Using Equity Market Reactions to Infer Exposure to Trade Liberalization *

Andrew Greenland

Mihai Ion

John Lopresti

Peter K. Schott†

Abstract

We propose a method for identifying exposure to changes in trade policy based on asset prices that has several advantages over standard measures: it encompasses all avenues of exposure, it is natively firm-level, it yields estimates for both goods and service producers, and it can be used to study reductions in difficult-to-quantify non-tariff-barriers in a way that controls naturally for broader macroeconomic shocks. Applying our method to two well-studied US trade liberalizations provides new insight into service sector responses to trade liberalizations as well as dramatically different responses among small versus large firms, even within narrow industries.

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†Corresponding author. E-mail: peter.schott@yale.edu; Mailing address: Yale School of Management, 165 Whitney Ave, New Haven CT 06511; Phone: 203-436-4260; Fax: 203-536-4200.

1 Introduction

A firm's exposure to trade liberalization is typically measured via the average change in import tariffs among the set of goods it produces (Bernard et al., 2006). While easily observed, this metric limits understanding of globalization in several ways. First, it focuses attention on the relatively small manufacturing sector, neglecting services. Second, it does not cover the difficult-to-quantify changes in non-tariff barriers that are an increasingly important component of trade policy, such as national treatment, product standards and intellectual property rights. Finally, it ignores avenues of exposure beyond a firms' outputs, such as its major customers and suppliers or its inputs (Amiti and Konings, 2007a; Ding et al., 2019).

In this paper, we propose an alternate measure of firm exposure to policy changes derived from financial markets' reactions to key events associated with the new regime, such as the legislative votes by which they become law. We take our cue from the vast "event study" literature in financial economics that seeks to rationalize firms' abnormal stock returns on key trading days. In our case, however, we use these returns as "all in", natively firm-level measures of policy exposure that can be used as an *explanatory* variable to predict and understand subsequent firm outcomes. Leveraging the "wisdom of the crowds" in this way addresses each of the limitations noted above: abnormal returns yield estimates of exposure for both goods and service producers; they capture the net impact of liberalizations' costs and benefits on each firm without requiring difficult-to-obtain information on their operations; and they can be used to study any change in policy that can be associated with one or more events. Moreover, they can be analyzed jointly with "benchmark" returns computed on random days around the events to account for firm-specific exposure to broader macroeconomic trends.

As proof of concept, we apply this new measure of firm exposure to two important changes in US trade policy: the granting of Permanent Normal Trade Relations (PNTR) to China in 2000 and the Canada-United States Free Trade Agreement (CUSFTA) in 1989. We find that use of our measure provides a broader view of these liberalizations by highlighting starkly different outcomes across firms, even within the same narrow industry.[1] Comparison of exposure-driven outcomes across these two policy changes also offers direct empirical support for the sort of cross-country variation in fixed supply-chain search costs implied by recent quantitative models of global sourcing, e.g., Antràs et al. (2017). Indeed, large firms exhibit disproportionate growth in sales and employment after PNTR relative to CUSFTA, consistent with greater fixed costs associated with accessing the Chinese market.

PNTR was a non-traditional trade liberalization in that it effectively eliminated the possibility that China would lose access to low US import tariffs.[2] For this application, we compute US firms' average abnormal returns (AARs) across the five legislative events required for its passage: the introduction of the bill in the US House of Representatives, the House vote, Senate cloture, the Senate vote, and President Bill Clinton's signature. For goods-producers, we find that these AAR^{PNTR} vary as expected with standard measures of exposure used in this literature, e.g., subsequent levels of imports, but provide explanatory power beyond them. For service producers, for which calculating standard measures is not possible, we provide external validation in two separate environments. First, we show that firms with lower AAR^{PNTR} exhibit relatively higher returns on the day of NATO's accidental bombing of China's Belgrade embassy in 1999, which was viewed at the time as reducing the probability of Chinese WTO entry. Second, we document that industries exhibiting higher AAR^{PNTR} exhibit lower returns upon the election of Donald Trump in anticipation of a looming trade war (Huang et al., 2018).

Employing a difference-in-differences (DID) approach, we use our measure to examine

[1]Within computer producers, for example, Apple and Dell have positive abnormal returns while those of Gateway are negative, consistent with well-known differences in their approach to offshoring.

[2]Handley and Limão (2017) estimate that the reduction in trade policy uncertainty associated with PNTR is equivalent to a reduction in tariff rates of approximately 13 percent. Pierce and Schott (2016) show that US manufacturing establishments facing greater reductions in expected tariffs exhibit relative declines in employment. Autor et al. (2013, 2014) find that US regions more exposed to Chinese import competition during this period experience relative declines in employment and earnings. In contemporaneous research Bianconi et al. (2018) show that industries with greater PNTR reductions in tariff rate uncertainty exhibit relatively lower stock returns.

a wide set of firm outcomes. We find that both goods *and* service producers with larger AAR^{PNTR} are relatively more likely to survive and grow their operating profit after the change in policy versus before. Differences across firms, however, are stark: while almost all firms are predicted to have relative declines in operating profit after 2001, a small group of the very largest firms exhibit relative gains sufficient to outweigh the losses of all others. As noted above, this outcome is consistent with large firms' greater ability to absorb the relatively high fixed costs of sourcing cheaper inputs from China, allowing them to thrive while smaller firms contract or exit.

For employment, we find a similar, but flatter profile across the firm-size distribution – the largest firms expand, but by relatively less in terms of employment than in terms of profit. The implied relative increase in large firms' operating profit per worker suggests a link between PNTR and the rise of "superstar" firms documented in Decker et al. (2014) and Autor et al. (2017), as well as the substantial rise in US manufacturing productivity during the 2000s (Fort et al., 2018). The predicted relative growth of physical and intangible capital is similarly skewed, providing further support for the idea that industry "leaders" are able to invest more in response to rising import competition from China than followers (Gutierrez and Philippon, 2017).

Outside manufacturing, we find relatively greater predicted gains in operating profit and employment in Professional Services (e.g., accounting, law, engineering and R&D), consistent with an anticipated, post-PNTR shift in the United States towards the design, engineering and marketing of goods as physical production migrates to China (Ding et al., 2019). In Wholesale and Retail, by contrast, almost all firms are anticipated to shrink in relative terms. This result conforms with Wall Street's *ex ante* expectations that greater availability of Chinese goods would lead to an increase in competition among retailers, and thereby an erosion of markups (Kurtz and Morris, 2000). It suggests the relationship between the increasing "toughness" of competition and declining markups following trade liberalization developed in Melitz and Ottaviano (2008) may also apply to services.

Our second application, CUSFTA, considers a change in US trade policy with a closer and more similar trading partner, Canada. In contrast to PNTR, CUSFTA encompassed both traditional bilateral tariff reductions and a substantial loosening of restrictions on services trade via its inclusion of "national treatment", for which there is no standard tariff equivalent.[3] In this application, we compute abnormal returns for US firms during the 1988 Canadian federal election, which amounted to a referendum on the trade agreement (Breinlich, 2014). As with AAR^{PNTR}, we find that goods producers' AAR^{CUSTFA} are correlated with the conventional measures of exposure: they fall with US tariff reductions and rise with Canadian tariff reductions. Among service firms, we find, intuitively, that average returns are higher among those in industries covered by national treatment.

In contrast with the results for PNTR, we find no significant relationship between outcomes and exposure to CUSFTA among goods producers using either our method or the standard measures of exposure in the literature, potentially due to CUSFTA's long time horizon, or the subsequent implementation of NAFTA, unforeseen in 1988. We do, however, find that service providers with higher AAR_j^{CUSFTA} exhibit greater operating profit after PNTR versus before, in line with the change in national treatment. In this case, we do not find as sharp a distributional impact across large and small firms, consistent with the fixed costs of sourcing in Canada from the United States being relatively low.

In the final part of the paper, we exploit an additional advantage of our approach – its ability to compare disparate liberalizations using a common metric – to examine potential explanations for the relatively strong effect of PNTR versus CUSFTA on US firms. We demonstrate that this disparity remains after comparing our DID coefficients to "benchmark" estimates that account for potential variation in macroeconomic trends across the liberalizations, and after using call option prices to control for potential market anticipation of PNTR's ultimate passage prior to its introduction in the House. We then show that

[3] National treatment requires a country to treat foreign firms symmetrically to domestic firms. Trefler (2004) documents substantial reallocation among Canadian manufacturing sectors and plants following CUSFTA's passage. Breinlich (2014) demonstrates that changes in firm market value following CUSFTA are consistent with heterogeneous-firm models of international trade.

PNTR's estimated impact was both more immediate, and more durable, that CUSFTA's, potentially due to greater-than-anticipated Chinese growth in the 2000s.

Our method has two caveats that must be kept in mind in interpreting results. First, because it is based on equity market reactions, it can be implemented only for firms whose shares are traded publicly. If the consequences for private firms are distinct from publicly traded ones, our approach will not capture the complete effect of the policy. Second, because abnormal returns are net of the "market" impact of the change in policy, they may not capture its systemic components, e.g., the impact of changes in interest rates, exchange rates or other aggregate prices. As with estimates from virtually all reduced-form empirical studies of environments where general equilibrium effects are relevant, our measure is thus better suited to analyzing variation in trade exposure across firms rather than the policy's level impact on a particular firm. Even so, we demonstrate that our baseline results do not change substantially under plausible assumptions about the size of the market component.

Beginning with Ball and Brown (1968) and Fama et al. (1969), event studies have been used extensively in corporate finance to estimate the effect of new information on firm value.[4] Though not widely used within international trade, a number of papers examine the link between stock prices and exposure to trade, starting with Grossman and Levinsohn (1989a), who find a positive relationship between firm returns and the prices of competing import goods. More recently, Huang et al. (2018) report a negative relationship between firms' previous sales to China and their abnormal returns at the onset of the 2018 US-China trade war.[5] To our knowledge, we are the first to employ AARs as an explanatory variable summarizing the effect of policy changes on firms, and to use that variable to predict and investigate subsequent firm outcomes. Our approach is conceptually similar to Kogan et al. (2017), who use firm returns after patent grants as a measure of *patent* value. Here, we show

[4] Khotari and Warner (2006) document that this approach has been used in over 565 articles appearing in the top finance journals through 2006. For a recent discussion of this literature, see Wolfers and Zitzewitz (2018).

