aggregate effect is driven by the March

Table IV: Protection and Abnormal Returns

	Cumulative	23Jan18	01Mar18	22Mar18	19Jun18	06May19	01Aug19
Protection	4.08** (1.82)	1.06 (0.91)	4.15*** (1.49)	−0.06 (0.18)	−0.48*** (0.14)	−0.39*** (0.15)	−0.20 (0.30)
N	5,434	5,434	5,434	5,434	5,434	5,434	5,434

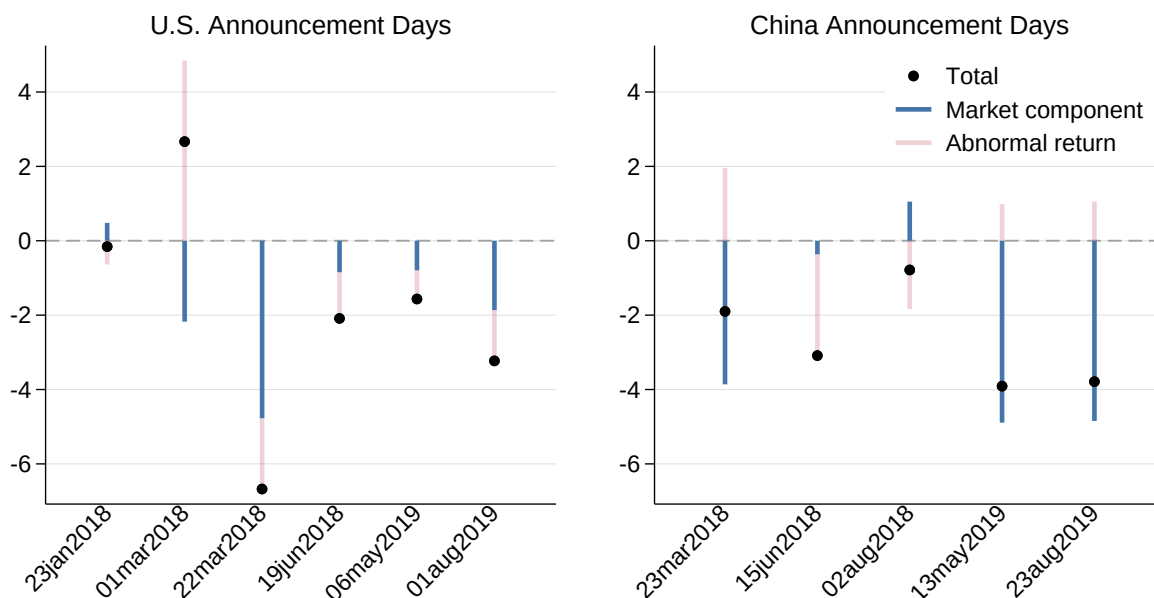
Note: *Protection* is an indicator equal to one if the industry receives positive output-tariff protection associated with that announcement. Each column reports the coefficient on the protection indicator from an industry-level pooled event-study regression of daily abnormal returns (multiplied by 100). The first column reports the cumulative coefficient across U.S. announcement days, and the other columns report the announcement-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. Industry averages are computed over firms in the cross-section sample. Standard errors are clustered by NAICS industry and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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% 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, at 4.15 percentage points.

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. buyers of 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 Announcement Date



Note: The figure plots the average return (dots) 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 announcement days, split into a market component, predicted by the market return and the firm's CAPM beta, and an abnormal return, the remainder (vertical lines; see Appendix A.F). 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 announcement 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 about 5 percentage points, a clear signal that markets expected these firms to benefit. Average returns were more muted, however, because the 1.1% broad market decline documented in Table I 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 I shows that retaliatory announcements drove U.S. equity markets down

by 6.5%—resulting in a net decline in steel and aluminum stock prices over the course of the trade war.

Table V: Trade Exposure and Abnormal Returns

	Industry Measures			Firm Measures			
	China Import Intensity (P75)	China Export Share (P75)	Manufacturing Industry (=1)	China Importer (=1)	China Exporter (=1)	China Revenue Share (P75)	Size (P75)
<i>Panel A: U.S. Announcement Days</i>							
Exposure	−1.76*** (0.55)	−1.54** (0.66)	−1.48*** (0.49)	−3.10*** (0.36)	−3.89*** (0.65)	−2.01*** (0.38)	−4.07*** (0.33)
<i>Panel B: China Announcement Days</i>							
Exposure	−0.73 (0.49)	−1.49** (0.58)	0.20 (0.53)	−0.42 (0.26)	−0.93** (0.46)	−0.10 (0.30)	−1.30*** (0.26)
N	5,434	5,434	5,434	26,741	26,741	25,993	26,741

Note: Each column reports a separate pooled regression of daily abnormal returns (multiplied by 100) on interactions between the announcement-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 announcement-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 import 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/suppliers 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, 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 for these measures is the number of industry-date observations rather than firm-date observations. Standard errors are clustered by NAICS industry for the industry-level measures and by firm for the firm-level measures, 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 V, 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,

⁸We identify the intermediate inputs of each industry using the BEA input-output table for 2017. Following standard approaches, we assume that each industry imports an input in the same proportion as the aggregate economy.

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, its subsidiaries, or its suppliers imported from China, whether a firm or its subsidiaries 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 III. 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 1.76 percentage points relative to other industries. The second column shows a similarly large 1.54 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 1.48 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 V. Consistent with this literature, we show in Panel A that firms that imported from China had abnormal returns 3.10 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. We also find 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, Panel B shows that 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. First, we examine the impact of the trade war on firms with high Chinese sales shares. Table III reveals that 41% of firms in our sample have positive revenues from China, whether through exports or affiliate sales, while only 4% 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 Webster (2022), 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.

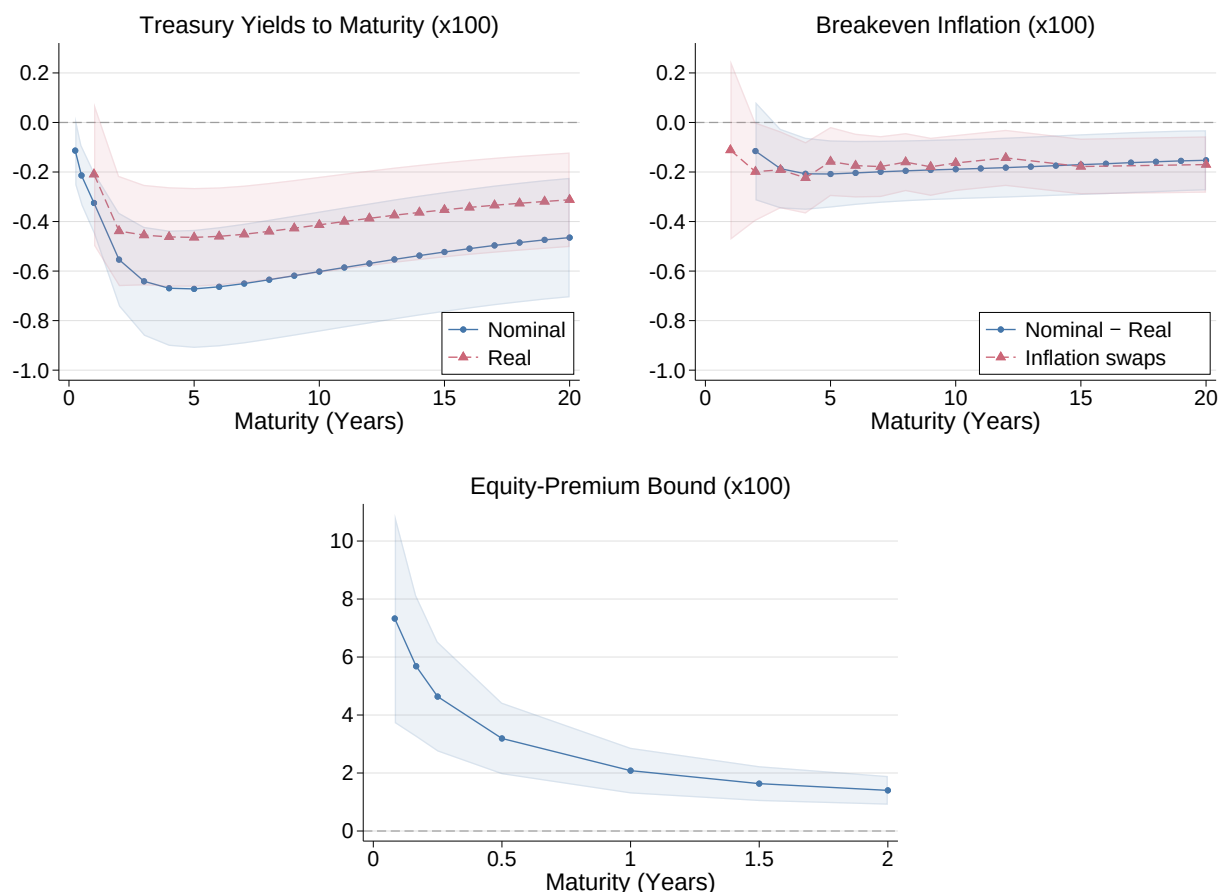
D. Response Across Asset Classes

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 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, Sack, and Wright (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 A.D). 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, 67

bps for 4-year maturities, and 46 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 Yields and the Equity-Premium Bound



Note: Each panel shows the cumulated daily change in the indicated annualized rates, yields or equity-premium bound, in percentage points, over all days with a tariff announcement, after controlling for surprises in macroeconomic releases. Shaded areas denote 95% confidence intervals. The top-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 are from [Gürkaynak, Sack, and Wright \(2007\)](#) and real yields at 2- to 20-year maturities from [Gürkaynak, Sack, and Wright \(2010\)](#). The one-year real yield is measured as the one-year nominal yield minus the one-year inflation swap rate. The top-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 bottom panel reports the equity-premium bound, constructed using the methodology of [Martin \(2017\)](#) on data from *OptionMetrics*.

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 top-left panel of Figure 4 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, Sack, and Wright \(2010\)](#). 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 top-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, Rognlie, and Straub \(2025\)](#)). Second, by raising government revenue, tariffs may improve the fiscal outlook and lower expected inflation ([Gómez-Cram, Kung, and Lustig \(2025\)](#)).

The Effect on [Martin \(2017\)](#)’s Equity-Premium Bound 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.

The bottom panel of Figure 4 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 1.4 percentage points 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 I, we reported stock-market returns announcement by announcement. In the same spirit, Appendix Table AVI reports the change in nominal yields, real yields, and the equity-premium bound announcement by announcement. This shows that our results are not driven by an outlier announcement: almost all announcements tend to decrease yields and increase the equity premium bound. As with stock-market returns, Appendix Figure A2 reports the dynamic effect of announcements on these variables over a ten-day window. The appendix figure shows that the change in these variables is concentrated on the announcement days, indicating that the market neither under- nor over-reacted on those days.

II. A Model Mapping Asset Prices to Welfare

We present the theory in three steps. First, in Section II.A, 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 fixed factor in this setup) pin down the movements in wages. Second, in Section II.B, 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. Third, in Section II.C, we express this welfare effect in terms of deviations in firm values and discount rates, which we can estimate from the reaction of asset prices to policy announcements. Finally, Section II.D shows how, under additional assumptions on tariff-induced ERP changes, the cash-flow welfare effect can be decomposed into static price, dynamic price, and TFP components. Proofs of all propositions are in Appendix B.A.

A. 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

⁹The firm-specific 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 fixed 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 fixed factor for modern listed firms.

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 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 $j \in \{1, \dots, J\}$. 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 $c_i(w_t, \pi_{it}, q_{1t}, \dots, q_{Jt}, A_{it})$, 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 ($q_{1t}, \dots, q_{Jt}$), 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 cost is equal to its output price,

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

We impose the full-employment condition for labor and the market-clearing condition for

¹⁰Our 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, fixed-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 fixed-factor rents and markup profits. Market valuations would then no longer measure the welfare-relevant component of firm value unless we separately identified the markup component.

¹¹One 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.

¹²The 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 $p_{it} = c_i(w_t, \pi_{it}, q_{1t}, \dots, q_{Jt}, A_{it})$. 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 2). Firm owners own the fixed factor, so they are paid $\pi_{it}V_i$ in each period.

each firm's fixed factor in each period:

$$\sum_i a_{Lit} y_{it} = L \quad \text{and} \quad a_{Vit} y_{it} = V_i, \quad (2)$$

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 full-employment condition in (2) requires that firm-level employment adjusts with firm-level production. In contrast, the market-clearing condition for the fixed factor in (2) stipulates that the unit-input requirement of the fixed 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 market-clearing 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), that is, $\pi_{it} V_i = (p_{it} - a_{Lit} w_t - \sum_j a_{jit} q_{jt}) y_{it}$.

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

We model a tariff change as causing a set of log-change deviations in output prices, input prices, and 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 fixed factor does not change ($\hat{V}_i = 0$), log changes in the shadow price of the fixed 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 fixed factor and labor (σ) enables us to write the factor intensity of production (a_{Vit}/a_{Lit}) as:

$$\hat{a}_{Vit} - \hat{a}_{Lit} = \sigma (\hat{w}_t - \hat{\pi}_{it}). \quad (3)$$

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 fixed 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, that is,*

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

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

The intuition behind the first equation in Proposition 1 is that firms expand employment when their cash flows rise relative to wages. Wages adjust so that employment gains and losses balance across firms, which requires that the changes in relative wages ($\hat{w}_t - \hat{\pi}_{it}$) are zero “on average,” that is, 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 ($\sum_i \frac{L_i}{L} \hat{\pi}_{it}$). The second equation follows immediately from this equation and the fact that the amount of the fixed factor does not change, so the left-hand side of equation (3) 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 fixed factor, we simplify the expressions in his canonical model and show that changes in cash flow alone pin down wage and employment changes.¹⁴ Wages move one-for-one with the employment-weighted average of log changes in cash flow.¹⁵

¹³We relax the assumption of fixed factors in Appendix B.D.

¹⁴By 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, for example, assuming that $\sigma = 1$ (cf., Kovak (2013)). Knoblauch 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.