[5] Fisman and Zitzewitz (2019) go one step further, proposing that initial winner versus loser firms be tracked in the months after an event, such as Brexit, as a barometer of any revisions to initial expectations of the event.

how AARs can be used to gauge firms' exposure to changes in policy, and that this measure both predicts firm outcomes and sheds new light on their responses. Our measure is agnostic with respect to the underlying mechanism which ties trade policies to stock prices and future firm-level outcomes. In a related study, Amiti et al. (2021) propose such a mechanism based on Jones (1975) specific factors model and on Grossman and Levinsohn (1989b).

Our use of AARs as "all in", right-hand side explanatory variables contributes more broadly to the very large effort within trade to develop metrics of policy exposure. A popular approach, inspired by Bartik (1991), interacts agents' – generally firms' or regions' – activity shares with industry shocks, e.g., Topalova (2010). Such "direct" measures are often combined with additional industry-level information, such as input-output tables, to measure additional "indirect" channels of exposure, e.g., those associated with a firm's customers or suppliers (Amiti and Konings, 2007b). A virtue of our approach is that it is *natively firm-level*. As a result, it captures variation across firms within industries and identifies the *net* impact of all channels of firm exposure without requiring any knowledge or assumptions regarding firms' supply chains, managerial capabilities, or labor-market relationships.

Finally, our results with respect to PNTR and CUSFTA contribute to the very active literature in international trade studying the impact of import competition on workers and firms. Though researchers starting with Tybout et al. (1991) have examined plant and firm responses to greater openness, we are the first to use the same, "all-in" measure of firm exposure in two different trade liberalizations, and to compare a range of outcomes across them. Our finding that large firms exhibit larger growth in operating profit relative to employment during PNTR than CUSFTA provides a clearer picture of liberalizations' distributional effects in general, and *vis à vis* China in particular. In this sense, we provide an additional rationale for why trade with China might be "different".

The paper proceeds as follows. Section 2 outlines the theory behind our approach, deferring details to the Appendix. Section 3, validates and applies our method to PNTR. Section 4 applies our method to the Canada-US Free Trade Agreement. Section 7 concludes.

2 Estimating Firm Exposure

In this section we briefly outline the conditions under which financial market reactions can be used to quantify firms' exposure to changes in policy, highlighting the key challenges that must be addressed for our purposes and outlining approaches that may mitigate them. We start with the assumption that markets are informationally efficient, i.e., that the impact of a particular event on a firm's market value can be estimated via the change in the firm's stock price during the event period, controlling for all other information relevant for firm value that may have been released at the same time.

We assume a firm's stock price at time t is a function of a state space partitioned as (X_t, e_t). Here, e_t represents the information about the policy event of interest available at time t, and X_t contains all other information relevant for firm value, including other firm-specific events (e.g. dividend announcements), or broader events such as the release of macroeconomic information (e.g. Fed policy).[6] We assume that the policy event under consideration takes place at time τ and, as in our applications below, that the information released is whether the policy is approved or denied. We assume that the event is unanticipated, deferring discussion of partial anticipation to Appendix Section F.

Let $P_{j,t}$ be the stock price of firm j at time t, and $R_{j,t} = (P_{j,t} - P_{j,t-1})/P_{j,t-1}$ be the stock return of the firm during period t.[7] The effect of the event on firm j's stock price is given by

$$AR^*_{j,\tau} = R_{j,\tau} - E(R_{j,\tau}|X_\tau) \tag{1}$$

where $E(R_{j,\tau}|X_\tau)$ is the "normal" return we would expect to observe if the event did not occur. $AR^*_{j,\tau}$ is referred to in the event-study literature as the "abnormal return" of the firm. We use the superscript $*$ to denote that it is the true impact of the change in policy,

[6] For simplicity, we omit firm subscripts from the state space notation. In that sense, (X_t, e_t) can be seen as the information needed to price all assets in the economy. Throughout our analysis, "at time t" stands for "at the end of time period t".

[7] This expression for stock returns assumes that stock prices have been adjusted for dividend payments and stock splits, as they are in our dataset.

as distinct from the estimated effect described below.

Estimating the normal return function $E(R_{j,\tau}|X_\tau)$ is crucial. The standard approach relies on a reduced-form model in which a firm's returns are a linear function of sensitivities to systematic factors and firm-specific shocks:

$$R_{j,t} = \alpha_j + \beta_j F_t + \epsilon_{j,t}. \tag{2}$$

F_t is a $(K \times 1)$ vector of systematic factors affecting all firms and β_j is a $(1 \times K)$ vector of "factor loadings" quantifying how shocks to the systematic factors affect firm j. The residuals $\epsilon_{j,t}$ are referred to as the "idiosyncratic" component of returns.

Systematic factors F_t are identified using either statistical or economic frameworks. A common statistical approach uses principal component analysis on the space of realized firm returns. A popular economic framework is the capital asset pricing model (CAPM), which identifies conditions under which F_t consists of a single factor – the return on the market portfolio (Sharpe, 1964; Lintner, 1965). In statistical approaches, model parameters (α_j, β_j) and factors often are estimated simultaneously. In economic approaches, they are constructed according to theory, and (α_j, β_j) are obtained by estimating equation (2) on a sample of realized returns prior to, and disjoint from, the event window. In our applications below we adopt by far the most common approach in the event-study literature, a model informed by the CAPM, known as the "market model", that uses the market portfolio as the single factor. We show that our baseline results are robust to using multi-factor asset pricing models in the online Appendix.

Once the systematic factors F_t are identified and the parameters (α_j, β_j) are estimated, the "normal" return during the event generally is estimated as $E(R_{j,\tau}|X_\tau) \approx \hat{\alpha}_j + \hat{\beta}_j F_\tau$ which yields the standard estimate for abnormal returns:

$$AR_{j,\tau} = R_{j,\tau} - (\hat{\alpha}_j + \hat{\beta}_j F_\tau). \tag{3}$$

Note, however, that this estimate is unbiased – i.e. $AR_{j,\tau} = AR^*_{j,\tau}$ – only if $E(R_{j,\tau}|X_\tau) = \hat{\alpha}_j + \hat{\beta}_j F_\tau$. That requires two assumptions:

(A1) X_t do not affect the idiosyncratic component of returns $\epsilon_{j,\tau}$

(A2) $e_{j,\tau}$ does not have an effect on the systematic factors F_τ

To see why, decompose F_τ additively into the component F^X_τ caused by X_t, and the component F^e_τ caused by the event e_τ, such that $F_\tau = F^X_\tau + F^e_\tau$. Similarly, decompose the idiosyncratic term as $\epsilon_{j,\tau} = \epsilon^X_{j,\tau} + \epsilon^e_{j,\tau}$.[8] Substituting these expressions into equation (2), we obtain

$$R_{j,\tau} = \alpha_j + \beta_j(F^X_\tau + F^e_\tau) + (\epsilon^X_{j,t} + \epsilon^e_{j,t}) \tag{4}$$

With this substitution, the non-event state space X_τ is summarized by $\{\hat{\alpha}_j, \hat{\beta}_j, F^X_\tau, \epsilon^X_{j,\tau}\}$, implying that the normal return absent the event is given by

$$E(R_{j,\tau}|X_\tau) = \alpha_j + \beta_j F^X_\tau + \epsilon^X_{j,\tau} \tag{5}$$

and the abnormal return estimate in equation (3) can be rewritten as

$$AR_{j,\tau} = R_{j,\tau} - (\hat{\alpha}_j + \hat{\beta}_j F^X_\tau + \epsilon^X_{j,\tau}) - \hat{\beta}_j F^e_\tau + \epsilon^X_{j,\tau} = AR^*_{j,\tau} - \hat{\beta}_j F^e_\tau + \epsilon^X_{j,\tau} \tag{6}$$

Equation (6) shows that the abnormal returns estimate, $AR_{j\tau}$, equals the true effect of the event ($AR^*_{j,\tau}$) less the impact of the event on the firm caused by its influence on systematic factors ($\hat{\beta}_j F^e_\tau$) plus the idiosyncratic effect of confounding events that may have occurred at the same time as the policy event ($\epsilon^X_{j,\tau}$). Under assumptions A1 and A2, these last two terms are zero, and $AR_{j,\tau} = AR^*_{j,\tau}$.[9] In practice, however, the researcher should take steps to mitigate the influence of both terms.

[8] While these decompositions need not be linear, they can be linearized, with only the interpretation of the coefficients changing.

[9] Our discussion makes the standard assumption that $\hat{\beta}_j$'s do not change as a result of the event.

Mitigating $\epsilon^X_{j,\tau} \neq 0$: In our estimations below, we follow the event study literature in trying to increase the likelihood that $\epsilon^X_{j,\tau} = 0$ by using short windows around the policy event (two days before and after) and by excluding firms experiencing significant confounding events during the event window (e.g., dividend announcements).

Mitigating $\hat{\beta}_j F^e_\tau \neq 0$: Avoiding the bias induced by the effect of the event on systematic factors (e.g., the influence of PNTR on interest rates) is more challenging. While the assumption that $\hat{\beta}_j F^e_\tau$ is close to zero is reasonable for firm-specific events (e.g., a patent grant or an earnings announcement), it is more tenuous for changes in policy of broad interest with potential macroeconomic consequences, such as a trade liberalization or a change in the minimum wage. As a result, our baseline abnormal return estimates must be interpreted as the effect of the policy on firms *relative* to its impact on systematic factors.

If one is willing to assume that no confounding systematic shocks occur at the same time as the change in policy (i.e. $F^X_\tau = 0$), its systematic component F^e_τ can be estimated using the factor realizations themselves (F_τ).[10] This approach might be reasonable for very short windows, during which it is unlikely that any other meaningful macroeconomic shock takes place. Toward that end, in Section 6 we explore the robustness of our results to narrower event windows, and we also examine the robustness of our results to adding a range of plausible values of F^e_τ into our estimates of AR^*, and re-computing our DID results.

While the caveats outlined in this section must be kept in mind, they should be weighed against our new measure's benefits, as well as the limitations of standard approaches in the trade literature, as discussed in the introduction.

3 PNTR

In this section we apply the method outlined above to measure US firms' exposure to the US granting of permanent normal trade relations (PNTR) to China in 2000.

[10] Amiti et al. (2021), for example, assume both $F^X_\tau = 0$ and $\epsilon^X_{j,\tau} = 0$ in their study of US firms' investment during the US-China trade war.

The United States has two sets of import tariff rates. The first set, known as "normal trade relations" or NTR tariffs, are generally low and are applied to goods imported from other members of the World Trade Organization (WTO). The second set, known as non-NTR tariffs, were set by the Smoot-Hawley Tariff Act of 1930 and are often substantially higher than NTR rates. While imports from non-market economies such as China are by default subject to the higher non-NTR rates, US law allows the President to grant such countries access to NTR rates on a year-by-year basis, subject to potential overrule by Congress.

US Presidents began requesting that China be granted such a waiver in 1980. Congressional approval of these requests was uncontroversial until the Chinese government's crackdown on the Tiananmen Square protests in 1989, after which it became politically contentious and less certain. This uncertainty reduced US firms' incentive to invest in closer economic relations with China, and *vice versa*. Goldman Sachs, for example, wrote that "the annual debate has been a highly politicized process, posing a substantial threat to Chinese exporters and US importers" (Hu, 1999). It ended with Congress' passage of bill HR 4444 granting China permanent normal trade relations (PNTR) status in October 2000, which formally took effect upon China's entry into the WTO in December, 2001.[11]

At the time of PNTR's passage, investment bankers expected that China's entry into the WTO would benefit US firms in a variety of industries. Goldman Sachs expected US producers to have an easier time selling into the Chinese market and using China as an export platform, while US service providers, particularly in telecommunications, insurance, and banking, would be granted greater access to Chinese consumers via the loosening of restrictions on foreign direct investment (Hu, 1999). The AARs computed in the next section are designed to aggregate investors' expectations regarding the impact of all of such channels.

[11]PNTR was accompanied by several additional changes in policy in both the United States and China, including reductions in Chinese import tariffs, elimination of China's export licensing regime, production subsidies, and barriers to foreign investment, and the removal of US quotas on China's textile and clothing quotas as part of the phasing out of the global Multifiber Arrangement (Pierce and Schott, 2016).

3.1 Computing and Describing AAR^{PNTR}

We choose events based on the US legislative process, calculating abnormal returns over the five steps by which a US bill becomes law: (1) introduction of the PNTR bill in the US House of Representatives on May 15, 2000; (2) the vote to approve PNTR in the House on May 24; (3) the successful cloture motion to proceed with a vote on PNTR in the US Senate on July 27; (4) the vote to approve PNTR by the Senate on September 19; and (5) the signature of PNTR into law by President Clinton on October 10.[12]

The salience of these events was noted among Wall Street analysts and in newspaper articles at the time.[13] Writing in early 2000, Goldman Sachs, for example, notes that

> "The event that deserves close watch is the forthcoming US Congressional debate on permanent normal trading relations (NTR) for China, which is required to bring current U.S. trade policies pertaining to China into conformity with the basic WTO principle of most favored nation (MFN) treatment for all members." (Kurtz and Morris, 2000)

Articles in the New York Times noted that the successful vote in the House represented a "stunning victory for the Clinton administration and corporate America" (Schmitt and Kahn, 2000), and that Senate Majority Leader Trent Lott's decision to proceed to a vote in the Senate removed a "major hurdle" to considering the policy change: while a majority of Senators were in favor of PNTR, Lott had been holding up a move of the bill to the floor to achieve greater leverage in budget negotiations with the Clinton administration (Reuters, 2000; Schmitt, 2000).

As noted in Section 2, to estimate abnormal returns we first calculate "normal" or "expected" returns using the standard "market model", which, motivated by the CAPM, im-

[12]The full text of HR 4444 is available at `https://www.congress.gov`. The substantial gap between cloture and the vote in the Senate is due to that body's August recess.

[13]Appendix Figure A.1 tracks the number of articles appearing in major news outlets jointly containing the phrases "Permanent Normal Trade Relations," "China" and "United States" during 2000.

poses the market portfolio return $R_{m,t}$ as the only systematic factor in equation (2):

$$R_{j,t} = \alpha_j + \beta_j R_{m,t} + \epsilon_{j,t}. \tag{7}$$

We separately estimate this regression for every firm in our sample over all available dates in 1999, the year prior to PNTR. We choose this period to ensure that our coefficient estimates $\hat{\alpha}_j$ and $\hat{\beta}_j$ are not affected by periods when relevant legislative information about PNTR became known.[14] Daily returns for these regressions come from the Center for Research in Security Prices (CRSP). We follow the literature and restrict ourselves to common shares (i.e. CRSP share code 10 or 11) of firms incorporated in the United States, traded on one of the three main exchanges – NYSE, AMEX, and Nasdaq (i.e. CRSP exchange codes 1, 2, or 3).[15]

In order to capture any anticipatory movements prior to each event, as well as any lagged response over the subsequent days, we use a 2-day window surrounding each of the legislative event days mentioned above, for a total of 5 days for each event, or 25 days across all 5 events. For each day t in our event windows, we calculate normal returns for each firm j as $\hat{\alpha}_j + \hat{\beta}_j R_{m,t}$ and subtract this sum from the return of the firm on that day to obtain its abnormal return: $AR_{j,t} = R_{j,t} - \hat{\alpha}_j + \hat{\beta}_j R_{m,t}$. Finally, we calculate our primary measure of the firm's exposure to the policy, hereafter AAR_j^{PNTR}, by taking an average of all the non-missing abnormal returns of the firm over the 25 days spanning all 5 events.[16] Our procedure yields AAR_j^{PNTR}

[14] To minimize noise in our coefficient estimates, we keep only firms with at least 120 non-missing dates in 1999. We also show in Appendix Section G.2 that our results are robust to using "multi-factor" asset pricing models. Finally, in unreported results, we find that our results are robust to utilizing $\hat{\alpha}_j$ and $\hat{\beta}_j$ coefficients estimated using the 250 days that end 30 days before each event.

[15] Following convention, $R_{j,t}$ and $R_{m,t}$ are excess returns with respect to the risk-free rate, i.e., the one-month T-bill. Data on the daily market return and the risk-free rate are taken from Kenneth French's website. The market return is the value-weighted return for all firms meeting the criteria noted in the main text. Appendix Figures A.3 and A.4 report the simple return of the market ($R_{m,t}$) and the total volume of shares traded in the market across the PNTR event windows.

[16] By averaging across events, we treat each day as an independent draw from the distribution of returns. In Appendix Section G.2, we demonstrate the robustness of our results to use of an alternate "buy-and-hold" average, i.e., the geometric mean of the cumulative abnormal return associated with purchasing firms' stock prior to the first event and holding them across all five events. In the asset pricing literature, the term "exposure" generally refers to factor loadings (i.e. elasticities to risk factors). Here, we refer to abnormal

for 5,378 firms that are present during 1999 (the pre-period used to estimate $\hat{\beta}_j$) and at least one of the five legislative events. Across all five events the mean AAR_j^{PNTR} is -0.37 percent, with a standard deviation of 1.04 percent.[17]

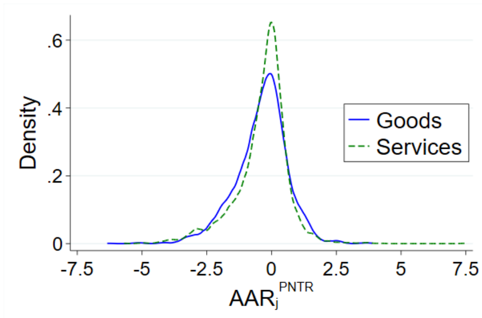


Figure 1: PNTR Average Abnormal Returns, By Type of Firm

Source: CRSP and authors' calculations. Figure plots distribution of AAR_j^{PNTR} for two mutually exclusive firm types: Goods producers, which have business segments in NAICS 11, 21, 3X, and service firms, which do not. Values below -7.5 and above 7.5 percent are dropped to improve readability. The means, standard deviations and inter-quartile ranges for the these two groups of firms are -0.38, 1.00 and 1.16 percent for goods producers and -0.35, 1.06 and 0.97 percent for service firms.

We begin by documenting the heterogeneity in our measure of exposure along two important dimensions size and sector. Using data from COMPUSTAT, we classify firms into two mutually exclusive categories depending on the mix of 6-digit NAICS codes spanned by their major business segments. We define firms to be goods producers if their business segments include Manufacturing (NAICS 31 to 33), Mining, Quarrying, Oil and Gas Extraction (NAICS 21), or Agriculture, Forestry, Fishing and Hunting (NAICS 11). We classify all remaining firms as "service" firms.[18] This results in a sample consists of 2,385 goods and 2,993 service firms respectively.

Figure 1 reports the *unweighted* distributions of these AAR. As the market-capitalization weighted average abnormal return across all firms is mean zero by definition, the greater left skewness of goods producers in the figure indicates these firms have a more positive

returns as a measure of exposure to trade liberalization, that is, as a measure of the expected impact of trade liberalization.

[17] Appendix Figure A.2 reports the distribution at each stage of the legislative process.

[18] COMPUSTAT reports firms' sales in up to 10, 6-digit NAICS business segments. In 2000, approximately 71, 16 and 7.5 percent of firms have 1, 2 or 3 segments listed, while the remaining 4 percent of firms have up to 10 segments listed. We classify the 57 firms with missing segment information as goods producers.

correlation between market capitalization and AAR_j^{PNTR}. This outcome may reflect goods-producing firms' greater exposure to increased import competition from China following PNTR. The means, standard deviations and inter-quartile ranges for the these two groups of firms are -0.38, 1.00 and 1.16 percent for goods producers and -0.35, 1.06 and 0.97 percent for service firms.

Table 1: $AAR_j^{PNTR} > 0$ Size Premia

	(1) All	(2) Goods	(3) Services
Sales	0.497 (0.134)	0.758 (0.230)	0.333 (0.127)
COGS	0.371 (0.108)	0.607 (0.168)	0.226 (0.115)
Operating Profit	0.458 (0.117)	0.655 (0.195)	0.346 (0.123)
Employment	0.421 (0.102)	0.599 (0.185)	0.314 (0.098)
PPE	0.513 (0.128)	0.666 (0.212)	0.370 (0.143)
Intangibles	0.374 (0.092)	0.509 (0.137)	0.284 (0.102)
Market Capitalization	0.712 (0.145)	0.877 (0.199)	0.602 (0.177)

Source: CRSP, COMPUSTAT and authors' calculations. Table presents firm-level OLS regressions of the log of various measures of firm size on an indicator variable for whether $AAR_j^{PNTR} > 0$, a constant, and 6-digit NAICS fixed effects. Each cell represents the result of a separate regression. Each column focuses on a different set of firms. Goods firms have a business segment active in NAICS sectors 11, 21 and 3X. Service firms have no business segments in these sectors. The maximum number of observations are 5269, 2302, and 2967 for the regressions in columns 1, 2 and 3. Standard errors are reported below coefficient estimates and are clustered by 4-digit NAICS industries.