¹⁵At 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.

B. 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, that is, $C_t = I_t$. 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:

$$\hat{C}_t = \frac{wL}{C} \hat{w}_t + \sum_i \frac{\pi_i V_i}{C} \hat{\pi}_{it} + \frac{TR}{C} \widehat{TR}_t. \quad (4)$$

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 (4) 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 neo-classical models of how tariffs affect welfare. For example, the monopolistic competition model of [Ossa \(2014b\)](#) presents an expression (see his equation 14) for how tariffs affect welfare. The welfare effect 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

We define the “consumption-equivalent welfare effect” of this deviation, denoted $\mathcal{C}$,

¹⁶For 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 terms on the right-hand side of equation (4)). 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.

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

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

$$\mathcal{C} = \sum_{t=0}^{\infty} (1 - \rho) \rho^t \mathbb{E}_0 [\hat{C}_t], \quad (5)$$

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 B.A).

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

C. 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

¹⁷In Appendix B.C, 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 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.

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 (4) into equation (5), 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:

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

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:

$$\mathcal{C} = \underbrace{\sum_i \frac{wL_i + \pi_i V_i}{C} \left(\sum_{t=0}^{\infty} (1 - \rho) \rho^t \mathbb{E}_0 [\hat{\pi}_{it}] \right)}_{\text{Deviation in firm cash flows } \mathcal{C}_{\pi}} + \underbrace{\frac{\text{TR}}{C} \left(\sum_{t=0}^{\infty} (1 - \rho) \rho^t \mathbb{E}_0 [\widehat{\text{TR}}_t] \right)}_{\text{Deviation in tariff revenues } \mathcal{C}_{\text{TR}}}. \quad (6)$$

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, $\mathbb{E}_0 [\hat{\pi}_{it}] = 0$. 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 $\mathbb{E}_0 [\hat{\pi}_{it}] = \frac{1}{2} \ln 1.5 + \frac{1}{2} \ln 0.5 \approx -0.14$, so welfare would fall. Equation (6) 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.

The first term in equation (6) 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 $\lim_{t \rightarrow \infty} R_{it}^{-1} M_{it} = 0$, we can express a firm's value as the discounted value of its future cash flows:¹⁸

$$M_{i0} = E_0 \left[\sum_{t=0}^{\infty} \frac{\pi_{it} V_i}{R_{i1} \dots R_{it}} \right]. \quad (7)$$

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 (so that the same discount factor ρ applies to firm values and to household welfare), we have:*

$$\hat{M}_{i0} = \sum_{t=0}^{\infty} (1 - \rho) \rho^t E_0 [\hat{\pi}_{it}] - \sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{it}].$$

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 announcement-induced revisions to future firm discount rates ($\sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{it}]$). We refer to this discounted sum as the discount-rate adjustment. While equation (6) tells us that tariff-induced movements in prices and uncertainty only matter for welfare insofar as they affect cash flow (and tariff revenues), 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

¹⁸The 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.

¹⁹Since 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.

discount rates by, say raising the equity premium and making investors reluctant to hold stocks, this will cause $\sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{it}]$ to rise and firm market values, $\hat{M}_{i0}$, to fall.

Combining this result with equation (6) allows us to write the aggregate welfare effect as follows

$$\mathcal{C} = \underbrace{\sum_i \frac{wL_i + \pi_i V_i}{C} \left(\hat{M}_{i0} + \sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{it}] \right)}_{\text{Deviation in firm cash flows } \mathcal{C}_{\approx}} + \underbrace{\frac{\text{TR}}{C} \sum_{t=0}^{\infty} (1 - \rho) \rho^t E_0 [\widehat{\text{TR}}_t]}_{\text{Deviation in tariff revenues } \mathcal{C}_{\text{TR}}}. \quad (8)$$

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 (8) rewrites equation (6) in terms of variables we can estimate: the deviation in firm values associated with the tariff announcement and the discount-rate adjustment.

D. 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:

$$\hat{p}_{it}^e \equiv \frac{\hat{p}_{it} - \sum_j \omega_{jit} \hat{q}_{jt}}{1 - \sum_j \omega_{jit}}, \quad (9)$$

where ω_{jit} denotes the expenditure shares of firm i on input j as a share of total revenue (similarly, we will denote by 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 $\hat{p}_{i0}^e$, we can write the welfare effect we measure as a function of the change in ERP, future price move-

²⁰For example, [Corden \(1966\)](#)’s classic paper assumes perfect passthrough of tariffs, so $\hat{p}_{it} = \Delta \ln(1 + \tau_{it}^O)$ and $\hat{q}_{jt} = \Delta \ln(1 + \tau_{jt})$, where τ_{it}^O 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 $\hat{p}_t = \Delta \ln(1 + \tau_t^O)$ and $\hat{q}_{jt} = 0$.

ments, 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:*

$$\begin{aligned}
C_\pi = & \underbrace{\sum_i \frac{wL_i + \pi_i V_i}{C} \hat{p}_{i0}^e}_{\text{Static Price Effect}} \\
& + \underbrace{\sum_i \frac{wL_i + \pi_i V_i}{C} \sum_{t=1}^{\infty} \rho^t E_0 [\hat{p}_{it}^e - \hat{p}_{it-1}^e]}_{\text{Dynamic Price Effect}} \\
& + \underbrace{\sum_i \frac{wL_i + \pi_i V_i}{C} \sum_{t=0}^{\infty} (1 - \rho) \rho^t E_0 \left[\frac{\hat{A}_{it}}{1 - \sum_j \omega_{ji}} \right]}_{\text{TFP Effect}}. \tag{10}
\end{aligned}$$

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 effect, 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 expected TFP now and in the future. In theory, if we could measure the static and dynamic price effects exactly, the TFP effect would correspond to productivity shifts because all price and cost movements would be contained in the price effects. However, we cannot measure every tariff-induced expected price movement in practice, so our *estimate* of the TFP effect is a residual: it captures productivity shifts along with any other effect on cash flows that the measured price effects miss, including supply-chain costs, competition and innovation in exposed industries, and other future policies that the announcements made more likely (for example, export controls or restrictions on investment).

Equation (10) makes clear the difference between measuring welfare using a comparative static exercise and our approach. In comparative static exercises, $\hat{p}_{i0}^e$ 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 ($\hat{p}_{it}^e = \hat{p}_{i0}^e$). 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 III.F, we quantify the relative importance of each of these components for the overall welfare effect we estimate.

III. Estimating the Welfare Effect of Tariff Announcements

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 III.A 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). It also validates these estimates by comparing the VAR-implied path of discount rates to reduced-form evidence from the term structure. Section III.B reweights our sample of public firms to match the sector and firm-size composition of the overall U.S. economy and uses these weights to aggregate the firm-level estimates to the economy level. Section III.C discusses the estimation of tariff revenues. Section III.D presents the results for our estimated welfare effect. Section III.E shows how the decline in firm cash flows varies across industries, and Section III.F decomposes the cash-flow welfare effect into static price, dynamic price, and TFP effects.

A. Estimating the Deviation in Firm Cash Flows

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:

$$\hat{\Pi}_i \equiv \underbrace{\sum_{t=0}^{\infty} (1-\rho)\rho^t E_0[\hat{\pi}_{it}]}_{\text{Deviation in firm cash flows}} = \underbrace{\hat{M}_{i0}}_{\text{Deviation in firm value}} + \underbrace{\sum_{t=1}^{\infty} \rho^t E_0[\hat{R}_{it}]}_{\text{Discount-rate adjustment}}. \quad (11)$$

A.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:

$$\ln R_{it}^E = \alpha_i + \sum_{k=1}^K \theta_{i,k} D_{kt} + \sum_{d=1}^D \gamma_{i,d} \text{ES}_{d,t} + \epsilon_{i,t}, \quad (12)$$

where $\ln R_{it}^E$ is firm i 's daily log equity return; the coefficients $\theta_{i,k}$ are our empirical estimates of the announcement-induced change in firm equity value for each announcement k ; K is the number of tariff announcements; 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 $d \in \{1, \dots, D\}$. We estimate this regression using all trading days between 2017 and 2019, separately for each firm i in our *Compustat-CRSP* sample.

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

$$\hat{M}_{i0} = \sum_{k=1}^K \kappa_i \theta_{i,k}, \quad (13)$$

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.

A.2. Estimating the Discount-Rate Adjustment

We now turn to the estimation of the discount-rate adjustment, which enters the first term in the deviation in aggregate welfare in equation (8). The challenge in computing this term is in obtaining an expression for the change in discount rates induced by the policy $(\sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{it}])$. 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 ($\hat{R}_{it}^E$):

$$E_0 [\hat{R}_{it}] = (1 - \kappa_i) E_0 [\hat{R}_{it}^D] + \kappa_i E_0 [\hat{R}_{it}^E], \quad (14)$$

²¹Because 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.

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:

$$E_0 [\hat{R}_{it}^D] = \hat{R}_{f,t}; \quad \text{and} \quad E_0 [\hat{R}_{it}^E] = \hat{R}_{f,t} + \beta_{i,MKT} (\hat{R}_{MKT,t} - \hat{R}_{f,t}), \quad (15)$$

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

$$\underbrace{\sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{it}]}_{\text{Firm } i \text{ discount-rate adjustment}} = \underbrace{\sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{f,t}]}_{\text{Deviation in future risk-free rates}} + \kappa_i \cdot \beta_{i,MKT} \cdot \underbrace{\sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{MKT,t} - \hat{R}_{f,t}]}_{\text{Deviation in expected excess stock-market returns}}. \quad (16)$$

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 discount-rate adjustments to the estimation of two aggregate quantities: the path of future risk-free rates and the path of future expected 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 (value-weighted betas average to one, so the aggregate discount-rate adjustment equals the market's regardless of how individual firms are priced). 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 quanti-

ties. More precisely, we assume that a vector of asset prices x_t , which includes the log risk-free rate and the log excess stock-market return as its first two elements, evolves according to a VAR process:

$$x_{t+1} = a + Bx_t + u_{t+1}. \quad (17)$$

This VAR structure allows us to express the expected effect of a policy announcement on x_t in terms of its effect on x_0 : $E_0[dx_t] = B^t dx_0$. Hence, the VAR structure implies that the deviation in future risk-free rates and future excess stock-market returns defined in equation (16) can be obtained as the first two elements of the vector $\rho B(I - \rho B)^{-1} dx_0$.²²

In summary, the problem of estimating the discount-rate adjustment (the left-hand-side in equation (16)) is reduced to the problem of estimating two aggregate quantities: the matrix B , which governs the law of motion of variables in the VAR, and the vector dx_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 C.A for more details). For our baseline results, we consider the VAR system in equation (17) where the vector x_t contains seven variables:

$$x_t = \left(\ln R_{f,t}, \ln R_{EMKT,t}, TS_t, EPB_t, VS_t, CS_t, \ln PD_t \right),$$

where $\ln R_{EMKT,t} \equiv \ln R_{MKT,t} - \ln R_{f,t}$ denotes the log excess return of the stock market.

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-Bills at the start of the quarter, divided by four). 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 at the 90th and

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

$$\sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{f,t}] = \sum_{t=1}^{\infty} \rho^t (e_1' E_0 [dx_t]) = \sum_{t=1}^{\infty} \rho^t (e_1' B^t dx_0) = e_1' \left(\sum_{t=1}^{\infty} (\rho B)^t \right) dx_0 = e_1' \rho B(I - \rho B)^{-1} dx_0.$$

A similar derivation holds for the deviation in future excess stock-market returns. Since 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 0.03 percentage points and leaves the reported welfare estimates unchanged at the displayed precision.

10th percentiles of the cross-section of stocks), the credit spread CS_t (the difference in the yield of BAA and 3-month T-Bill), and the log price-dividend ratio $\ln PD_t$ (the ratio between the value of the stock market and the dividends distributed in the previous year). One key difference, relative to [Campbell and Vuolteenaho \(2004\)](#), is that we augment the VAR with the equity-premium bound defined by [Martin \(2017\)](#), which is available starting from 1996. We will examine the robustness of our results with respect to changing the set of variables in the VAR below.

We first estimate the unexpected change in the VAR variables due to tariff announcements, dx_0 . Similar to the procedure used to estimate the deviation in firm values, we estimate dx_0 as the sum of daily changes in the vector x_t over all announcement days after controlling for the release of macroeconomic surprises; that is, as the sum of θ_k in the regression

$$\Delta x_t = \alpha + \sum_{k=1}^K \theta_k D_{kt} + \sum_{d=1}^D \gamma_d ES_{d,t} + \epsilon_t, \quad (18)$$

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 VI reports the results of the estimation. As discussed in Section I, 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 that of value firms in response to the announcements.

Table VI: Cumulative Effect of Tariff Announcements on the VAR vector dx_0

	$\ln R_f$ (x100)	$\ln R_{EMKT}$ (x100)	TS (x100)	EPB (x100)	VS (x100)	CS (x100)	$\ln PD$ (x100)
Announcement	-0.03* (0.02)	-12.53*** (2.56)	-0.47*** (0.14)	4.64*** (0.97)	9.56*** (2.92)	-0.05* (0.03)	-12.68*** (2.98)
N	753	753	753	753	753	753	753

Note: The table reports the sum of θ_k in the regression (18), that is, 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 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 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 x_{t+63} on 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 CI reports the result of this estimation. Consistent with the literature, we find that the log price-dividend ratio is an important predictor of log excess returns, and intuitively, the equity-premium bound predicts higher expected excess returns $\ln R_{EMKT}$, although this coefficient is imprecisely estimated. The R^2 of this regression is approximately 15% (at a quarterly horizon), suggesting that our VAR captures a large amount of excess return predictability.

Table VII combines the estimates for dx_0 (Table VI) and the estimate for B (Appendix Table CI) to compute the deviation in future risk-free rates and future excess stock-market returns as the first two elements of the vector $\rho B(I - \rho B)^{-1} dx_0$. 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 4.0 percentage points (second column). The former is close to zero and imprecisely estimated. These estimates imply that the drop in aggregate stock-market value due to higher required returns on equity is 4.2 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)).