We find that firms with positive AAR_j^{PNTR} are larger along almost every dimension than firms with negative relative returns, even within narrow industries, and that these premia are higher for goods-producers than for service firms.[19] These relationships are illustrated in Table 1, which summarizes the results of a series of OLS regressions of various measures of firm size on a dummy variable indicating whether AAR_j^{PNTR} is greater than zero, as well as 6-digit NAICS industry fixed effects. Each cell in the table reports the coefficient and standard error for the dummy variable of interest from a different regression. The sample for results in the first column is all firms, while the samples for results in the second and third columns are goods producers and service firms, respectively. Standard errors are clustered at

[19] Griffin (2018) also finds that abnormal returns rise with firm size following the house vote on PNTR.

the 4-digit NAICS level. As indicated in the table, goods producers with positive AAR_j^{PNTR} have size premia of 0.66, 0.60 and 0.88 log points in terms of operating profit, employment and market capitalization, with each of these relationships being statistically significant at conventional levels. The analogous premia for service firms are 0.35, 0.31 and 0.60.

To the extent that firm size is correlated with firm efficiency, the relationships displayed in Table 1 are consistent with models of international trade predicting that high-efficiency firms are better able to take advantage of reductions in trade costs (Melitz, 2003; Breinlich, 2014; Antràs et al., 2017; Bernard et al., 2018), for example because larger firms are more likely to be using the types of information and communication technologies that facilitate trade (Fort, 2017).

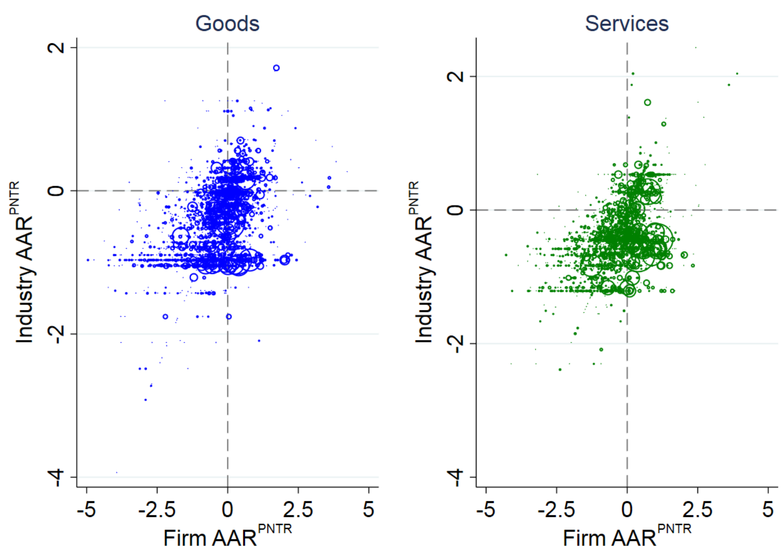


Figure 2: Firm- versus Industry-Level Average Abnormal Returns

Source: CRSP, COMPUSTAT and authors' calculations. Figure compares firms' AAR_j^{PNTR} to the unweighted average industry AAR_i^{PNTR} of their primary 6-digit NAICS segment. Values below -5 and above 5 percent are dropped to improve readability. Each point's size is scaled to the firm's market capitalization in 2000.

Finally, we find that firms' AAR_j^{PNTR} vary widely even within 6-digit NAICS industries. Figure 2 compares firms' AAR_j^{PNTR} to their major industry's AAR_i^{PNTR}, i.e, the unweighted average abnormal return of all firms whose largest segment is 6-digit NAICS industry i. Results for goods-producing firms are in the left panel, while results for service firms are in the right panel, and the size of the markers is scaled to firms' market capitalization prior to the first PNTR legislative event. To the extent that import competition in firms' major business segments is the sole determinant of their exposure to PNTR, the points in this figure would be clustered along the 45 degree line. Instead, we find a broad cloud of points, potentially reflecting underlying heterogeneity in other forms of exposure to PNTR. For example, some firms within an industry subject to the same degree of import competition might be better able to take advantage of freer trade with China. Even in industries exhibiting a negative AAR_i^{PNTR}, many firms have a positive AAR_j^{PNTR}. This deviation from industry averages appears to be more pronounced among firms with a larger market capitalization – particularly in the goods-producing sectors.

"Electronic Computer Manufacturing" (NAICS 334111), for example, includes a number of firms with both positive and negative AAR_j^{PNTR}. Among them, Apple Computer Inc. and Dell Computer Corporation are positive, while Gateway Inc., also a supplier of PCs, is negative. The former two firms thrived after PNTR, in part by taking advantage of supply chains in China. Gateway, which attempted to produce computers solely within the United States, shrank steadily during the 2000s before abandoning its US operations altogether.[20] These differences are consistent with stock traders anticipating the firms' divergent post-PNTR business strategies.

3.2 Validity of AAR_j^{PNTR}

In this section we perform a proof of concept by using *contemporaneous*, *ex post* and *external* validity checks to demonstrate the correlation of AAR_j^{PNTR} with standard measures of exposure to PNTR available at the time, subsequently, and from unrelated events.

Contemporaneous validity: We establish the contemporaneous validity of our measure by examining its relationship to the standard metric for PNTR used in the literature, the "NTR gap". This gap is defined as the difference between the higher non-NTR rate to which

[20]For a history of Gateway, see http://www.fundinguniverse.com/.

tariffs would have risen if annual renewal had failed, and the often much lower NTR rates permitted under temporary NTR status,

$$NTR\,Gap_i = Non\;NTR\,Rate_i - NTR\,Rate_i, \tag{8}$$

where i indexes 6-digit NAICS industries. These gaps are computed for 1999, the year before the change in policy, using data on US import tariff rates reported in Feenstra et al. (2002).[21] Their mean and standard deviation are 0.29 and 0.15. We summarize their distribution visually in Appendix Figure A.5.

Specifically, we use an OLS specification of the form

$$AAR_j^{PNTR} = \delta NTR\,Gap_j + \epsilon_j, \tag{9}$$

where $NTRGap_j$ is the sales-weighted average of the industry-level NTR gap ($NTRGap_i$) in firms' major segments. As $NTRGap_j$ is not defined for service firms, estimation is restricted to firms with sales in at least one goods-producing industry, substituting a gap of zero for any service segments when computing the sales-weighted averages. To ease interpretation, all variables are de-meaned and divided by their standard deviation. Standard errors are clustered at the 4-digit NAICS level.

Results are reported in Table 2. As shown in column 1, we find a negative and statistically significant relationship between $NTR\,Gap_j$ and AAR_j^{PNTR}. A one standard deviation increase in the sales-weighted average $NTR\,Gap_i$ facing firms corresponds to a reduction in AAR_j^{PNTR} of 0.20 standard deviations. That is, firms more exposed to PNTR via direct import competition are re-valued downward relative to less-exposed firms.[22]

[21] Tariff rates are assigned according to 8-digit Harmonized System (HS) commodity codes. Following Pierce and Schott (2016), we take the average NTR gap across HS codes within each 6-digit NAICS code, using the concordance reported in Pierce and Schott (2012).

[22] In Table A.1 of Section B of the Appendix, we repeat this specification for each of the five events separately. We find a negative relationship for all events that is statistically significant for three: the House vote, Senate cloture, and Clinton's signing.

Table 2: AAR_j^{PNTR} versus the NTR Gap and Firm Attributes

	(1) $\text{AAR}_\text{j}^{PNTR}$	(2) $\text{AAR}_\text{j}^{PNTR}$	(3) $\text{AAR}_\text{j}^{PNTR}$	(4) $\text{AAR}_\text{j}^{PNTR}$
NTR Gap_j	-0.202	-0.244	-0.139	-0.076
	(0.054)	(0.057)	(0.046)	(0.032)
NTR Gap_j^{Up}		0.114	0.075	0.088
		(0.052)	(0.047)	(0.034)
NTR $\text{Gap}_\text{j}^{Down}$		-0.038	-0.028	-0.086
		(0.040)	(0.042)	(0.029)
MFA Exposure_j			0.006	0.009
			(0.012)	(0.009)
Δ China $\text{Licensing}_\text{j}$			-0.219	-0.173
			(0.064)	(0.038)
Δ China Import Tariffs_j			-0.074	-0.040
			(0.027)	(0.017)
Ln(PPE per $\text{Worker})_\text{j}$				0.071
				(0.035)
Ln(Mkt $\text{Cap})_\text{j}$				0.088
				(0.022)
$\frac{CashFlows}{Assets}{}_\text{j}$				0.236
				(0.023)
Book Leverage_j				0.039
				(0.030)
Tobins Q_j				0.046
				(0.035)
Constant	-0.018	-0.092	0.091	0.051
	(0.058)	(0.074)	(0.091)	(0.052)
Observations	2271	2271	2270	2270
R^2	0.044	0.056	0.076	0.175

Source: CRSP, COMPUSTAT and authors' calculations. Table presents firm-level OLS regressions of AAR_j^{PNTR} on $NTRGap_j$, other policy variables and a series of year-2000 firm accounting attributes that are winsorized at the 1 percent level. Policy variables are expiration of textile and clothing quotas under the global Multi-Fiber Arrangement (MFA), elimination of export licensing restrictions and decreases in Chinese import tariffs. All covariates are de-meaned and divided by their standard deviation. Goods firms have a business segment active in NAICS sectors 11, 21 and 3X. Service firms have no business segments in these sectors. Standard errors are reported below coefficient estimates and are clustered by 4-digit NAICS industries.

Columns 2 to 4 examine firms' exposure to the change in policy via their supply chains, as proxied by their up- and downstream NTR gaps, $NTR\,Gap_j^{Up}$ and $NTR\,Gap_j^{Down}$.[23] To the

[23]Following Pierce and Schott (2016), we compute weighted averages of the NTR gaps across the firm's up- and downstream industries using the 1997 US Bureau of Labor Statistics input-output total-use coefficients as weights. Given the high correlation between an industry's own $NTR\,Gap_i$ and those of other industries within the same 3-digit sector, we omit from these averages all 6-digit industries within the same 3-digit NAICS root. The correlations between $NTR\,Gap_i$ and $NTR\,Gap_i^{Up}$ and $NTR\,Gap_i^{Down}$ when we do not omit sectors are 0.55 and 0.08. The analogous correlations after removal are 0.38 and -0.01. For firms with multiple segments, we compute $NTR\,Gap_j^{Up}$ and $NTR\,Gap_j^{Down}$ as the sales weighted average of the respective industry-level gaps across segments.

extent that greater upstream exposure lowers firms' input costs, and greater downstream exposure reduces customer demand, we expect the relationship between AAR_j^{PNTR} and $NTR\,Gap_j^{Up}$ to be positive and that with $NTR\,Gap_j^{Down}$ to be negative. Estimates in column 2 are consistent with these expectations: greater Chinese import competition among firms' suppliers is associated with a relative increase in market value while greater import competition among firms' customers has an adverse impact on relative market value, though the point estimate for $NTR\,Gap_j^{Down}$ is not statistically significant at conventional levels.[24]

The third column of Table 2 considers variables capturing three other policy changes associated with China's entry into the WTO: decreases in Chinese import tariffs, elimination of export licensing restrictions, and the expiration of the global Multi-Fiber Arrangement (MFA).[25] Including these additional variables does not change the sign and statistical significance of the NTR gap variables, but it does reduce the magnitude of the own-gap estimate from -0.24 to -0.14. Among the new policy variables, we find negative and statistically significant relationships with respect to changes in China's import tariffs and export licensing, and a positive relationship with respect to MFA exposure. The negative associations between AAR_j^{PNTR} and changes in Chinese import tariffs is consistent with higher expected profit in industries where it will be easier for US firms to export to China. The negative association between AAR_j^{PNTR} and the share of Chinese firms eligible export is also intuitive, as removal of these restrictions may increase competition for US producers in the exposed industries. The positive association between AAR_j^{PNTR} and exposure to elimination of MFA quotas may reflect the ability of some goods-producing firms to take advantage of greater production in China.

[24]One concern with this regression is that most firms are observed to operate in just one business segment. A regression of the market-capitalization weighted average AAR_j^{PNTR} across firms in each 6-digit NAICS industry on the industry-level $NTR\,Gap_j$ also yields a negative and statistically significant relationship of similar magnitude.

[25]Industry-level data on the change in Chinese import tariffs from 1996 to 2005 and the share of Chinese firms eligible to export are from Brandt et al. (2017) and Bai et al. (2015). As discussed in greater detail in Section A of the Appendix, we follow Pierce and Schott (2016) in using the import-weighted average fill rate of the quotas removed in each 6-digit NAICS industry as of the PNTR votes as a control. Fill rates are defined as actual divided by allowable imports; higher values indicate greater exposure to MFA quota reductions.

Finally, the fourth column of Table 2 includes a set of firm attributes, based on accounting information, commonly included in regressions of abnormal returns in the finance literature as proxies for firms' investment opportunities and their ability to finance them. They are property, plant and equipment (PPE) per worker, firm size (as measured by the log of market capitalization), profitability (cash flows to assets), book leverage, and Tobin's Q.[26] As is common in the finance literature, we winsorize these accounting variables at the 1 percent level to reduce the influence of outliers, i.e., we replace observations below the first percentile and above the ninety-ninth percentile with the values at those percentiles.

With these additional covariates included, the coefficients on all three NTR gap variables retain their signs from previous columns. The own-gap coefficient drops further in magnitude, to -0.08, and all three gap controls are now statistically significant. Among the additional firm attributes, we find positive and statistically significant relationships for all except book leverage, which is positive but not statistically significant at conventional levels.

The results in Table 2 indicate that AAR_j^{PNTR} is related to the standard metric of exposure used in the literature and indeed goes beyond it to capture additional dimensions of the change in policy. As a result, they highlight a key benefit of our approach, which is to provide an all-in measure of firm exposure. This attribute is particularly useful as gathering data on all possible dimensions of firm exposure is impractical.

Ex Post validity: Table 3 examines the link between firms' AAR_j^{PNTR} and post-PNTR US import growth from China, an outcome not knowable in 2000, but useful for assessing the *ex post* validity of AAR_j^{PNTR}. For each firm, we calculate weighted average US import growth across observed business segments in 2000. Given that imports are not observed for service-firm industries, the sample for this analysis is restricted to firms with sales in at least one goods-producing industry. Among those firms, we assign zero import growth to all service segments in calculating the firm average. The sample period is from 2000 to 2006,

[26] In this section, all firm attributes are measured before the first legislative event we consider, and are drawn from COMPUSTAT. All columns in the table are restricted to the sample of firms for which all five controls are reported. Results using the full sample are very similar.

from passage of PNTR until the year before the Great Recession. As above, all variables are de-meaned and divided by their standard deviation and standard errors are clustered at the 4-digit NAICS level.

Table 3: AAR_j^{PNTR} versus Chinese Import Growth

	(1) AAR_j^{PNTR}	(2) AAR_j^{PNTR}	(3) AAR_j^{PNTR}
Δ Ln(Imports)$_j^{2000-6}$	-0.123	-0.123	-0.093
	(0.045)	(0.045)	(0.030)
Δ Ln(Imports)$_j^{1990-00}$		0.001	-0.009
		(0.035)	(0.041)
Ln(PPE per Worker)$_j$			0.000
			(0.038)
Ln(Mkt Cap)$_j$			0.113
			(0.021)
$\frac{CashFlows}{Assets}_j$			0.232
			(0.034)
Book Leverage$_j$			0.080
			(0.034)
Tobins Q$_j$			0.027
			(0.032)
Constant	-0.081	-0.081	-0.069
	(0.052)	(0.052)	(0.042)
Observations	1901	1901	1901
R^2	0.016	0.016	0.121

Source: CRSP, COMPUSTAT and authors' calculations. Table presents firm-level OLS regressions of AAR_j^{PNTR} on US import growth from China in firms' largest business segment and a series of year-2000 firm accounting attributes that are winsorized at the 1 percent level. Regression sample is restricted to firms in goods-producing industries for which imports are observed. All covariates are de-meaned and divided by their standard deviation. Goods firms have a business segment active in NAICS sectors 11, 21 and 3X. Service firms have no business segments in these sectors. Standard errors are reported below coefficient estimates and are clustered by 4-digit NAICS industries.

As indicated in the first column of the table, we find a negative and statistically significant relationship between AAR_j^{PNTR} and post-PNTR import growth. In column 2, we add the change in imports between 1990 and 2000 as a placebo exercise and find that the coefficient for *ex post* import growth remains as before while the coefficient for prior period is close to zero and statistically insignificant. In column 3, we find that these relationships are robust to the inclusion of the accounting attributes introduced in the last section. The estimated coefficient estimate on post-2000 import growth from China in the final column, -0.093, indicates that a 1 standard deviation increase in subsequent imports from China is associated with a 0.093 standard deviation decline in average abnormal returns, or a loss in market value of about 2.4 percent.[27] Together, the results in Table 3 indicate that during PNTR's passage investors' bid down the returns of firms that subsequently experienced greater import competition from China, and that this behavior is not the continuation of a prior trend.

External validity: We also include *external* validity tests which, unlike the previous two, can be performed for service producers. In these cases we examine the correlation between firms' AAR's and similarly constructed measures calculated during events that may *reverse* the effects of the liberalization. We consider two such events– the accidental accidental NATO bombing of the Chinese embassy in Belgrade, Yugoslavia on May 7, 1999, and the election of President Donald Trump.[28] For brevity, we relegate our analysis of the 2016 Presidential Election to Appendix Section C. Given that the bombing was unanticipated, and that information about it unfolded slowly, we compute firms' $AAR_j^{Belgrade}$ across the seven trading days after the bombing occurred. We analyze the association between $AAR_j^{Belgrade}$ and AAR_j^{PNTR} via the following OLS regression:

$$AAR_j^{PNTR} = \delta AAR_j^{Belgrade} + \epsilon_i. \tag{10}$$

Results are presented in Table 4. We find that the relationship between the AARs is *negative* and statistically significant at conventional levels for all firms as well as goods and service providers separately, indicating that firms which are expected to benefit relative to the market from a potential breakdown of US-China relations due to the bombing in 1999 are expected to be harmed in relative terms by the trade liberalization in 2000.[29]

[27]Multiplying the coefficient (-0.093) by the standard deviation of AAR_j^{PNTR} (1.03 percent) provides the daily effect. Multiplying this number by 25 to account for all 25 days in our event windows yields 2.4 percent.

[28]The bombing occurred during an 11-week NATO campaign intended to end Serbian aggression against ethnic Albanians in Kosovo, and was recognized at the time as a potential threat to China's entry into the WTO. Three days after the bombing, for example, the Wall Street Journal noted that "prospects for a speedy end to negotiations on China's accession to the World Trade Organization just got a lot worse" (Brauchli and Cooper, 1999).

[29]Across goods firms, we find the expected *positive* relationship between the $AAR_j^{Belgrade}$ and the NTR

Table 4: $\boldsymbol{AAR_j^{PNTR}}$ versus $\boldsymbol{AAR_j^{Belgrade}}$

	(1) $\text{AAR}_\text{j}{}^{PNTR}$	(2) $\text{AAR}_\text{j}{}^{PNTR}$	(3) $\text{AAR}_\text{j}{}^{PNTR}$
$\text{AAR}_\text{j}{}^{Belgrade}$	-0.082	-0.051	-0.121
	(0.020)	(0.022)	(0.034)
Constant	0.010	-0.018	0.032
	(0.063)	(0.074)	(0.089)
Observations	5055	2269	2786
R^2	0.007	0.004	0.012
Firm Type	All	Goods	Services

Source: CRSP, COMPUSTAT and authors' calculations. Table presents firm-level OLS regressions of AAR_j^{PNTR} on $AAR_j^{Belgrade}$. All covariates are de-meaned and divided by their standard deviation. Goods firms have a business segment active in NAICS sectors 11, 21 and 3X. Service firms have no business segments in these sectors. Standard errors are reported below coefficient estimates and are clustered by 4-digit NAICS industries.

3.3 Using AAR_j^{PNTR} to Assess Firm Outcomes

Standard event studies in the finance literature focus on whether a particular event has a significant impact on stock returns. Hence, the object of interest is usually the cross-sectional average of abnormal returns.[30] In this paper we argue that abnormal returns provide an all-in summary of the impact of a change in policy on the firm. As such, they are a natively *firm-level* measure of exposure to trade liberalization that can be employed in the standard difference-in-difference identification strategies used in the trade literature.

We first examine the impact of exposure on firm survival and their sales, cost of goods sold and operating profit conditional on survival. As AAR_j^{PNTR} represent traders' assessment of the effect of PNTR on firms' cash flows (and discount rates), we expect firms with relatively low AAR_j^{PNTR} to be less profitable and less likely to survive. Then, following much of the "China shock" literature, we examine the link between AAR_j^{PNTR} and firms' employment and capital.