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 I. We consider a number of additional external validity checks in Sections IV.A, IV.B, and IV.C. The left panel of Figure 5 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 5 reproduces the change in the term structure of real Treasury yields and in the equity-premium bound around announcement days obtained in Section I. These two figures give similar results regarding the evolution of discount rates following tariff announcements: both approaches find the risk-free component small relative to the equity-premium component (although the VAR implies a slight increase in

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

Table VII: Discounted Sum of Revisions to Future Discount Rates

Deviation in Future Risk-free Rates	Deviation in Future Excess Returns	Total
$\sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{f,t}]$ (x100)	$\sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{MKT,t} - \hat{R}_{f,t}]$ (x100)	$\sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{MKT,t}]$ (x100)
0.2 (1.0)	4.0 (4.4)	4.2 (4.4)

Note: The table reports the present discounted sum of revisions to future risk-free rates, $e'_1 \rho B (I - \rho B)^{-1} dx_0$, and the present discounted sum of revisions to future equity premia, $e'_2 \rho B (I - \rho B)^{-1} dx_0$. Note that the matrix B is reported in Appendix Table CI while the vector dx_0 is reported in Table VI. 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 cash-flow 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 dx_0 (as reported in Table VI) and the uncertainty in the estimation of the matrix B (as reported in Appendix Table CI).

the real risk-free rate while real yields fall slightly), and the VAR matches the shape of the reduced form on the equity premium (a sharp rise that decays with horizon), with a larger magnitude, consistent with the equity-premium bound being only a lower bound on the equity premium. Thus, the VAR is consistent with our earlier reduced-form evidence, presented in Section I, on the evolution of discount rates.²⁴

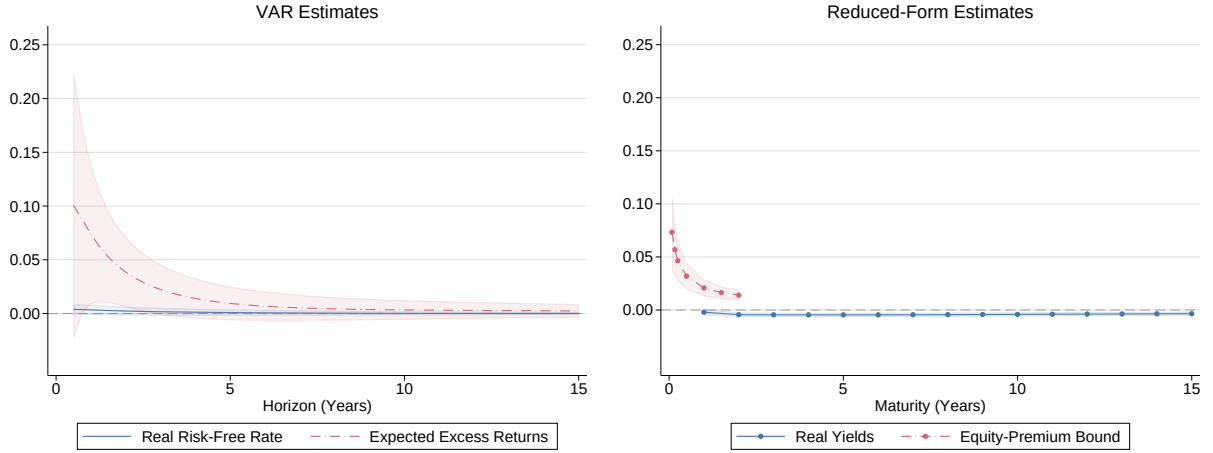
B. Reweighting the Compustat-CRSP Sample

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 C.C for details). First, we classify *Compustat* firms into 18 sectors (2-digit NAICS) and four employment-size bins (below 500, 500–4,999, 5,000–19,999, and 20,000 or more employees), and compute an employment-

²⁴An alternative approach, proposed by Knox and Vissing-Jorgensen (2022), backs out discount rates directly from reduced-form changes in Treasury yields and in the equity-premium bound. This approach imposes less structure than ours, but the equity-premium bound is only a lower bound on the equity premium and is available only up to a three-year maturity. Our VAR recovers discount-rate changes at all horizons by imposing more structure on the evolution of the economy. The two approaches are therefore complementary, and over the horizons where both are available, they deliver similar answers (Figure 5).

Figure 5: Effect of Tariff Announcements on Discount Rates: VAR versus Reduced-Form



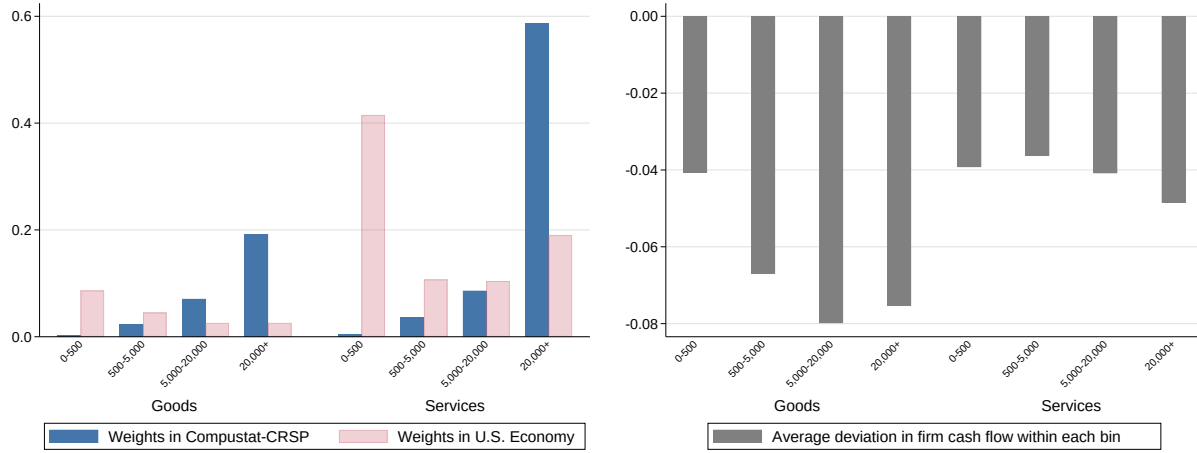
Note: The figure in the left panel plots the effect of tariff announcements on the annualized (real) risk-free rate and excess stock-market return between 0 and t ; that is, $(4/T) \sum_{t=1}^T E_0[\hat{R}_{f,t}] = (4/T) \sum_{t=1}^T e_1' B^t dx_0$ and $(4/T) \sum_{t=1}^T E_0[\hat{R}_{MKT,t} - \hat{R}_{f,t}] = (4/T) \sum_{t=1}^T e_2' B^t dx_0$. The right panel plots the effect of tariff announcements on the yield to maturity of TIPS as well as on the equity-premium bounds across different maturities, as defined by [Martin \(2017\)](#) (the TIPS yields and the equity-premium bounds were reported earlier in Figure 4).

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 each sector's share of value added across these 18 sectors as weights, based on *BEA* data. Finally, we multiply the result by $1 - TR/C$, the share of consumption not financed by tariff revenue in equation (8), where we measure C as personal consumption expenditures plus tariff revenue.

The left panel in Figure 6 compares our constructed weights with the relative employment share of cells within our *Compustat-CRSP* sample. Our weighting procedure assigns greater weight to small firms and services than our *Compustat-CRSP* sample. The right panel of Figure 6 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 return of our *Compustat-CRSP* sample.

We find that tariff announcements caused aggregate firm values to fall 7.0% (see Table VIII). This drop is just over half the decline in the aggregate stock-market return reported

Figure 6: 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. For agriculture (NAICS 11), the first bin covers firms with fewer than 20,000 employees; for education, health care, and other services (NAICS 61, 62, and 81), it covers firms with fewer than 5,000 employees.

in Table I. The difference between the two numbers is due to two effects: first, as we can see from equation (13), 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 6).

C. 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 revenues on our estimation. We have yearly U.S. tariff rates for each product h (HS10) and exporting country c . Let $\Omega_{h,2017}^{US}$ be the set of countries that export product h to the U.S. in 2017 and Ω_{2017}^{US} the set of products the U.S. imported in 2017, keeping only product-country pairs with a tariff rate in both December 2017 and December 2019; TR_{2017} denotes the 2017 tariff revenue on these pairs.

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 percentage 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:

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

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 $\widehat{\text{TR}} = -1$. 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 (8) is small, there is little scope for different assumptions about the movement in tariff revenues to affect the results.

D. Aggregate Welfare Results

We now compute the aggregate welfare effect of the tariff announcements, which is the sum of the three components in equation (8), across all announcement days: the change in firm values, the discount-rate adjustment, and the change in tariff revenues. We report the impact of the tariff announcements on welfare in Table VIII. In our baseline specification, firm values fall by 7.0%. Part of this drop reflects higher discount rates rather than lower expected cash flows: the rise in discount rates accounts for 2.5 percentage points of the decline, so expected firm cash flows fall by 4.4% ($= 6.97 - 2.54$). Tariff revenues raise welfare by at most 0.6%. As discussed in Section III.C, this upper bound assumes that higher tariffs leave import values unchanged. Using the estimates of Fajgelbaum et al. (2020) instead, tariff revenues raise welfare by only 0.3%. The overall welfare effect of tariff announcements is therefore -3.8% with our upper bound and -4.2% with their estimates.

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 VIII.

Firm Sample We explore how changes to the firm sample affect our results in the next three rows in Table VIII. We begin by showing 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*). Next, we estimate the welfare effect assuming that firms in the financial sector are unaffected by tariffs. This reflects two concerns: our model applies more naturally to nonfinancial firms, and 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. Finally, 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 as-

Table VIII: Welfare Effect of Tariff Announcements

	Components			Welfare effect
	Change in firm values (x100)	Discount-rate adjustment (x100)	Change in tariff revenues (x100)	(x100)
Baseline	−7.0 (1.6)	2.5 (2.7)	0.6	−3.8 (2.7)
<i>Robustness w.r.t. firm sample</i>				
Drop firms w/ specific ann.	−7.2 (1.6)	2.5 (2.7)	—	−4.0 (2.7)
Zero effect on fin. firms	−6.6 (1.5)	2.4 (2.6)	—	−3.5 (2.5)
Zero effect on small firms	−4.1 (1.0)	1.6 (1.7)	—	−1.9 (1.7)
<i>Robustness w.r.t. ann. window</i>				
3-day window	−6.0 (2.7)	4.1 (2.9)	—	−1.2 (2.8)
<i>Robustness w.r.t. VAR</i>				
Without TS	—	3.6 (2.6)	—	−2.8 (2.5)
Without EPB	—	3.2 (3.2)	—	−3.1 (3.0)
Without VS	—	5.6 (1.9)	—	−0.8 (1.7)
Without CS	—	3.9 (2.4)	—	−2.4 (2.2)
Without ln PD	—	−0.9 (3.4)	—	−7.2 (3.5)
Adding Covid Period	—	2.0 (3.0)	—	−4.3 (3.0)
3-FFM instead of CAPM	—	2.6 (2.4)	—	−3.7 (2.5)
Corp. yields instead of risk-free	—	2.4 (2.7)	—	−3.9 (2.6)

Note: The table reports the welfare effect of trade announcements, as well as its three components defined in equation (8): the change in firm values, the discount-rate adjustment, and the change in tariff revenues. The first two columns sum to the cash-flow component of welfare. A positive discount-rate adjustment indicates that part of the decline in firm values reflects higher discount rates rather than lower expected cash flows. The welfare effect is expressed in % and its components in percentage points; standard errors use the same units. Standard errors, reported in parentheses next to each estimate, are obtained using the delta method (see Appendix C.D for details). An em dash indicates a component whose estimate and standard error are unchanged from the baseline by construction. Small firms are firms with fewer than 500 employees.

sume 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 −1.9%.

Announcement Window In the baseline results, we estimate deviations in firm values and the discount-rate adjustment 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 −6.0%, while the discount-rate adjustment increases from 2.5 to 4.1 percentage points. Overall, the estimated welfare effect is smaller in magnitude using the three-day window.

We explore the sensitivity of our estimated discount-rate adjustment in Appendix Ta-

ble [CIII](#). Compared to the estimates obtained using the one-day window (Table [VI](#)), 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, except the equity-premium bound, 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 [A1](#), 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 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 x_t . We report the results for the deviation in future risk-free rates and expected excess stock-market returns in Appendix Table [CIV](#) and the resulting numbers for the welfare effect in Table [VIII](#). Overall, we find similar changes in discount rates after successively removing each variable from the VAR with two exceptions. The first is 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.

Our baseline VAR is estimated using data through December 2019, that is, 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 [VIII](#), this specification yields a welfare estimate that is very similar to our baseline (−4.3% vs. −3.8%), suggesting that our results are not sensitive to the inclusion of the COVID period.

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. We estimated the CAPM betas used to compute the discount-rate adjustment using data over 2017 to 2019 and for firms traded on at least 360 days over this period. We winsorize betas at the 1st and 99th percentiles. 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 over the same period. 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 VIII, 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 C.F for more details.

Sources of Uncertainty To summarize, our aggregate welfare estimate is subject to four sources of uncertainty. The first is sampling uncertainty about the reaction of the stock market to the eleven announcements (a standard error of 1.6 percentage points). The second is sampling uncertainty about the discount-rate adjustment, which combines uncertainty about the VAR coefficients and about the announcement-day shocks to the VAR variables (a standard error of 2.7 percentage points, although its negative correlation with the sampling error in stock returns (a larger drop in the stock market leads the VAR to attribute more of the drop to higher discount rates) dampens its contribution to the uncertainty in the welfare estimate). The third is specification uncertainty, which reflects different sample or methodology choices, as shown in the rows of Table VIII (across the baseline and the alternative specifications, the welfare effect has a standard deviation of 1.6 percentage points). The fourth is uncertainty about the model that maps firm cash flows into welfare: for instance, we assume that tariffs do not change markups, that firm-specific factors are fixed, and that labor is perfectly mobile across firms. Allowing firms to adjust their firm-specific factors makes the loss larger (Appendix B.D), but the other assumptions could move the estimate in either direction.

E. Heterogeneity across Industries

The aggregate decline in firm cash flows masks substantial heterogeneity across industries. Appendix Figure C1 reports the deviation in firm cash flows separately for each of the Fama-French 30 industries. The decline is broad-based—cash flows fall in every

industry except utilities and food products—and its magnitude varies widely, from about 13% for machinery and 12% for steel to about 3% for communication and finance. The figure also decomposes the deviation of each industry into a market component (which reflects the expected decline due to the industry’s beta with respect to the market) and an idiosyncratic component (which captures the residual). The idiosyncratic component is negative in trade-exposed manufacturing industries such as machinery, steel, electrical equipment, and apparel, and positive in industries that are largely sheltered from trade, such as healthcare, utilities, and food products. Figure C2 shows that the idiosyncratic component tends to be more negative in industries whose inputs faced larger tariff increases (correlation of -0.71), which is consistent with the cross-sectional results in Table V. While our model assumes that labor is perfectly mobile across firms, these losses would be borne disproportionately by workers in the most affected industries if there were frictions to the reallocation of workers across industries.

F. 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 (10) 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 C.G, we can estimate the static price effect ($\hat{p}_{i0}^e$) by applying tariff pass-through estimates during the 2018 to 2019 trade war from Fajgelbaum et al. (2020) and Amiti, Redding, and Weinstein (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 0.15 to 0.25% (see Appendix C.G for details). These estimates are remarkably similar to those obtained by Amiti, Redding, and Weinstein (2019) and Fajgelbaum et al. (2020) who estimate welfare losses of around 0.3%. 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 trade 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). An upper bound on the magnitude 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 additional tariffs of 60% on China and 20% 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 to 2019 trade war, we calculate that the dynamic price effect would have lowered U.S. welfare by 0.72 to 1.59% depending on the assumptions made about tariff passthrough into domestic prices (see Appendix [C.G.2](#) for details). Subtracting the largest possible losses due to the price effects (using the upper ends of both ranges) still leaves a large welfare loss that the measured price effects cannot account for: -2.6% ($\approx -4.4 + 0.25 + 1.59$). In other words, our baseline estimates imply that markets anticipated the tariffs would cause a welfare loss much larger than static estimates suggest, and that most of this gap remains even after allowing for the largest plausible dynamic price effects.

This residual is the TFP effect of our decomposition. As discussed after Proposition [4](#), it captures any effect on cash flows that our measured price effects miss, including other future policies that the announcements made more likely (although, as shown in Appendix Table [AV](#), markets barely responded to non-tariff executive actions and orders targeting China). The split between the price effects and the residual therefore depends on how completely we measure tariff-induced price changes, but the total cash-flow welfare effect does not: we estimate it directly from asset prices.

IV. Validation and External Validity

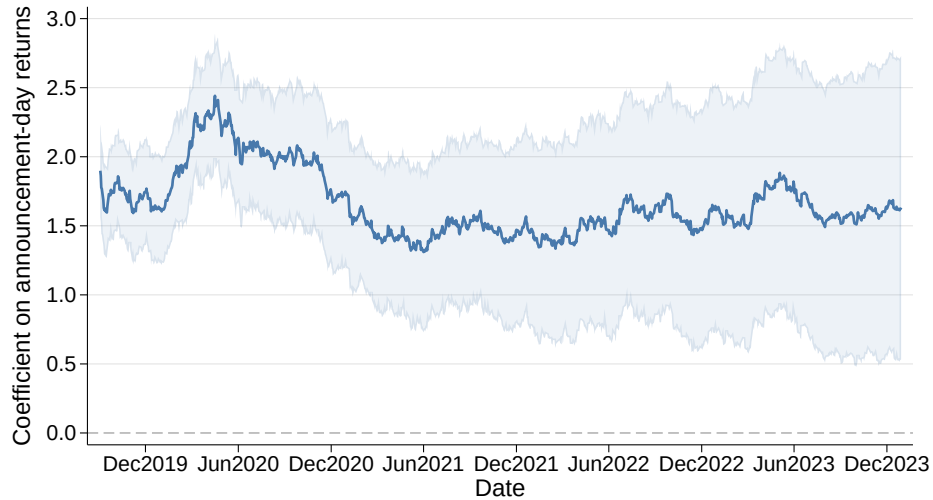
In this section, we validate our estimates and examine their external validity. First, we test whether announcement-day stock price movements persist over longer horizons, as they should if they reflect durable changes in firm values rather than short-lived overreaction. Second, we examine whether our cash-flow estimates predict realized cash-flow and other outcomes. Third, we examine whether the asset pricing patterns documented during the 2018 to 2019 trade war extend to the more recent trade policy announcements in 2025 to 2026.

A. Persistence of Announcement 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 to 2023 period on its cumulative return during announcement days alone. If announcement effects are

not undone by subsequent events, the coefficient should be 1, that is, 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.

Figure 7: 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% 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. Daily log returns are winsorized at the 1st and 99th percentiles on both sides of the regression, and the confidence band uses heteroskedasticity-robust standard errors. Firms are from our *Compustat-CRSP* sample.

We present the results from this exercise in Figure 7. The figure shows that the coefficient begins at approximately 2 at the end of the announcement sample, peaks at approximately 2.4 in April 2020, and then fluctuates around 1.5 through the end of 2023. Thus, if anything, the initial cross-sectional response is amplified rather than reversed. The coefficient remains above 1 throughout, its 95% confidence band excludes zero on every date, and from early 2021 onward the band includes 1: the cross-sectional differences in returns induced by tariff announcements are preserved 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.

B. Cash-Flow Validation

Did the cash-flow changes priced on announcement days materialize? We test whether the cash-flow changes estimated using equation (11) predict realized accounting 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 abnor-

mal returns on tariff-announcement dates also experienced worse future real outcomes. This relationship may be obscured if the effects of the trade war take time to appear in accounting data or if subsequent shocks are correlated with those during the trade war. Our theory may also 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:

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

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 over 2019 to 2024 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 discount-rate adjustment, obtained from the VAR, which is likely estimated with substantial error. We define an instrument, Z_i , as

$$Z_i \equiv \hat{M}_{i0} - \kappa_i \beta_{i,MKT} \sum_{k=1}^K \theta_{MKT,k}, \quad (19)$$

where $\theta_{MKT,k}$ is the market return (relative to the risk-free rate) on announcement day k , and $\beta_{i,MKT}$ is the same CAPM beta estimate we use in our welfare calculation. 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 C.B](#), is orthogonal to the measurement error in the VAR. Thus, the instrument is valid because it also satisfies the exclusion restriction.

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

	(1) $\ln(CF_{it})$	(2) $\ln(Prof_{it})$	(3) $\ln(Sales_{it})$	(4) $\ln(L_{it})$	(5) $\ln(Sales_{it}/L_{it})$	(6) $\ln(Inv_{it})$
<i>Panel A: Second Stage</i>						
$Post \times \hat{\Pi}_i$	1.20*** (0.35)	1.10*** (0.42)	0.93*** (0.21)	0.68*** (0.22)	0.27** (0.13)	0.86*** (0.24)
<i>Panel B: First Stage</i>						
$Post \times Z_i$	1.06*** (0.01)	1.06*** (0.01)	1.06*** (0.01)	1.06*** (0.01)	1.06*** (0.01)	1.05*** (0.01)
First-stage F-stat	5702	5702	5702	5688	5688	5496
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Within-R2	0.835	0.835	0.835	0.834	0.834	0.850
Observations	14,456	14,456	14,456	14,439	14,439	12,729

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. $\hat{\Pi}_i$ is our estimate of the expected present discounted value of deviations in firm cash flow, cumulated across all announcement days using one-day windows. Z_i is defined in equation (19). $Post$ is a dummy variable that equals one for years 2019 to 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 $xrd + (0.3 \times sga)$ 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table IX 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 1.20, which is not statistically different from 1. In other words, we can reject the hypothesis that $\hat{\Pi}_i$ is uncorrelated with future accounting cash flow and cannot reject the hypothesis that cash flow estimates from financial markets move on average one-to-one with realized cash flows over 2019 to 2024. 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 0.93 log-point decrease in sales but only a 0.68 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 0.27 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 B.D 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.²⁵

C. *The Effect of Trade Policy Announcements in President Trump’s Second Term*

The first version of this paper, which documented the asset-pricing patterns described above, circulated before the 2024 presidential election. The tariff announcements of President Trump’s second term therefore provide a new set of episodes to examine whether

²⁵Because 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 B.D 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 effect 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.

these patterns extend. As of this writing, the data needed to construct cash-flow estimates for this more recent trade war are not yet available, so we focus on asset prices. 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 to 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 (IEEPA) in the recent period was viewed as legally questionable.²⁶ 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.

In Table X, 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 announcements, like the “Liberation Day” tariffs, which imposed very high rates on all countries including China; we exclude announcements solely targeting non-China countries or particular industries, such as steel tariffs. The announcement dates for the 2025 to 2026 trade war are more difficult to identify cleanly than those from the 2018 to 2019 period, as in some cases multiple announcements occurred on the same day—sometimes moving in opposite directions. The second column indicates whether each announcement date consisted of an announced increase in tariffs, a decrease (or pause), or a mix of both.

The first announcement in 2025 was on January 22, when the U.S. announced it was considering an additional 10% 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. On the first date, the offsetting announcement was not trade-related—there was an AI investment announcement of \$500 billion. On the second date, 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

²⁶For 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% as early as September 2025.

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

Event Date	Tariff Change	Description	Log 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	0.8
		U.S. paused 25% tariff on Mexico and Canada for 30 days	
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%	8.7
		China retaliates with 84% tariff	
		U.S. suspends Liberation tariffs on all countries	
		U.S. increases tariff on China to 125%	
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	0.6
		U.S. imposes 10% global tariff on all countries under Section 122	
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 announcement dates where a mixture of increases and decreases occurred.

U.S. exports. The next two announcements 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 5% 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% reciprocal tariff on top of the existing 20% fentanyl tariff, bringing the total tariff on Chinese goods to 54%. The following day, April 4, China retaliated by imposing 34% 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%.

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 announcement day, 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%.

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 0.2%, 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% 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% the following day.

The final events reported in Table X 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 to 2026, Table X demonstrates that the cumulative stock-market declines on tariff-increase announcement days in 2025 to 2026 are similar in magnitude to those in 2018 to 2019. 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 to 2019 trade war. Equity returns fell 6.1% on U.S. announcement days and a further 5.4% on Chinese announcement days. On announcement dates consisting solely of announced tariff decreases or pauses, aggregate returns increased 3.8%. Days with 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 announcement dates was 10.1%.

These tariff announcements also had an impact on yields in predictable ways. We report the impact of the 2025 to 2026 tariff announcements on yields in Appendix Table DI in the Internet Appendix, which we compare with the 2018 to 2019 results in Appendix Table AVI. 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 to 2019 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.

V. 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 to 2019. We document four stylized facts that motivate our approach: tariff announcements produced large, broad, and persistent declines in stock prices; tariff protection benefited domestic firms only when it was applied broadly across foreign suppliers rather than targeted at China alone; firms directly exposed to China through importing, exporting, or multinational sales suffered relatively worse returns;

and announcements lowered nominal and real yields while raising equity-risk premia. Using an infinite-horizon specific factors model, we show how changes in firm valuations map into 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 baseline point estimate of the welfare loss, 3.8%, is imprecise, but it is more than ten times the loss implied by static trade models. This gap suggests that markets expected tariffs to affect firms well beyond their static price effects, for example through lower innovation. The announcements may also have raised the probability that investors attached to other policies harmful to firms, such as export controls or restrictions on investment.

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.

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Internet Appendix for “Trade Protection, Stock-Market Returns, and Welfare”¹

September 29, 2026

A. Appendix for Section I (Stylized Facts)

A. *Announcement Dates*

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

Table AI: Details on Announcement Dates, 2018–2019

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

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Table AII: Details on Announcement Dates, 2025–2026