Gap_j in Section B of the Appendix.

[30] See for example the textbook treatment in Campbell et al. (1997).

3.3.1 Firm Survival

In this section, we examine the relationship between AAR_j^{PNTR} and firm survival, where exit from our sample signifies a firm's de-listing from the stock exchange. We group the CRSP flags for these de-listings into three categories: (1) bankruptcy and contraction of firm assets, equity, or capital below the levels required to be listed; (2) merger; and (3) exit for other reasons, e.g., protection of investors and the public interest, or failure to meet equity requirements.[31]

Table 5: AAR_i^{PNTR} and Firm Exit, Multinomial Logit

	Survival	Contraction/Bankruptcy	Merger	Other
	Panel A: All Firms			
AAR_j^{PNTR}		-0.268	0.022	-0.081
		(0.072)	(0.050)	(0.089)
Marginal Effect	0.017	-0.026	0.011	-0.001
	(0.012)	(0.007)	(0.008)	(0.002)
Unconditional Probability	0.586	0.169	0.21	0.04
Δ Prob.	0.027	-0.15	0.06	-0
Pseudo R^2	.122	.122	.122	.122
Observations	4377	4377	4377	4377
	Panel B: Goods Only			
AAR_j^{PNTR}		-0.211	0.146	-0.129
		(0.090)	(0.066)	(0.084)
Marginal Effect	-0.006	-0.018	0.028	-0.003
	(0.013)	(0.008)	(0.010)	(0.002)
Unconditional Probability	0.634	0.146	0.18	0.04
Δ Prob.	-0.01	-0.118	0.13	-0.1
Pseudo R^2	.128	.128	.128	.128
Observations	2266	2266	2266	2266
	Panel C: Service Only			
AAR_j^{PNTR}		-0.299	-0.048	-0.006
		(0.095)	(0.061)	(0.174)
Marginal Effect	0.031	-0.034	0.002	0.001
	(0.017)	(0.010)	(0.010)	(0.005)
Unconditional Probability	0.535	0.193	0.23	0.04
Δ Prob.	0.058	-0.17	0.01	0.01
Pseudo R^2	.121	.121	.121	.121
Observations	2102	2102	2102	2102

Source: CRSP, COMPUSTAT and authors' calculations. Table presents results of firm-level multinomial logit model of exit (i.e., de-listing from their exchange) between 2000 and 2006. De-listing codes are described in text and Appendix Table A.4. The base outcome (column 1) is survival through the end of 2006. Right-hand side variables included in the regression but whose estimates are suppressed are a series of year-2000 firm accounting attributes that are winsorized at the 1 percent level. All covariates are de-meaned and divided by their standard deviation. Standard errors are reported below coefficient estimates and are clustered by 4-digit NAICS industries.

[31] Appendix Table A.4 provides a more detailed breakdown of these flags. We observe 1814 firms de-list between 2000 and 2006. The distribution of these de-listings across the three categories is 743, 893, and 178, respectively.

Table 5 presents the results from a multinomial logit regression of exit,

$$Pr(Y_j = d) = \delta AAR_j^{PNTR} + \mathbf{X_j^{2000}}\gamma + \epsilon_j, \tag{11}$$

where $Pr(Y_j = d)$ is the probability that firm j exits between 2000 and 2006 due to de-listing category d, and $\mathbf{X}_j^{2000}$ represents the vector of accounting variables employed in our earlier specifications, e.g., Table 2.[32] The latter are included because the fundamental attributes governing firms' success or failure during trade liberalization may affect their performance more broadly. For example, firms with higher productivity may earn greater profit after PNTR (Melitz, 2003), but they may also earn greater profit for other reasons, e.g., via their easier access to capital markets or their greater ability to achieve operational efficiencies from investments in technology. If ignored, these attributes would confound our ability to use AAR_j^{PNTR} to predict subsequent changes in firm outcomes.

The base outcome is survival. As with our previous firm-level regressions, we standardize all variables by subtracting their mean and dividing by their standard deviations. We report both coefficients and marginal effects evaluated at the mean of all dependent variables for δ; results for all other covariates are suppressed to conserve space.

Panel A of the table focuses on the full sample of firms, and indicates that higher AAR_j^{PNTR} is indeed correlated with reduced exit via contraction and bankruptcy. The marginal effects indicate that a one standard deviation increase in AAR_j^{PNTR} is associated with a relative decrease in the probability of exit for these causes of 2.6 log points, an economically meaningful impact given that the unconditional probability of exit due to these causes, reported in the fourth to last line of the panel, is 16.9 percent. We do not find any significant relationships between AAR_j^{PNTR} and "other" forms of de-listing.

In panels B and C, we estimate the multinomial logit separately for goods and service

[32] We cannot use a difference-in-differences specification to examine exit due to how our sample is constructed. That is, firms must be present in 2000 for AAR_j^{PNTR} to be measured. Balance sheet information is missing for 771 firms in 2-digit NAICS sector 52 (Finance). This information is also missing for 221 firms in other sectors. All of these firms are excluded from the analyses in the remainder of the paper.

firms. We find that higher AAR_j^{PNTR} are negatively associated with the likelihood of exit via bankruptcy and contraction for both types of firms, though the magnitude of the effect is comparatively larger for service firms. A one standard deviation increase in AAR_j^{PNTR} is associated with a relative decline in exit of 1.8 and 3.4 log points, versus unconditional probabilities of exit of 14.8 and 19.3 percent. For manufacturing firms, we find a positive association with respect to de-listing due to merger, which may indicate the relative attractiveness of firms with a "China strategy" as acquisitions targets. Further research into such an explanation is warranted.

Overall, the results in Table 5 provide additional support for our approach, as they suggest investors anticipated future firm survival. The greater overall importance of AAR_j^{PNTR} in explaining service firm survival may be due to their thinner profit margins. That is, to the extent that less profitable firms are more likely to exit in the face of negative economic shocks, one might expect the impact of PNTR on exit to be larger among these firms.

3.3.2 Relative Growth in Operating Profit, Employment and Capital

This section explores the relationship between AAR_j^{PNTR} and operating profit among surviving firms using a generalized difference-in-differences specification,

$$ln(OperatingProfit_{j,t}) = \delta Post \times AAR_j^{PNTR} + \gamma Post \times \mathbf{X_j^{1990}} + \alpha_j + \alpha_t + \epsilon_{j,t}.$$

The sample period is 1990 to 2006. The left-hand side variable represents one of a range of firm outcomes available in COMPUSTAT, discussed in detail below. The first term on the right-hand side is the difference-in-differences term of interest – an interaction of firms' average abnormal return and an indicator variable ($Post$) for years after 2000 – which captures the relative change in outcomes among firms with differential exposure to the change in policy after versus before it occurs. The second term on the right-hand side again represents the vector of winsorized initial (here 1990) firm accounting attributes that may influence profitability through channels unrelated to PNTR.[33] The final terms on the right-hand side are the firm and year fixed effects required to identify the difference-in-differences coefficient. Firm fixed effects capture the impact of any time-invariant firm characteristics, while year fixed effects account for aggregate shocks that affect all firms. As above, all independent variables have been standardized so that the coefficients may be interpreted as the impact of changing the covariate by one standard deviation, and standard errors are clustered by 4-digit NAICS industry.

Sales, Costs and Operating Profit: Estimates for firms' worldwide sales, cost of goods sold (COGS) and operating profit (i.e., sales less COGS) are reported in Table 6. Columns 1, 4, and 7 contain results for all firms. In the first two of these columns, we find positive and statistically significant relationships between abnormal returns and both sales and cost of goods sold, indicating that firms with higher AAR_j^{PNTR} expand after PNTR relative to firms with lower abnormal returns. The positive relationship between AAR_j^{PNTR} and operating profit in column 7 suggests that firms with positive returns relative to the market during key PNTR legislative events do in fact exhibit relatively higher profits through 2006. The coefficient estimates in these columns imply that a one standard deviation increase in AAR_j^{PNTR} is associated with relative increases in sales, COGS and operating profit of 13.0, 10.5 and 12.9 log points, respectively.

Columns 2, 5, and 8 report results for goods-producing firms, while columns 3, 6, and 9 are restricted to service firms. As indicated in the table, we find positive and statistically significant relationships for all three outcomes among both sets of firms. Magnitudes for sales and operating profit are larger for goods firms, while the opposite is true for COGS.[34]

[33]For firms that enter the sample after 1990, we use their attributes upon entry in constructing $\mathbf{X_j}$.

[34]Results in Table 6 are restricted to firms with positive operating profit. We find qualitatively similar results using an inverse hyperbolic sine transform (e.g., $ln(OperatingProfit_{j,t}+(1+OperatingProfit_{j,t}^2)^{0.5})$, which approximates the natural log but allows for values weakly less than zero. In Appendix Table A.6 we examine the relationship between operating profit and the average abnormal returns associated with each event, finding negative and statistically significant relationships except for the Senate vote. Appendix Tables A.7 and A.8 demonstrate that we find similar results when we add $NTRGap_j$, $NTR\,Gap_j^{Up}$ and $NTR\,Gap_j^{Down}$ as additional covariates to the baseline specification, suggesting that AAR_j^{PNTR} captures the effects of PNTR through channels beyond direct import competition.