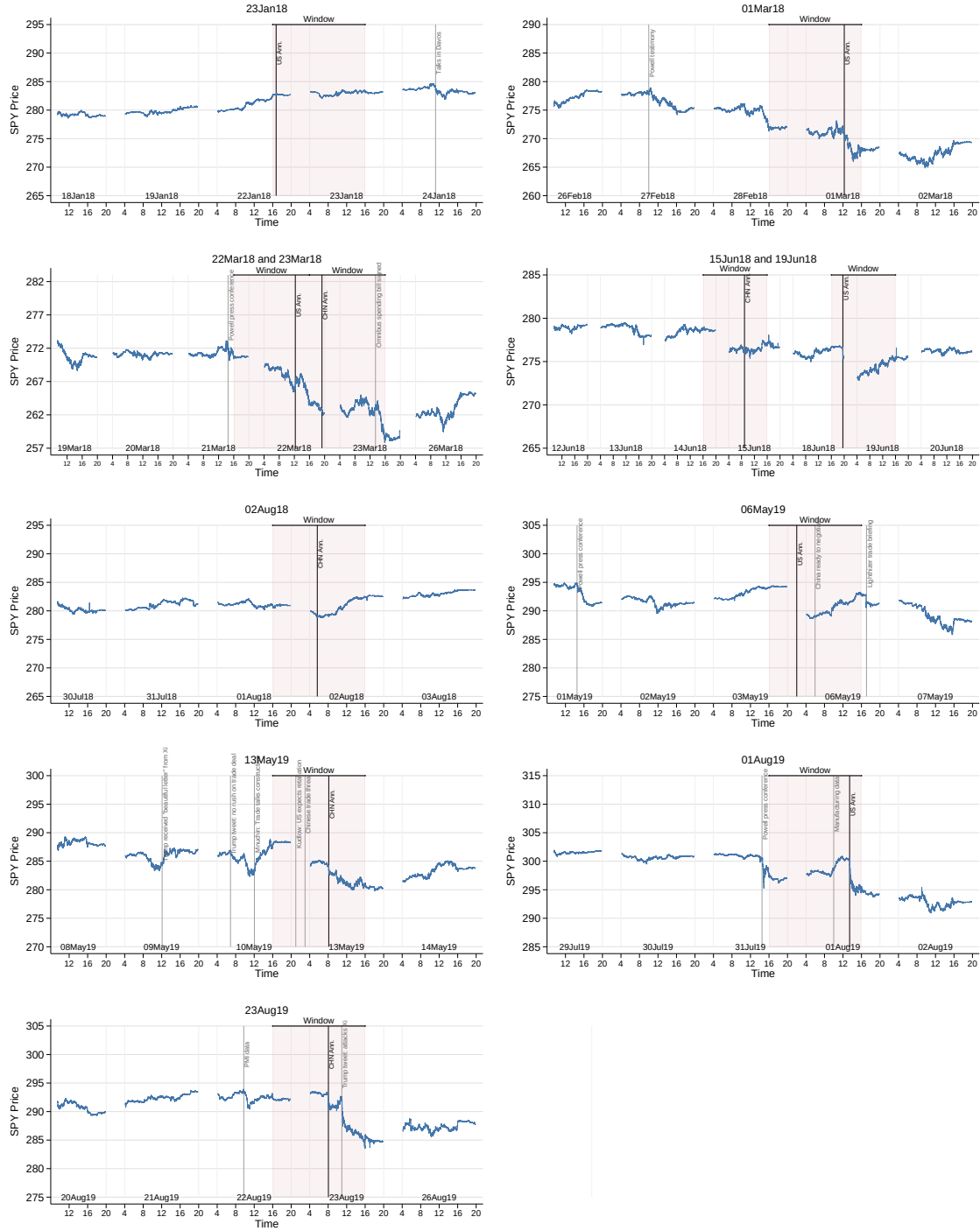
Announcement Date	Implementation Date	Country	News Link
22jan2025*	04feb2025	U.S.	NYT
04feb2025	10feb2025	China	NBC News
27feb2025	04mar2025	U.S.	Barron's
04mar2025	10mar2025	China	Bloomberg
03apr2025*	05apr2025	U.S.	Bloomberg
04apr2025	10apr2025	China	Bloomberg
09apr2025*	09apr2025	U.S.	Reuters
09apr2025	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: Announcement dates with the first news release on a weekday after trading hours (4:00 PM EST) are flagged by an asterisk (*). Announcement dates with the first news release on a weekend are flagged by two asterisks (**). In these instances, the trading day for the announcement is the first trading day after the news release, which is listed as the announcement date in the table.

B. 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). To minimize microstructure noise, we take the median bid-ask midpoint within each 10-second interval 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 A1: 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 announcements listed in Table I.

Figure A1 plots SPY prices over several trading days around each announcement, with

the announcement times marked with solid vertical lines (black for the tariff announcements, gray for other news). Table AIII 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 AIII: Notable Intraday Price Movements in Figure A1

Date	Largest Move	Likely Cause
<i>Moves inside announcement windows</i>		
23Jan18	+0.4%	Solar/washing machine tariffs
01Mar18	−2.5%	Steel/aluminum tariffs
22Mar18	−2.6%	U.S. \$60B tariffs on China
23Mar18	−2.6%	China retaliates on 128 products
15Jun18	−1.2%	China retaliates on \$50B
19Jun18	−1.1%	U.S. announces tariffs on \$200B
02Aug18	−0.6%/+1.2%	China retaliates on \$60B
06May19	−1.7%	Trump tweet: raise tariffs to 25%
13May19	−2.8%	China retaliates on \$60B
01Aug19	−2.2%	Trump tweet: 10% on \$300B
23Aug19	−3.1%	China retaliates; Trump escalates
<i>Moves outside announcement windows</i>		
27Feb18	−1.5%	Powell congressional testimony
19Mar18	−2.1%	Cambridge Analytica scandal
21Mar18	−1.0%	FOMC meeting
26Mar18	+2.8%	Reports of U.S.-China negotiations
13Jun18	−0.5%	FOMC rate hike
01Aug18	−0.7%	FOMC statement / trade escalation reports
10May19	−1.5%/+2.3%	25% tariff takes effect; talks resume
31Jul19	−1.9%	FOMC hawkish rate cut

Note: This table lists all notable intraday price movements visible in Figure A1. “Largest Move” reports the largest fall (or rise) in the SPY price during the regular trading session, measured from its highest (or lowest) level since the previous day’s close, using one-minute rolling medians of the 10-second SPY price series plotted in the figure; both are shown when the day had large moves in both directions.

C. *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 to 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 30-minute window after each tweet (when the tweet occurs during extended trading hours, 4:00 AM to 8:00 PM EST) or in the close-to-open return (when it occurs outside extended trading hours). Table [AIV](#) reports these results. The cumulative market effect of these escalation tweets outside our announcement windows is small (-0.47% over 30-minute windows), suggesting that tweets not tied to concrete policy actions had little market impact.

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 [AV](#) 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 announcement days are specifically related to the expected economic impact of the tariff announcements.

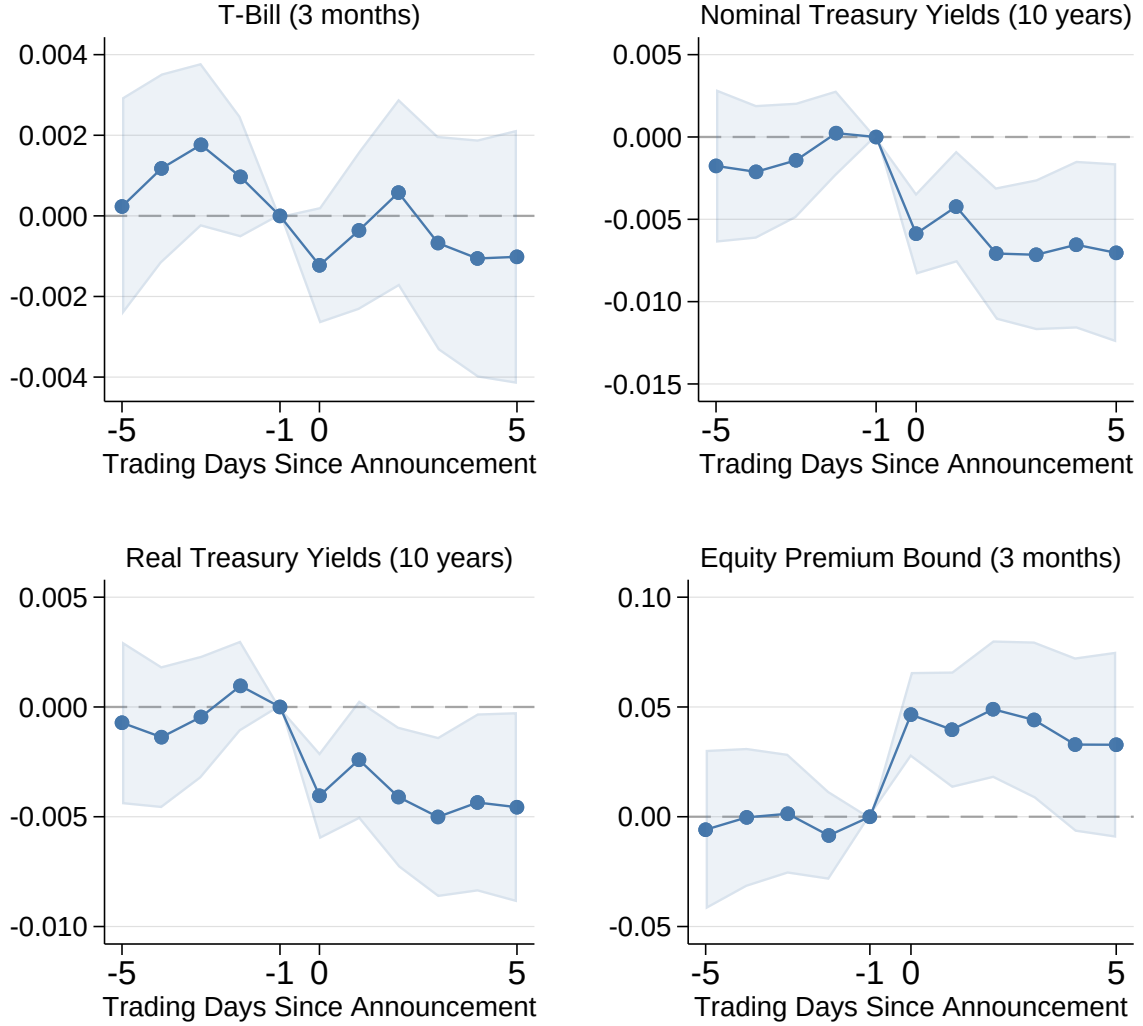
D. *Returns of Other Asset Classes Pre and Post Announcement Days*

In Figure [1](#), we reported the dynamic effect of announcements on stock-market returns over a ten-day window. In the same spirit, Figure [A2](#) reports the dynamic effect of announcements on the changes in nominal yields, real yields, and the equity-premium bound over a ten-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.

E. *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

Figure A2: The Dynamics of Discount Rates around Tariff Announcements



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

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

where $D_{s,t} = 1$ if day t is s days after an announcement; $D_{s,t} = 0$ otherwise, and $\text{ES}_{d,t}$ 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 $s \geq -1$. Shaded areas correspond to the 95% confidence interval computed using homoskedastic standard errors.

Table AIV: Stock-Market Returns around Trade-Related Presidential Tweets

Date	Time	Summary	Log Return (x100)	
			30min-window	Close-to-open
<i>Panel A: Outside Announcement Windows</i>				
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
<i>Panel B: Inside Announcement Windows</i>				
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	U.S. losing \$500-800B/yr on trade; not anymore	0.09	
13may19	06:08	China pays tariffs not U.S. 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 30-minute window after the tweet (when the tweet occurs during extended trading hours, 4:00 AM to 8:00 PM EST) or as close-to-open returns (when the tweet occurs outside extended trading hours). Returns use SPY bid-ask quote midpoints; the close-to-open return runs from the median quote in the last hour of the previous extended session (7:00 to 8:00 PM) to the median quote in the first hour of the next one (4:00 to 5:00 AM). Stars indicate statistical significance under a normal approximation, using the standard deviation of daily market returns over 2017–2019, divided by the square root of 13 for 30-minute windows (a trading day has 13 half-hours); cumulative returns are divided by the square root of the number of windows. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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

Table AV: Stock-Market Returns around Non-Tariff Actions Targeting China

Date	Description	Log Return (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 two columns report the date and description of each event. The last column reports the log stock-market return on each day. The log return is the log of one plus the proportional change of the value-weighted market portfolio return from *CRSP*.

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% of all imports from China and 58% 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

Table AVI: Change in Other Asset Prices on Tariff-Announcement Days

Announcement Date	Country	T-Bill (x100)	Nom. 10y Yield (x100)	Real 10y Yield (x100)	Breakeven Inflation (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 yield-to-maturity on 10-year Treasuries from [Gürkaynak, Sack, and Wright \(2007\)](#), and the real yield-to-maturity from [Gürkaynak, Sack, and Wright \(2010\)](#). 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 \(2017\)](#).

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 the 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.

F. 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 for firms that traded on at least 120 days:

$$R_{it} - R_{f,t} = \alpha_i + \beta_{i,MKT}^{2017} [R_{MKT,t} - R_{f,t}] + \epsilon_{it},$$

Table AVII: Summary Statistics on Exposure Variables

	N	Mean	p10	p25	p50	p75	p90
China Import Intensity	2,431	0.01	0.00	0.00	0.01	0.02	0.03
China Export Share	2,431	0.01	0.00	0.00	0.00	0.02	0.03
Manufacturing Industry	2,431	0.40	0.00	0.00	0.00	1.00	1.00
China Importer	2,431	0.31	0.00	0.00	0.00	1.00	1.00
China Exporter	2,431	0.04	0.00	0.00	0.00	0.00	0.00
China Revenue Share	2,363	0.03	0.00	0.00	0.00	0.02	0.07
Size (Employment)	2,431	14,018	68	419	2,102	8,700	29,060

Note: Summary statistics for 2017 exposure measures in the cross-section sample. N denotes nonmissing observations, after setting missing China imported-input intensity and China export share to zero; p10–p90 denote percentiles. Shares are fractions, indicators are zero-one, and employment is measured in workers. Variables are defined in Table V.

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

$$AR_{it} = R_{it} - R_{f,t} - \left(\hat{\alpha}_i + \hat{\beta}_{i,MKT}^{2017} [R_{MKT,t} - R_{f,t}] \right).$$

B. Appendix for Section II (A Model Mapping Asset Prices to Welfare)

A. Proofs

Proof of Proposition 1. Totally differentiating the conditions in (2) yields:

$$\hat{y}_{it} = -\hat{a}_{vit}, \tag{B1}$$

and

$$\sum_i \frac{L_i}{L} (\hat{a}_{Lit} - \hat{a}_{vit}) = \hat{L},$$

where we have used the fact that in the baseline equilibrium $L_{it} = L_i$. Substituting equation (3) into the previous equation yields

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

or

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

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

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

Substituting equation (B1) into equation (3) yields

$$-\hat{y}_{it} - \hat{a}_{Lit} = \sigma (\hat{w}_t - \hat{\pi}_{it}),$$

or

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

The value function of an agent with log utility is

$$\mathcal{W}_0 = \sum_{t=0}^{\infty} \beta^t \mathbb{E}_0 [\ln C_t],$$

where β denotes the agent's subjective discount factor. The consumption-equivalent welfare effect $\mathcal{C}$ is defined as the percentage 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:

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

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 B.C).

Differentiating the PDV relationship (7) gives

$$\begin{aligned}
\hat{M}_{i0} &= \frac{1}{M_{i0}} E_0 \left[\sum_{t=0}^{\infty} \frac{\pi_{it} V_i}{R_{i1} \dots R_{it}} \left(\hat{\pi}_{it} - \sum_{s=1}^t \hat{R}_{is} \right) \right] \\
&= \frac{1}{M_{i0}} E_0 \left[\sum_{t=0}^{\infty} \frac{\pi_{it} V_i}{R_{i1} \dots R_{it}} \hat{\pi}_{it} \right] - \frac{1}{M_{i0}} \sum_{t=1}^{\infty} E_0 \left[\left(\sum_{s=t}^{\infty} \frac{\pi_{is} V_i}{R_{i1} \dots R_{is}} \right) \hat{R}_{it} \right] \\
&= \frac{1}{M_{i0}} E_0 \left[\sum_{t=0}^{\infty} \frac{\pi_{it} V_i}{R_{i1} \dots R_{it}} \hat{\pi}_{it} \right] - \frac{1}{M_{i0}} \sum_{t=1}^{\infty} E_0 \left[\frac{1}{R_{i1} \dots R_{it}} E_t \left[\sum_{s=t}^{\infty} \frac{\pi_{is} V_i}{R_{it+1} \dots R_{is}} \right] \hat{R}_{it} \right] \\
&= \sum_{t=0}^{\infty} E_0 \left[\frac{\pi_{it} V_i}{M_{it}} \frac{M_{it}/M_{i0}}{R_{i1} \dots R_{it}} \hat{\pi}_{it} \right] - \sum_{t=1}^{\infty} E_0 \left[\frac{M_{it}/M_{i0}}{R_{i1} \dots R_{it}} \hat{R}_{it} \right],
\end{aligned}$$

where the second line uses the fact that $M_{it} = E_t \left[\sum_{s=t}^{\infty} \frac{\pi_{is} V_i}{R_{it+1} \dots R_{is}} \right]$, following (7). 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 \(1988\)](#)).² 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:

$$\hat{M}_{i0} = \sum_{t=0}^{\infty} (1 - \rho) \rho^t E_0 [\hat{\pi}_{it}] - \sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{it}].$$

□

Before we prove Proposition 4, we prove the following lemma which maps movements in prices and productivity into movements in cash flow:

LEMMA B.1: *The sum of log changes in the effective rates of protection ($\hat{p}_{it}^e$) 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 ($\hat{\pi}_{it}$):*

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

²The 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.

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

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

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

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

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

$$\omega_{Lit} \hat{w}_t + \omega_{Vit} \hat{\pi}_{it} + \sum_j \omega_{jit} \hat{q}_{jt} - \hat{A}_{it} = \hat{p}_{it}, \quad (\text{B2})$$

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 (9) and Proposition (1), we can rearrange equation (B2) to arrive at the first equation in the proposition:

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

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

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

where Proposition (1) was used to derive the second line. Substituting the solution for $\hat{w}_t$

back into the first line, we get

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

□

Proof of Proposition 4. The first term in the equation gives us the role that cash flow plays in determining welfare:

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

Define

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

Then Lemma B.1 can be written compactly as

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

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

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

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

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

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

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

Finally, since

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

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,

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

Equivalently,

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

Using the identity

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

we obtain

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

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

B. 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 effect of increasing productivity in this setup is to cause output, wages, and payments to the fixed 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

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

where $\phi \geq 1$ is TFP growth. Since labor and the fixed 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

$$\sum_i \frac{a_{Li0}}{\phi^t} (\phi^t y_{i0}) = L \quad \text{and} \quad \frac{a_{Vi0}}{\phi^t} (\phi^t y_{i0}) = V_i.$$

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, that is, $\Delta \ln m_{jit} = \Delta \ln y_{it} = \phi$. 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

$$\begin{aligned} a_{Lit} w_t + a_{Vit} \pi_{it} + \sum_j a_{jit} q_{jt} &= p_{it}, \\ \frac{a_{Li0}}{\phi^t} (\phi^t w_0) + \frac{a_{Vi0}}{\phi^t} (\phi^t \pi_{i0}) + \sum_j a_{ji0} q_{jt} &= p_{it}, \\ a_{Li0} w_0 + a_{Vi0} \pi_{i0} + \sum_j a_{ji0} q_{jt} &= p_{it}. \end{aligned}$$

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 fixed factor productivity growth affects all firms equally because intermediate input usage, consumer demand, and supply will all grow at a rate of ϕ .

C. 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 B.2: *The consumption-equivalent welfare effect of the deviation path $(\hat{C}_t)_{t=0}^\infty$ is*

$$\mathcal{C} = \frac{\sum_{t=0}^\infty \mathbb{E}_0 [\Lambda_{0 \rightarrow t} C_t \hat{C}_t]}{\sum_{t=0}^\infty \mathbb{E}_0 [\Lambda_{0 \rightarrow t} C_t]},$$

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

Proof: Denote by $\mathcal{W}_0$ 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:

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

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

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

Solving for $\mathcal{C}$ gives:

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

To conclude, notice that, for any available asset i with return $R_{i,0 \rightarrow t}$ 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

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

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

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

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

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 B.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

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

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 by $\Lambda_{t \rightarrow t+k}$ the household SDF between t and $t+k$ and $W_t = \mathbb{E}_t [\sum_{k=0}^{\infty} \Lambda_{t \rightarrow t+k} C_{t+k}]$ 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:

$$\Lambda_{t \rightarrow t+k} = \left(\beta^k \left(\frac{C_{t+k}}{C_t} \right)^{-1/\psi} \right)^\theta \left(R_{W,t \rightarrow t+k}^{-1} \right)^{1-\theta}, \quad (\text{B3})$$

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 $R_{W,t \rightarrow t+k} = R_{W,t+1} \dots R_{W,t+k}$ denotes the cumulative return on the wealth portfolio between t and $t+k$. In the special case where $\psi = 1/\gamma$ (separable preferences), equation (B3) gives the familiar expression $\Lambda_{t \rightarrow t+k} = \beta^k (C_{t+k}/C_t)^{-\gamma}$.

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:

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

where the last equality uses the definition of $\rho \equiv 1 - C_t/W_t$. Combining with (B3) allows us to simplify the expression for the SDF along the baseline path:

$$\Lambda_{t \rightarrow t+k} = \left(\beta^k \left(\frac{C_{t+k}}{C_t} \right)^{-1/\psi} \right)^\theta \left(\rho^k \frac{C_t}{C_{t+k}} \right)^{1-\theta} = \beta^{\theta k} \rho^{(1-\theta)k} \left(\frac{C_{t+k}}{C_t} \right)^{-\gamma}, \quad (\text{B4})$$

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

definition of total wealth, we get

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

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

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

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

Plugging this into (B4) gives a simplified expression for the SDF along the baseline path:

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

Combining this formula for the SDF with the expression for the welfare effect $\mathcal{C}$ obtained

in Lemma B.2 gives:

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

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

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 $\frac{C_t^{1-\gamma}}{E_0[C_t^{1-\gamma}]}$ represent the agent's discounting of different states of nature (they sum up to one across states of nature in a given period).

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

$$\mathcal{C} = \sum_{t=0}^{\infty} (1-\rho) \rho^t E_0 [\hat{C}_t] + \sum_{t=1}^{\infty} (1-\rho) \rho^t \text{cov}_0 \left(\frac{C_t^{1-\gamma}}{E_0[C_t^{1-\gamma}]}, \hat{C}_t \right).$$

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 B.1.1: *For an agent with arbitrary Epstein-Zin preferences, the consumption-*

equivalent welfare effect of the deviation path $(\hat{C}_t)_{t=0}^\infty$ is

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

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

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

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

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

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:

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

where $\kappa_{l,0 \rightarrow t}$ 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:

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

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. $\square$

When the representative agent has a risk aversion different from one, the consumption-equivalent welfare effect depends not only on the change in average log 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.

D. Extension for Endogenous Factors

In the baseline model, the quantity of each firm-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 firm-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 effect—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:

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

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 firm-specific factor is endogenous, the market-clearing condition for the fixed factor becomes $a_{Vit} y_{it} = V_{it}$, and log-differentiating gives

$$\hat{y}_{it} = \hat{V}_{it} - \hat{a}_{Vit}. \quad (\text{B5})$$

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

$$\sum_i \frac{L_i}{L} (\hat{a}_{Lit} + \hat{y}_{it}) = \hat{L}_t. \quad (\text{B6})$$

Substituting (B5) into (B6) and using the CES condition $\hat{a}_{Vit} - \hat{a}_{Lit} = \sigma(\hat{w}_t - \hat{\pi}_{it})$ yields

$$\hat{w}_t = \sum_i \frac{L_i}{L} \hat{\pi}_{it} + \frac{1}{\sigma} \left(\sum_i \frac{L_i}{L} \hat{V}_{it} - \hat{L}_t \right). \quad (\text{B7})$$

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 firm-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.

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

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

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

The first term is identical to the baseline welfare expression and can be estimated from stock prices and the VAR as in Section III. 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 firm-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 (B7) and solving for $\hat{w}_t$ gives

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

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

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

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

C. Appendix for Section III (Estimating the Welfare Effect of Tariff Announcements)

A. Details on VAR estimation

We now describe more precisely how we construct the set of variables used in the VAR discussed in (17). 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, divided by four. 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, Sack, and Wright \(2007\)](#)) 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 difference in log book-to-market value between the top 10% and the bottom 10% 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 annualized yield of 3-month T-Bills, both in logs and divided by four. 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. We winsorize all variables in the VAR at the 1st and 99th percentiles of their distribution over 1996 to 2022.

Table [CI](#) 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 the discount-rate adjustments.

B. The Construction and Validity of the Instrument

The Measurement Problem In Section [IV.B](#) 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:

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

Table CI: VAR Matrix B

	F.ln R_f	F.ln R_{EMKT}	F.TS	F.EPB	F.VS	F.CS	F.ln PD
ln R_f	0.77*** (0.07)	3.03 (2.44)	0.12 (0.13)	-0.09 (0.85)	-3.48 (2.70)	-0.06 (0.05)	6.50** (2.59)
ln R_{EMKT}	-0.00 (0.00)	0.14 (0.09)	0.00 (0.01)	-0.04 (0.03)	-0.10 (0.13)	-0.00 (0.00)	0.12 (0.09)
TS	0.07 (0.05)	2.92* (1.59)	0.39*** (0.13)	-0.21 (0.34)	1.96 (2.75)	-0.08** (0.03)	4.92*** (1.64)
EPB	0.02** (0.01)	0.61 (0.40)	-0.00 (0.02)	0.56*** (0.09)	0.52 (0.47)	0.00 (0.01)	0.88** (0.38)
VS	-0.00 (0.00)	0.00 (0.02)	-0.00* (0.00)	-0.01 (0.01)	0.95*** (0.04)	-0.00 (0.00)	0.05** (0.02)
CS	-0.39** (0.17)	-11.63* (6.27)	1.80*** (0.48)	1.73 (1.43)	-14.68 (9.12)	1.15*** (0.12)	-16.55** (6.52)
ln PD	-0.00 (0.00)	-0.17*** (0.04)	0.01* (0.00)	0.03*** (0.01)	-0.01 (0.07)	0.00*** (0.00)	0.79*** (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 (17): $x_{t+63} = a + Bx_t + u_{t+63}$ 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 CII: Effect of Tariff Announcements on VAR Variables (One-Day Window)

Variable	Announcement (x100)	
ln R_f	-0.03*	(0.02)
ln R_{EMKT}	-12.53***	(2.56)
TS	-0.47***	(0.14)
EPB	4.64***	(0.97)
VS	9.56***	(2.92)
CS	-0.05*	(0.03)
ln PD	-12.68***	(2.98)
SMB	1.72	(1.66)
HML	-4.08**	(1.91)

Note: The table reports the sum of θ_k in the regression (18). The sample includes all 753 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 discount-rate adjustment (estimated

Table CIII: Effect of Tariff Announcements on VAR Variables (Three-Day Window)

Variable	Announcement (x100)	
$\ln R_f$	-0.04	(0.03)
$\ln R_{EMKT}$	-11.45***	(4.43)
TS	-0.31	(0.23)
EPB	3.98**	(1.67)
VS	5.64	(5.00)
CS	-0.01	(0.05)
$\ln PD$	-13.08**	(5.10)
SMB	2.83	(2.79)
HML	-2.09	(3.25)

Note: The table reports the sum of $n_k \theta_k$ in the regression (18), using three-day windows around announcements, where n_k is the number of trading days in the window of announcement k (three, or two when adjacent announcements truncate the window). The sample includes all 753 trading days from 2017 to 2019. Standard errors in parentheses.

via the VAR described in Section III.A).

Following equation (12) of the paper, we estimate the effect of tariff announcement k on the log equity return of firm i from the regression:

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

where D_{kt} is an indicator equal to one if day t falls in the window of announcement k , and $\text{ES}_{d,t}$ is the surprise in macroeconomic release series d on day t . The deviation in firm value is then constructed as in equation (13) 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 announcements, after controlling for contemporaneous macroeconomic surprises on each day.

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

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

Table CIV: Robustness of Discount-Rate Adjustments

Specification	Discount-rate adjustments $\sum_{t \geq 1} \rho^t E_0[\hat{R}_{j,t}]$				
	RF (x100)	MKT-RF (x100)	MKT (x100)	SMB (x100)	HML (x100)
Baseline	0.2 (1.0)	4.0 (4.4)	4.2 (4.4)		
Without TS	-0.1 (1.1)	6.2 (4.4)	6.1 (4.3)		
Without EPB	-0.0 (1.1)	5.5 (5.3)	5.5 (5.3)		
Without VS	0.8 (0.7)	8.0 (3.3)	8.8 (3.2)		
Without CS	-0.4 (1.0)	7.4 (4.3)	7.0 (4.1)		
Without ln PD	-0.1 (1.0)	-1.3 (5.0)	-1.4 (5.3)		
FF 3-Factor Model	0.6 (1.0)	2.9 (4.5)	3.4 (4.4)	0.6 (2.8)	2.9 (3.9)
3-Days Window	0.1 (0.9)	6.7 (4.5)	6.8 (4.6)		
Adding Covid Period	-1.3 (1.9)	5.7 (4.4)	4.4 (4.6)		

Note: The table reports $\rho B(I - \rho B)^{-1} dx_0$, where x_0 is reported in Table CII (using a one-day window) and Table CIII (using a three-day window). Each column reports the discounted sum of revisions to one return, $\sum_{t \geq 1} \rho^t E_0[\hat{R}_{j,t}]$: the risk-free rate (RF), the excess market return (MKT-RF), the market return (MKT), and the SMB and HML factor returns.

so that the observed cash-flow deviation satisfies:

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

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.