Table 6: AAR_i^{PNTR} and Firm Sales, COGS and Operating Profit

	Ln(Sales$_j$)			Ln(COGS$_j$)			Ln(Profit$_j^{OP.}$)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post*AAR$_j^{PNTR}$	0.130	0.150	0.095	0.105	0.097	0.103	0.129	0.143	0.098
	(0.026)	(0.036)	(0.032)	(0.020)	(0.023)	(0.028)	(0.026)	(0.026)	(0.036)
Post*PPE per Worker$_j$	0.053	0.147	-0.015	0.046	0.129	-0.007	0.037	0.152	-0.040
	(0.041)	(0.055)	(0.028)	(0.035)	(0.050)	(0.023)	(0.044)	(0.054)	(0.031)
Post*Ln(Mkt Cap)$_j$	-0.068	-0.091	-0.062	-0.076	-0.097	-0.072	-0.074	-0.105	-0.058
	(0.023)	(0.027)	(0.029)	(0.020)	(0.025)	(0.025)	(0.024)	(0.027)	(0.026)
Post*$\frac{CashFlows}{Assets}_j$	-0.136	-0.198	-0.044	-0.060	-0.098	-0.012	-0.137	-0.212	-0.045
	(0.031)	(0.033)	(0.029)	(0.020)	(0.021)	(0.028)	(0.035)	(0.040)	(0.027)
Post*Book Leverage$_j$	-0.037	-0.095	0.026	-0.027	-0.077	0.024	-0.033	-0.081	0.017
	(0.019)	(0.021)	(0.023)	(0.020)	(0.024)	(0.025)	(0.023)	(0.024)	(0.025)
Post*Tobins Q$_j$	0.128	0.163	0.097	0.126	0.143	0.107	0.114	0.156	0.074
	(0.023)	(0.042)	(0.024)	(0.021)	(0.035)	(0.025)	(0.025)	(0.040)	(0.028)
FE	j&t	j&t	j&t	j&t	j&t	j&t	j&t	j&t	j&t
Weights	Equal	Equal	Equal	Equal	Equal	Equal	Equal	Equal	Equal
Firm Type	All	Goods	Services	All	Goods	Services	All	Goods	Services
Years	1990-6	1990-6	1990-6	1990-6	1990-6	1990-6	1990-6	1990-6	1990-6
R2	.924	.926	.921	.927	.93	.922	.913	.92	.906
Observations	51121	28694	22427	51205	28778	22427	48551	26928	21623
Unique Firms	4516	2340	2176	4517	2341	2176	4360	2237	2123

Source: CRSP, COMPUSTAT and authors' calculations. Table presents firm-level OLS DID panel regressions of noted firm outcomes on firms' PNTR average abnormal returns (AAR_j^{PNTR}) and a series of 1990 firm accounting attributes that are winsorized at the 1 percent level. Sample period is 1990 to 2006. All covariates are de-meaned and divided by their standard deviation. Standard errors are reported below coefficient estimates and are clustered by 4-digit NAICS industries.

We discuss the implications of these results in Section 3.4 below.

Employment, Physical Capital and Intangible Capital: Estimates for firms' worldwide employment, physical capital and intangible capital are reported in Table 7. Physical capital is defined as the book value of property, plant and equipment, while intangible capital, following Peters and Taylor (2017), is measured as the sum of goodwill, capitalized research and development expenditures and capitalized "organizational" capital, defined as a fixed portion of selling, general and administrative expenses.

Both goods-producing and service firms with higher AAR_j^{PNTR} exhibit relative increases in employment after the change in policy versus before. The coefficient estimate for all firms is 0.098, implying that a one standard deviation increase in AAR_j^{PNTR} is associated with a relative increase in employment of 9.8 log points in the post period. Perhaps surprisingly, the magnitude of this point estimate is larger for service-producing firms – 10.2 log points –

Table 7: AAR_i^{PNTR} and Employment, PPE, and Intangible Capital

	Ln(Employment$_j$)			Ln(PPE$_j$)			Ln(Intangibles$_j$)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post*AAR$_j$^{PNTR}	0.098	0.086	0.102	0.091	0.112	0.061	0.064	0.053	0.066
	(0.018)	(0.023)	(0.030)	(0.024)	(0.025)	(0.038)	(0.019)	(0.019)	(0.030)
Post*PPE per Worker$_j$	0.036	0.102	-0.008	-0.062	0.012	-0.129	0.007	0.074	-0.021
	(0.020)	(0.022)	(0.027)	(0.045)	(0.066)	(0.025)	(0.024)	(0.026)	(0.030)
Post*Ln(Mkt Cap)$_j$	-0.071	-0.091	-0.067	-0.076	-0.116	-0.037	-0.025	-0.059	0.004
	(0.016)	(0.017)	(0.024)	(0.025)	(0.030)	(0.025)	(0.019)	(0.016)	(0.037)
Post*$\frac{CashFlows}{Assets}$$_j$	-0.024	-0.056	0.033	-0.030	-0.044	-0.003	-0.037	-0.062	0.003
	(0.020)	(0.019)	(0.027)	(0.015)	(0.018)	(0.026)	(0.021)	(0.017)	(0.031)
Post*Book Leverage$_j$	-0.052	-0.092	-0.010	-0.050	-0.109	0.022	-0.056	-0.077	-0.043
	(0.018)	(0.020)	(0.026)	(0.021)	(0.026)	(0.023)	(0.017)	(0.022)	(0.025)
Post*Tobins Q$_j$	0.119	0.166	0.084	0.169	0.227	0.130	0.189	0.232	0.146
	(0.015)	(0.027)	(0.017)	(0.027)	(0.042)	(0.028)	(0.032)	(0.029)	(0.047)
FE	j&t	j&t	j&t	j&t	j&t	j&t	j&t	j&t	j&t
Weights	Equal	Equal	Equal	Equal	Equal	Equal	Equal	Equal	Equal
Firm Type	All	Goods	Services	All	Goods	Services	All	Goods	Services
Years	1990-6	1990-6	1990-6	1990-6	1990-6	1990-6	1990-6	1990-6	1990-6
R2	.935	.941	.927	.944	.948	.939	.917	.943	.886
Observations	51007	28779	22228	51227	28968	22259	49468	28782	20686
Unique Firms	4522	2347	2175	4523	2347	2176	4442	2337	2105

Source: CRSP, COMPUSTAT and authors' calculations. Table presents firm-level OLS DID panel regressions of noted firm outcomes on firms' PNTR average abnormal returns (AAR_j^{PNTR}) and a series of 1990 firm accounting attributes that are winsorized at the 1 percent level. Sample period is 1990 to 2006. All covariates are de-meaned and divided by their standard deviation. Standard errors are reported below coefficient estimates and are clustered by 4-digit NAICS industries.

than goods firms – 8.6 log points. We return to the implications of this result in Section 3.4 below.

The remaining columns of Table 7 indicate positive relationships between AAR_j^{PNTR} and both forms of capital. Among goods producers, the coefficient for physical capital is more than twice as large as that for intangible capital, and both are statistically significant. For service firms, both associations are positive and of similar magnitude, but only the relationship with intangible capital is statistically significant at conventional levels. These positive relationships indicate a potential mechanism for the sort of product or process upgrading in response to low-wage country import competition found among US and European firms by Bernard et al. (2006), Khandelwal (2010), Bernard et al. (2011). Bloom et al. (2016) and Ding et al. (2019). They are consistent with Gutierrez and Philippon (2017), who find relative increases in intangible investment and innovation among industry leaders in response to PNTR, but at odds with Autor et al. (2017), who argue that increases in Chinese import penetration negatively affect patenting.

We note that while optimal employment and investment are functions of expected operating profits, there is no reason to believe that they are monotonically related. Expanding firms may invest in labor-saving technology, for instance, thereby reducing relative employment. Further, the relationship between profit and factor inputs may itself be affected by PNTR, for instance if PNTR causes general equilibrium changes in factor costs. Hence, the effect of PNTR on employment and investment is *a priori* unclear even if its impact on expected profits is not. Identifying the mechanisms through which PNTR's effect on expected profits alters employment and investment decisions is worthy of further inquiry but beyond the scope of this study.

3.4 The Firm-level Distributional Implications of PNTR

In this section we use the results above to examine the firm-level distributional implications of PNTR. For each firm j, we employ the estimates of $\hat{\delta}$ from DID specifications analogous to equation (12), but estimated using non-standardized covariates, to compute predicted relative operating profit for 2001 to 2006:

$$\widehat{Op\,Profit_j^{Post\,Period}} = \Big(exp(\hat{\delta} \times AAR_j^{PNTR}) - 1\Big) \times Op\,Profit_j^{2000} \tag{12}$$

The product of $\hat{\delta}$ and AAR_j^{PNTR} is the predicted growth in operating profit in the post-PNTR period relative to the pre-PNTR period, in log points. It is exponentiated and reduced by 1 to convert it into percentage terms, and then multiplied by operating profit in 2000 to convert it into levels. As we are focused on investors' expectations at the time of the policy change, we compute $\widehat{Op\,Profit_j^{Post\,Period}}$ for all firms, even if they subsequently exit the sample. In performing these calculations, we use the separately estimated $\hat{\delta}$'s for goods and service firms.

Figure 3 plots the cumulative predicted relative operating profit across all firms in the post period, calculated by summing the fitted value from equation (12) along the firm size distribution, from low to high market capitalization. Goods producers are represented by large black dots, while service firms are indicated by the red x's.

As illustrated in the figure, cumulative profit declines with firm size until market capitalization reaches approximately 10 billion dollars. Firms larger than this threshold exhibit modest relative increases in expected operating profit until market capitalization reaches around 100 billion dollars, at which point it rises substantially. This reversal is driven by firms both inside and outside manufacturing, though the former are more prevalent as size grows: above 20 billion dollars, 57 percent of firms are goods producers, while above 50 and 100 billion dollars, their share is two-thirds.[35]

The variation in Figure 3 is consistent with the existence of relatively high fixed costs to access Chinese suppliers. Antràs et al. (2017), for example, categorize China as one of the world's most attractive sources of imported intermediate inputs, with among the highest fixed costs. In such a setting, the largest US firms would have the greatest ability to access Chinese suppliers and thereby achieve lower costs and greater sales and operating profit. The results in Figure 3 also suggest a potential role for trade liberalization in the rising share of economic activity attributed to large, old, "superstar" firms documented in Decker et al. (2014) and Autor et al. (2017).

Figure 4, which no longer differentiates goods and service producers to promote legibility, reveals a different trend for employment. As with operating profit, small firms exhibit relative declines. The largest firms, however, have relative employment growth that is either flat or moderately declining. The implicit relative increase in labor productivity among the largest firms and overall suggests a link between PNTR and the substantial rise in US manufacturing labor productivity observed during the 2000s (Fort et al., 2018).

The remaining panels of Figure 4 provide analogous displays for physical and intangible

[35] As discussed further in Section E of the Appendix, large firms' size as well as their generally positive AAR_j^{PNTR} contribute to their predicted relative growth *vis a vis* small firms in Figure 3.