Defining the Instrumental Variable The coefficients $\theta_{i,k}$ from regression (12) 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 $\sum_d \gamma_{i,d} \text{ES}_{d,t}$ 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:

$$\Psi_i \equiv \sum_{k=1}^K \theta_{i,k} - \beta_{i,MKT} \sum_{k=1}^K \theta_{MKT,k}, \quad (C1)$$

where $\theta_{MKT,k}$ is the market return on announcement day k and $\beta_{i,MKT}$ is the same CAPM beta estimate we use in our welfare calculation. 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.

Relevance The instrument Z_i is correlated with $\hat{\Pi}_i$ through its relationship with $\hat{M}_{i0}$. From equations (13) and (C1), we can write:

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

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:

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

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:

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

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 adjustment is:

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

where the two infinite sums are computed as $\mathbf{e}_1' \rho \mathbf{B} (\mathbf{I} - \rho \mathbf{B})^{-1} d\mathbf{x}_0$ and $\mathbf{e}_2' \rho \mathbf{B} (\mathbf{I} - \rho \mathbf{B})^{-1} d\mathbf{x}_0$, respectively, using the VAR matrix $\mathbf{B}$ and the aggregate announcement surprise vector $d\mathbf{x}_0$. 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 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 adjustment is generated by an aggregate discount-rate error ϵ^{agg} that enters firm i 's measured discount-rate adjustment in proportion to its market beta. Then

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

so that

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

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. The identifying assumption would fail only if firms with larger idiosyncratic tariff-related cash-flow news also systematically had larger 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.

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.

C. Details on Reweighting the Compustat-CRSP Sample

We now detail how we reweight the sample of firms in our *Compustat-CRSP* sample to approximate the distribution of firms in the U.S. across sectors and employment size. We 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 (below 500, 500–4,999, 5,000–19,999, and 20,000 or more). For the 2-digit NAICS industry 11 (agriculture), we only use two employment bins, below or above 20,000, and for industries 61 (education), 62 (health care), and 81 (other services), we merge the two smallest bins into a single bin below 5,000, to ensure that there are enough firms within each bin. We denote by 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 announcement 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

$$X \equiv \left(1 - \frac{\text{TR}}{C}\right) \sum_{s \in \Omega^S} \frac{\text{VA}_s}{\sum_{s' \in \Omega^S} \text{VA}_{s'}} X_s,$$

where Ω^S denotes the set of 18 sectors, which excludes government, housing, other real estate, and management of companies (NAICS 55), VA_s is the value added of sector s and C is personal consumption expenditures plus tariff revenue, based on *BEA* and tariff-

revenue data. The factor $1 - \text{TR}/C$ is the share of consumption not financed by tariff revenue in equation (8). Note that the final expression can be thought of as a weighted average of X_i :

$$X = \sum w_i X_i \quad \text{where} \quad w_i \equiv \left(1 - \frac{\text{TR}}{C}\right) \frac{\text{VA}_s}{\sum_{s' \in \Omega^S} \text{VA}_{s'}} \cdot \frac{L_{sb}}{\sum_{b' \in \Omega_s^B} L_{sb'}} \cdot \frac{L_i}{\sum_{i' \in \Omega_{sb}} L_{i'}}.$$

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

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

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

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

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

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

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

which separates the welfare effect into cross-sectional quantities (which depend on in-

dividual 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 $\sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{MKT,t} - \hat{R}_{f,t}]$, and the deviation in future risk-free rates $\sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{f,t}]$ —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.

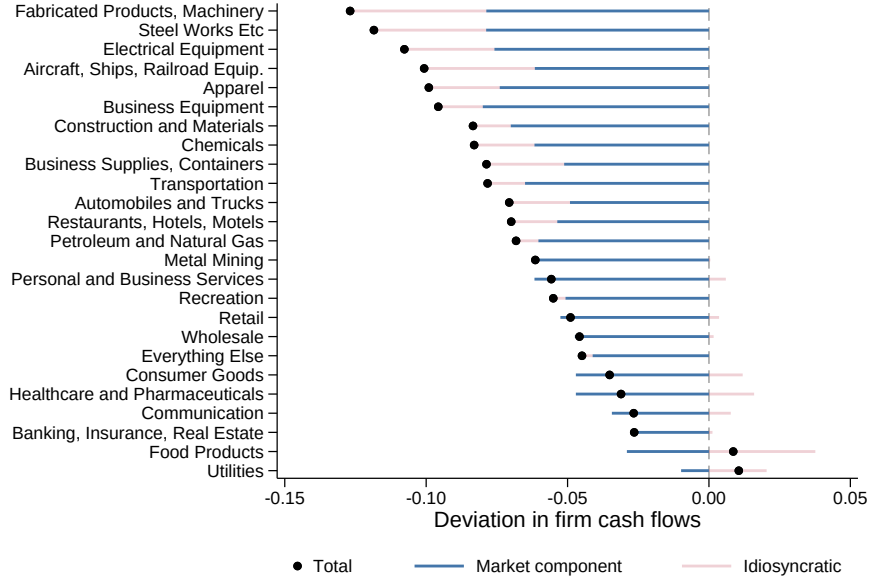
E. Average Deviation in Cash Flows by Industry

Figure C1 reports the deviation in firm cash flows by industry. We match each firm in our sample to one of the Fama-French 30 industries based on its SIC code, grouping industries with fewer than 20 firms into the “Everything Else” category. We then construct the industry-specific cash-flow loss as the average of firm-level deviations within each industry, weighting each firm by its employment. Let $\mathcal{C}_j$ denote the weighted average deviation in firm cash flows within industry j . For each industry j , we decompose the deviation into a market component (that captures the deviation one could expect from the industry’s beta) and an idiosyncratic component (that captures the idiosyncratic deviation of the industry). More precisely, we use the following formula:

$$\mathcal{C}_j = \underbrace{\beta_j \left(\hat{R}_{MKT,0} + \sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{MKT,t} - \hat{R}_{f,t}] \right)}_{\text{market component}} + \underbrace{\sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{f,t}] + \sum_{i \in j} \omega_i \kappa_i \hat{\epsilon}_{i0}}_{\text{idiosyncratic}},$$

where ω_i denotes the weight of firm i normalized to sum to one within the industry, $\beta_j \equiv \sum_{i \in j} \omega_i \kappa_i \beta_{i,MKT}$ is the industry’s leverage-adjusted market beta, and $\hat{\epsilon}_{i0} = \hat{R}_{i0} - \beta_{i,MKT} \hat{R}_{MKT,0}$ is the firm-specific component of announcement returns. Figure C2 plots the idiosyncratic component of each industry against the increase in tariffs on its inputs between December 2017 and December 2019. The input tariff increase multiplies the tariff change of each input by the share of imports of that input in the industry’s total inputs, including goods, services, and wages, and sums across inputs. It is averaged across the firms of the industry using the same weights.

Figure C1: Average Deviation in Cash Flows by Industry



Note: The figure reports the deviation in firm cash flows, cumulated across all announcement days and averaged within each Fama-French 30 industry, weighting each firm by its employment. Industries are ranked from most to least affected. The dot reports the total deviation, which is split into a market component and an idiosyncratic component. Industries with fewer than 20 firms in the sample (beer and liquor, tobacco, printing and publishing, textiles, and coal) are grouped into “Everything Else”.

F. Robustness to Using a Factor Model for Firm Discount Rates

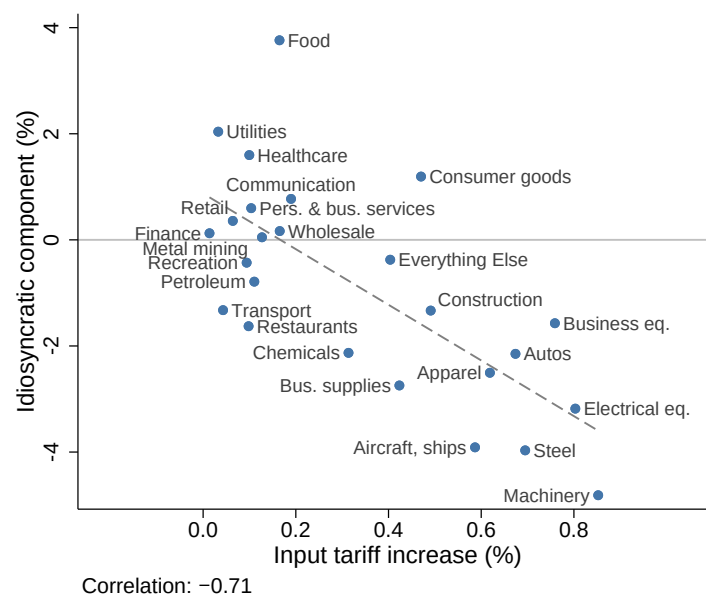
In the baseline results, we made the simplifying assumption that the log deviation in the interest rate paid on firm debt was the same as the log deviation in the risk-free rate and that the deviation in the required return on firm equity was given by its beta exposure to the stock market times the deviation 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 (15) by

$$\begin{aligned} E_0 [\hat{R}_{it}^E] = & E_0 [\hat{R}_{f,t}] + \beta_{i,MKT} E_0 [\hat{R}_{MKT,t} - \hat{R}_{f,t}] \\ & + \beta_{i,SMB} E_0 [\hat{R}_{SMB,t}] + \beta_{i,HML} E_0 [\hat{R}_{HML,t}], \end{aligned}$$

where *SMB* denotes the portfolio of small minus big firms while *HML* denotes the portfolio of high minus low book-to-market values. The betas ($\beta_{i,MKT}$, $\beta_{i,SMB}$, $\beta_{i,HML}$) are

Figure C2: Idiosyncratic Cash-Flow Component and Input Tariffs



Note: The figure plots the idiosyncratic cash-flow component against the input tariff increase between December 2017 and December 2019, both in%. Each point represents a Fama-French 30 industry. The input tariff increase is the tariff change of each input multiplied by the share of imports of that input in the industry's total inputs (goods, services, and wages), summed across inputs. Both measures are averaged across firms within each industry using employment weights; firms without an input tariff measure are excluded from the tariff average. Industries with fewer than 20 firms are grouped into Everything Else. The dashed line is the linear fit across industries.

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 (14) implies the following equation for the discount-rate adjustment:

$$\underbrace{\sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{it}]}_{\text{Firm } i \text{ discount-rate adjustment}} = \underbrace{\sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{f,t}]}_{\text{Deviation in future risk-free rates}} + \underbrace{\kappa_i \beta_{i,MKT} \sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{MKT,t} - \hat{R}_{f,t}]}_{\text{Deviation in expected excess MKT returns}} + \underbrace{\kappa_i \beta_{i,SMB} \sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{SMB,t}]}_{\text{Deviation in expected SMB returns}} + \underbrace{\kappa_i \beta_{i,HML} \sum_{t=1}^{\infty} \rho^t E_0 [\hat{R}_{HML,t}]}_{\text{Deviation in expected HML returns}}.$$

We then use a VAR that includes the return of SMB and HML portfolios, $R_{SMB,t}$ and $R_{HML,t}$, to jointly estimate the deviation in future risk-free rates, expected excess stock-market returns, expected SMB returns, and expected HML returns. As reported in Table CIV, 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 raises the aggregate discount-rate adjustment 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 (15) by

$$E_0 [\hat{R}_{it}^D] = E_0 [\hat{R}_{f,t}] + E_0 [\widehat{CS}_t],$$

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 VIII, 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 CIV, 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 4.0 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 market-level discount-rate adjustment remains similar (4.2 vs. 4.4 percentage points), and the implied welfare effect is nearly unchanged (−4.3 vs. −3.8%, Table VIII).

G. Measuring the Static and Dynamic Price Effects

In this section, we describe how we compute the effective rate of protection, in order to calculate the first two terms in (10).

G.1. Construction of Industry-Level Tariffs

The first step is to construct the log change in the tariff on outputs in each 6-digit NAICS industry 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:

$$\hat{\tau}_\iota \equiv \sum_{h \in H_\iota} \sum_c \frac{mv_{hc,2017}}{\sum_{h' \in H_\iota} \sum_{c'} mv_{h'c',2017}} \Delta \ln(1 + \tau_{hc}), \quad (C2)$$

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

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

where $\Delta \ln(1 + \tau_{hc}^a) = \ln(1 + \tau_{hc,2019Dec} + 0.6) - \ln(1 + \tau_{hc,2017Dec})$ if $c = \text{China}$, and $\Delta \ln(1 + \tau_{hc}^a) = \ln(1 + \tau_{hc,2019Dec} + 0.2) - \ln(1 + \tau_{hc,2017Dec})$ otherwise.

G.2. Effective Rates of Protection Calculation

We use equation (9) to estimate how U.S. import tariff changes map into firm-level ERP ($\hat{p}_{i0}^e$) in a static model. Since firm-level intermediate-input use data are not available, we use industry-level data, that is, we assume that the shift in the ERP for all firms in industry ι is given by

$$\hat{p}_i^e \equiv \frac{\hat{p}_i^\tau - \sum_j \omega_{ji} \hat{q}_j^\tau}{1 - \sum_j \omega_{ji}}, \quad (\text{C3})$$

where $\hat{p}_i^\tau$ are estimates of how U.S. import tariff changes affected prices of U.S. outputs in industry ι , and $\hat{q}_j^\tau$ are estimates of how U.S. import tariff changes affected input prices i . The ω_{ji} 's denote the cost-share of intermediate input i used in the production of output in industry ι .³ We assign industry-level changes in ERP to each firm based on the industry it produces, that is, $\hat{p}_{i0}^e = \hat{p}_i^e \quad \forall i \in \iota$.

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.

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, that is, $\hat{p}_i^\tau = 0$, 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, Redding, and Weinstein \(2019\)](#) 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% passthrough of tariffs into tariff-inclusive import prices. In this scenario, $\hat{p}_i^\tau$ is set equal to zero, and the ERP is calculated as follows:

$$\hat{p}_i^{e1} = - \frac{\sum_j \omega_{ji} \lambda_j \hat{\tau}_j}{1 - \sum_j \omega_{ji}}. \quad (\text{C4})$$

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 (C3), 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 (ω_{ji}) by λ_j so that the tariff change is only applied to imported inputs and not to domestic inputs.

³Total 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. Intermediate input cost excludes the BEA rows for scrap, used and secondhand goods, noncomparable imports, and other government enterprises, which have no NAICS industry.

The price of the imported input increases by the full amount of the tariff $\hat{\tau}_j$ (calculated in equation (C2)). 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 Appendix C.C.

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

$$\hat{p}_i^{e2} \equiv \frac{\gamma \lambda_i \hat{\tau}_i - \sum_j \omega_{ji} [\lambda_j \hat{\tau}_j + (1 - \lambda_j) (\gamma \lambda_j \hat{\tau}_j)]}{1 - \sum_j \omega_{ji}}. \quad (C5)$$

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, Redding, and Weinstein \(2019\)](#), which found that domestic prices increased by $\gamma \lambda_j$ with $\gamma = 0.4$. That is, $\hat{p}_i^\tau = \gamma \lambda_i \hat{\tau}_i$. 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 reweighting scheme in Appendix C.C. We use equation (C4) to obtain an estimate for the welfare effect equal to -0.25% for the static price effect in equation (10). Our upper bound estimate of the static price effect uses equation (C5) to compute the ERP, which equals -0.15% .

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 $\hat{\tau}_i^a$. Using these hypothetical output tariffs to calculate the changes in ERP in equation (C4), the resulting future change in ERP is $\sum_i \frac{w_{Li} + \pi_i V_i}{C} \hat{p}_{i1}^e = -1.88\%$. The dynamic effect in equation (10) is then given by $\sum_i \frac{w_{Li} + \pi_i V_i}{C} \rho [\hat{p}_{i1}^e - \hat{p}_{i0}^e]$, which comes down to $0.975 \times (-1.88\% + 0.25\%) \approx -1.59\%$. If we instead use equation (C5) to calculate the changes in ERP, the resulting effect on ERP is $\sum_i \frac{w_{Li} + \pi_i V_i}{C} \hat{p}_{i1}^e = -0.89\%$ and the dynamic effect comes down to $0.975 \times (-0.89\% + 0.15\%) \approx -0.72\%$.

D. Appendix for Section IV (Validation and External Validity)

Table DI: Discount Rate Changes on 2025–2026 Trade Policy Announcement Days

Date	Tariff Change	Country	T-Bill (x100)	Nom. 10y Yield (x100)	Real 10y Yield (x100)	Breakeven Inflation (x100)	EPB (x100)
22jan2025	Increase	US	0.00	0.03	0.01	0.01	0.05
04feb2025	Mixed	US & CHN	0.00	−0.01	−0.02	0.00	−0.27
27feb2025	Increase	US	0.00	0.04	0.04	−0.00	0.42
04mar2025	Increase	CHN	−0.01	0.06	0.06	0.00	0.24
03apr2025	Increase	US	−0.01	−0.14	−0.10	−0.03	2.15
04apr2025	Increase	CHN	−0.03	−0.05	0.05	−0.10	4.07
09apr2025	Mixed	US & CHN	0.05	0.08	0.03	0.05	−6.06
11apr2025	Increase	CHN	0.01	0.07	0.06	0.00	−1.16
12may2025	Decrease	US & CHN	0.09	0.07	0.07	−0.00	−1.14
11aug2025	Decrease	US & CHN	0.01	−0.01	−0.01	−0.00	0.10
27oct2025	Decrease	US & CHN	−0.04	−0.01	−0.00	−0.01	.
20feb2026	Mixed	US	−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

Note: 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, the change in breakeven inflation, and the change in the equity premium bound (EPB) of Martin (2017). Note that the *OptionMetrics* data we use to construct the EPB is not available for the last two events, which the cumulative EPB therefore excludes. Cumulative Tariff Increases aggregates the variables of trading days on which only a tariff increase was announced. Cumulative Tariff Decreases aggregates the variables of trading days on which a tariff decrease, pause, or truce was announced, and Cumulative Mixed Events aggregates those of trading days with a mixture of increases and decreases.

E. Summary of Data Sources

Table EI: Summary of Data Sources

Variable	Construction
Book Leverage	<i>Source: CRSP-Compustat Annual Merged Dataset (2013)</i> Book leverage is total debt including current [dt] <i>divided by</i> assets (total) [at], dt/at.
Cash Flow to Asset Ratio	<i>Source: CRSP-Compustat Annual Merged Dataset (2013)</i> The Cash Flow-to-Asset Ratio is operating income after depreciation [oiadp] <i>plus</i> interest and related expense (total) [xint] <i>all divided by</i> assets (total) [at]; $(oiadp + xint)/at$.
China Export Share	<i>Source: U.S. Census Bureau, U.S. Department of Agriculture</i> China export share is an industry's 2017 exports to China <i>divided by</i> its 2017 shipments, capped at one.
China Import Intensity	<i>Source: BEA Detailed Input-Output Use Table (2017), U.S. Census Bureau</i> China import intensity is an industry's intermediate inputs imported from China <i>divided by</i> its intermediate inputs <i>plus</i> compensation of employees. We impute an industry's imports of each input from China using China's share of U.S. absorption of that input.

Variable	Construction
China Revenue Share	<i>Source: FactSet Geographic Revenue Exposure (2017)</i> These data report firms' China revenue shares for fiscal 2017. We match sample PERMNOs to FactSet symbols using the crosswalk. For successfully matched firms, we set missing China revenue shares in FactSet to zero; unmatched firms remain missing. More details are provided in Appendix A.E.
China Importer and Exporter	<i>Source: Datamyne (2017), S&P Capital IQ (subsidiaries), FactSet and Bloomberg (suppliers)</i> <i>China Importer (China Exporter)</i> equals one if the firm, a subsidiary, or a supplier (the firm or a subsidiary) imported from (exported to) China by sea in 2017; both are set to zero for financial firms. Appendix A.E describes how firms are matched to Datamyne.
China Stock-Market Returns	<i>Source: Refinitiv Datastream</i> Chinese stock-market returns are daily log changes in the CSI 300 return index [r1].
Economic Surprise Variables (ES_t)	<i>Source: Bloomberg for the economic surprises and Lewis (2025) for the monetary policy shocks</i> The difference between a macroeconomic data release value and the Bloomberg median of economists' forecast on the previous day. The 61 series are listed in the replication package. We also include the four monetary policy surprise variables that Lewis (2025) estimates for each Federal Reserve announcement day: a federal funds shock, a forward guidance shock, an asset purchase shock, and a Federal Reserve information shock.

Variable	Construction
Equity-Premium Bound (EPB_t)	<i>Source: OptionMetrics, dataset with prices of actively traded options on the S&P 500 (ticker SPX)</i> We follow the method of Martin (2017) for constructing EPB_t.
Firm	<i>Source: CRSP-Compustat Annual Merged Dataset (2017)</i> 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 (<code>permno</code>) and GVKEY (<code>gvkey</code>) interchangeably across datasets.
Firm Employment L_i	<i>Source: CRSP-Compustat Annual Merged Dataset (2013–2024)</i> The employment variable in Compustat [<code>emp</code>] 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 ($\ln R_{it}^E$)	<i>Source: CRSP U.S. Stock Database</i> We define log firm returns as the <i>log</i> of one <i>plus</i> net returns [<code>ret</code>]; $\ln(1 + \text{ret})$.

Variable	Construction
Firm-Specific Announcements	<i>Source: S&P Capital IQ Key Developments</i> The firm-specific announcement categories and their Key Developments codes are buyback transaction announcements and cancellations (232 and 233), dividend affirmations, increases and decreases (45, 46 and 47), earnings calls (48), stock splits and significant stock dividends (53), merger and acquisition announcements and cancellations (80 and 82), and follow-on equity offerings (86).
Input-Output Cost Shares (ω_{jl})	<i>Source: BEA Detailed Input-Output Use Table, after redefinitions, at producer prices (2017)</i> The cost share ω_{jl} is industry l's purchases of input j divided by its total output (Appendix C.G).
Ratio Between Market Value of Equity and Market Value of Assets κ_i	<i>Source: CRSP-Compustat Annual Merged Dataset (2017)</i> 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 bound κ_i between 0.1 and 1; negative values, which arise when the market value of assets is negative, are set to 1.

Variable	Construction
Market Value of Equity	<i>Source: CRSP-Compustat Annual Merged Dataset (2013 and 2017)</i> We use the market value of equity of a firm [mkvalt]. When this variable is unavailable we use the <i>product of</i> annual price close (fiscal) [prcc_f] <i>and</i> common shares outstanding [csho]; prcc_f $\times$ csho.
Profit	<i>Source: CRSP-Compustat Annual Merged Dataset (2013–2024)</i> Profit is “operating income after depreciation” [oiadp] <i>minus</i> “interest and related expense (total)” [xint]; oiadp $-$ xint.
Property, Plant, and Equipment (PPE) per worker	<i>Source: CRSP-Compustat Annual Merged Dataset (2013)</i> PPE per worker is property, plant, and equipment (gross total) [ppegt] <i>divided by</i> employees [emp]; ppegt / emp.
Protection	<i>Source: U.S. Trade Representative (USTR), U.S. International Trade Commission (USITC), U.S. Census Bureau</i> The change in an industry’s output tariff at a U.S. announcement is the 2017 import-weighted average of the additional duties imposed by the tariff actions that followed the announcement. <i>Protection</i> equals one if this change is positive.

Variable	Construction
Nominal Yields	1. Maturity: 3 and 6 months <i>Source: Board of Governors of the Federal Reserve System, {3-Month, 6-Month} Treasury Bill Secondary Market Rate, Discount Basis; retrieved from FRED, Federal Reserve Bank of St. Louis</i> We obtain the nominal yields with the following maturities from FRED: 3-Month [DTB3], 6-Month [DTB6]. 2. Maturity: 1 to 20 years <i>Source: daily U.S. yield curve dataset from Gürkaynak, Sack, and Wright (2007); dataset retrieved from the Federal Reserve Board's website</i> The U.S. yield curve dataset was published alongside Gürkaynak, Sack, and Wright (2007) and is updated regularly. The dataset reports nominal yields at maturities ranging from one to thirty years; we use maturities from one to twenty years. Nominal yields in the paper refers to "Zero-Coupon Yield (Continuously Compounded)" [SVENYxx].
Real Yields	<i>Source: daily U.S. TIPS curve dataset from Gürkaynak, Sack, and Wright (2010); dataset retrieved from the Federal Reserve Board's website</i> The TIPS curve dataset was published alongside Gürkaynak, Sack, and Wright (2010) and is updated regularly. Real yields are "TIPS Yield Zero Coupon (Continuously Compounded)" [TIPSYxx].

Variable	Construction
Inflation Swap Rates	<i>Source: Bloomberg (USSWIT)</i> We obtain U.S. dollar inflation swap rates at maturities of 1 to 10, 12, 15, and 20 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	<i>Source: CRSP-Compustat Annual Merged Dataset (2013)</i> Tobin's Q is market capitalization [$\text{prcc_f} \times \text{csho}$] <i>plus</i> book value of total assets [at] <i>minus</i> book value of common equity [ceq], <i>all divided by</i> the book value of total assets [at].
U.S. Market Return	<i>Source: CRSP U.S. Stock and Indexes Database</i> The U.S. market return is the log of one <i>plus</i> the CRSP value-weighted return including distributions [vwretd].
U.S. Import Value	<i>Source: U.S. Census Bureau</i> We obtain 2017 U.S. import values for each good (HTS10) and exporting country from the U.S. Census Bureau.
U.S. Export Value	<i>Source: U.S. Census Bureau and Peter Schott's website</i> We obtain 2017 U.S. export values for each good (HTS10) and importing country through Peter Schott's website, which originate from the U.S. Census Bureau.

Variable	Construction
U.S. Tariff Rates	<i>Source: U.S. Trade Representative (USTR), and U.S. International Trade Commission (USITC)</i> In the paper, the tariff rate in year y for an HTS10 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. Shipments by Industry	<i>Source: U.S. Census Bureau, U.S. Department of Agriculture</i> We obtain 2017 shipment values for U.S. industry from the 2017 Economic Census. The shipments for forestry industries (NAICS 113110, 113210, 113310, 114111, 114112, 114119 and 114210) are from the 2017 Annual Business Survey. The shipments for agricultural sectors are from the 2017 Census of Agriculture.
U.S. Firm-size Distribution (Goods and Services)	<i>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</i> The dataset reports the number of employees by sector (NAICS2) and employment bin.

Variable	Construction
VAR State Variables	<i>Source: FRED, CRSP, Fama-French Data Library, Moody's</i> 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 at the start of the quarter, divided by four. (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 at the 90th and 10th percentiles of NYSE stocks (Fama-French breakpoints), updated daily with the returns of the top and bottom book-to-market decile portfolios, constructed using data from the Fama-French Data Library. (6) The credit spread: the difference between Moody's Seasoned Baa Corporate Bond Yield [DBAA from FRED] and the annualized yield of 3-month T-Bills, both in logs and divided by four. (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	<i>Source: CRSP U.S. Stock Database, Fama-French Data Library</i> Firm-level market betas ($\beta_{i,MKT}$) are estimated from OLS regressions of daily firm returns on the CRSP value-weighted market return, both in excess of the risk-free rate from the Fama-French Data Library. The betas used to compute abnormal returns are estimated over the year 2017, for firms traded on at least 120 days in 2017. The betas used to compute the discount-rate adjustment are estimated over 2017–2019, for firms traded on at least 360 days over this period. We winsorize betas at the 1st and 99th percentiles. 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 over 2017–2019.
SPY ETF Intraday Prices	<i>Source: NYSE Trade and Quote (TAQ) Database</i> We obtain intraday bid and ask quotes of the SPY ETF from TAQ. To minimize microstructure noise, we take the median bid-ask midpoint within each 10-second interval. 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 10-second SPY price series.

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