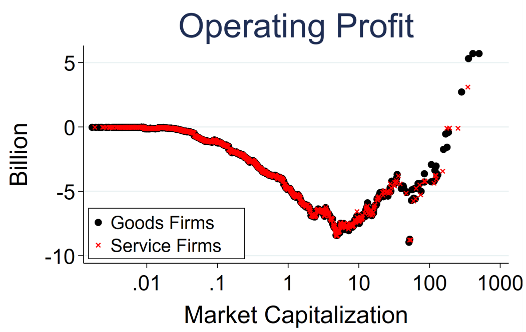


Figure 3: Cumulative Relative Change in Operating Profit: Service Firms Highlighted

Source: CRSP, COMPUSTAT, and authors' calculations. Figure displays the predicted cumulative relative change in goods versus service firms' operating profit implied by the baseline difference-in-differences estimates in Table 6. Firms' market capitalization (in billions) is from 2000, prior to PNTR.

capital. In both cases, the smallest firms show relative declines, and the largest firms show relative increases. The latter, however, are more modest than for operating profit, with the result that the relative gains of the largest firms do not offset the relative losses of the smaller firms. Even so, these outcomes are broadly consistent with recent research by Gutierrez and Philippon (2017) showing that industry "leaders" invest more in response to rising import competition from China than their followers.

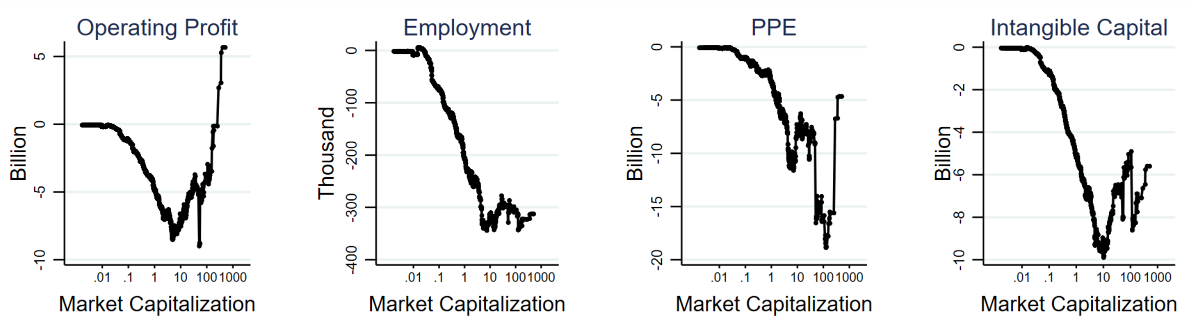


Figure 4: Cumulative Relative Change in Firm Outcomes

Source: CRSP, COMPUSTAT, and authors' calculations. Figure displays the predicted cumulative relative change in four firm outcomes implied by the baseline difference-in-differences estimates in Table 6. Firms' market capitalization (in billions) is from 2000, prior to PNTR.

Figure 5 reports the cumulative relative change in each outcome for each 2-digit NAICS sector for which we observe a large number of firms. The y-axis in each panel of the figure reports the cumulative relative change in each outcome as a share of its initial (year 2000) level so that the four outcomes can be plotted against each other. Sectors vary substantially in their predicted relative changes. Almost all mining firms, for example, exhibit predicted relative increases in the four outcome variables, while the opposite is true in Wholesale/Retail. The latter accords with analysts' expectations at the time that China's entry into the WTO would reduce US wholesale and retail markups, and that these reductions would not be offset by greater profit in China, at least initially.[36] It also suggests the relationship between the increasing "toughness" of competition and declining markups following trade liberalization developed in Melitz and Ottaviano (2008) applies to services.

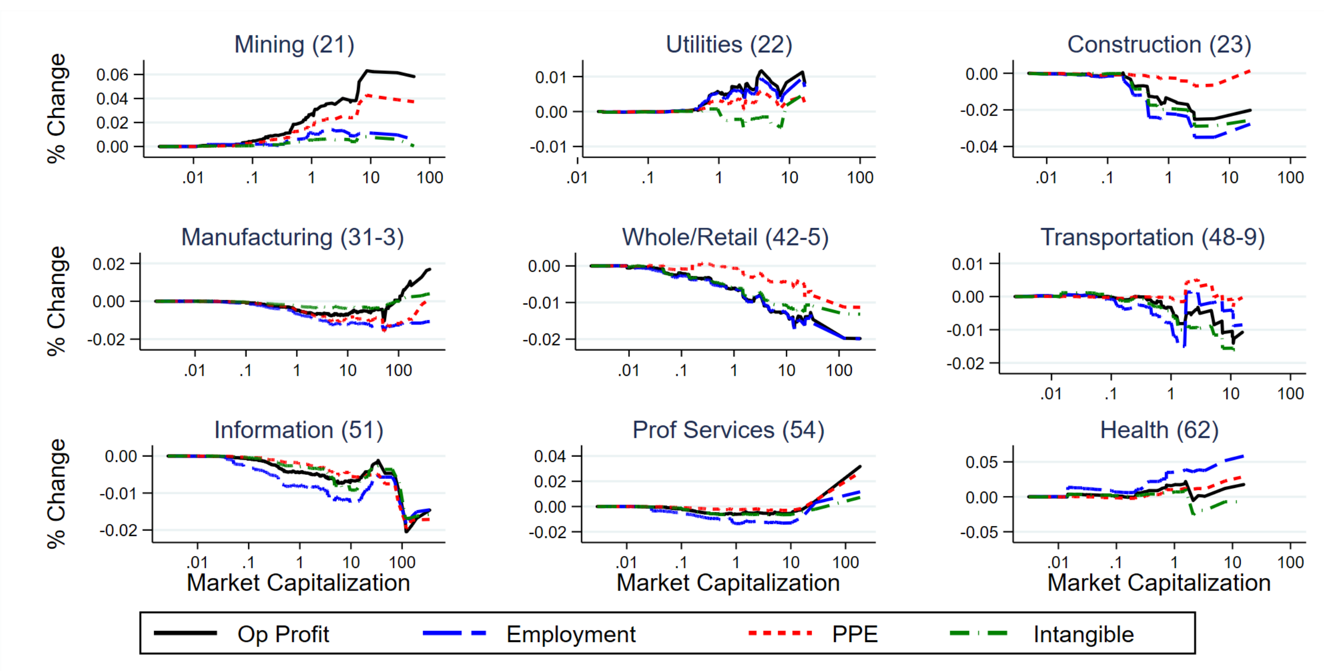


Figure 5: Cumulative Relative Changes by Sector

Source: CRSP, COMPUSTAT, and authors' calculations. Figure displays the predicted cumulative relative change in 4 firm outcomes implied by the baseline difference-in-differences estimates in Table 6 by noted 2-digit NAICS sector. Y-axis reports the cumulative predicted relative change as a share of the initial total of each outcome across firms in 2000, prior to PNTR. Each firm appears only in one panel, according to the NAICS code of largest business segment in 2000. Firms' market capitalization is from 2000, prior to PNTR. Note that y-axes vary across panels.

Two other sectors of note in Figure 5 are Professional Services and Information. Professional Services, which includes business services such as accounting and law as well as

[36] For example, while Goldman Sachs anticipated a near tripling of Chinese sales for Wal-Mart in the first five years after PNTR, it predicted that this growth would not make a meaningful contribution to Wal-Mart's bottom line (Kurtz and Morris, 2000).

engineering and research and development, exhibit a large cumulative relative gain. This increase may be driven by an anticipated, post-PNTR shift in the United States toward the design, engineering, sourcing, marketing and distribution of goods whose physical production would begin migrating to China (Ding et al., 2019). The Information sector, which includes publishing, motion pictures, broadcasting, telecommunications, and data processing, exhibits a large cumulative relative decline across all four outcomes, driven by negative average abnormal returns among 75 percent of the firms. The three largest firms (Microsoft, Oracle and AT&T) have positive *AAR*s and exhibit relative growth in all four outcomes. There is also a smaller cohort of relatively large internet and logistic firms, e.g., Ebay and I2 Technologies, which also exhibits relative gains.[37] These trends may be influenced by the fact that while China agreed to substantial liberalization of its telecommunications sector as part of its WTO accession, it was phased in gradually and subject to a number of limitations, such as temporary restrictions on foreign ownership shares, which may have affected different types of Information firms unevenly.[38] This delay may have affected the timing of revenues versus costs more for some firms than others, substantially backloading operating profit beyond our time horizon. Further research here would be interesting.

4 CUSFTA

We now turn to a second application of our method, the 1989 Canada-US Free Trade Agreement, one of the largest bilateral trade agreements of its time. It is an attractive target for our approach due to the fact that one of its central provisions, "national treatment," required the US and Canada to treat each countries' service firms symmetrically, for instance with respect to professional licensing standards and market access.[39] Measures for such provisions

[37] These two firms both have market capitalization on the order of 10 billion dollars in our sample.

[38] For a detailed discussion of telecommunications liberalization in China, see Pangestu and Mrongowius (2002) and Whalley (2003).

[39] For example, in the years leading up to CUSFTA, AT&T, GTE and Rockwell International had complained to the US Trade Representative about favoritism shown towards Bell-Canada in public procurement Chase (2009).

are difficult to quantify, and as a result tend to be ignored in standard analyses. CUSFTA is also appealing because it mandated declines in *both* countries' tariffs, inducing potentially complicated responses among firms operating in or drawing inputs from both markets. Though CUSFTA's impact on Canada is well-studied, there is little research on either its US effects or on service sector responses.[40]

We follow Breinlich (2014) in focusing on the November 21, 1988 Canadian federal election as the key event associated with the policy change. CUSFTA was by far the most important issue debated in this election, and its outcome was uncertain in the weeks leading up to it. While Prime Minister Brian Mulroney and the Progressive Conservative party favored CUSFTA, his opponent John Turner and the Liberal Party proposed abandoning it.

4.1 Computing AAR^{CUSFTA}

We compute US firms' average abnormal returns around the Canadian election, AAR_j^{CUSFTA}, analogously to those calculated for PNTR. We divide firms into goods producers and service firms using the 1988 SIC classification system. The average AAR is -0.33% among the 2305 goods producers and -0.28% among the 2589 service firms.

We display the industry (SIC 4-digit) and firm-level AARs in Figure 6. As with PNTR there is considerable variation in AAR among both goods and service firms and this variation occurs *within* narrow industries. We similarly observe that larger firms tend to have higher AAR than smaller firms within the same 4-digit SIC industry. This pattern holds both for goods and service firms.

4.2 Validity of AAR_j^{CUSFTA}

In Table 8 we perform a contemporaneous validation of AAR_j^{CUSFTA} by comparing them to the agreement's terms using the same specification employed in Table 2 for PNTR. In column

[40] Trefler (2004) documents substantial reallocation between sectors and plants within Canadian manufacturing following its passage, while Breinlich (2014) and Thompson (1993) show that abnormal returns during CUSFTA are consistent with Canadian firms' and industries' *ex ante* characteristics.

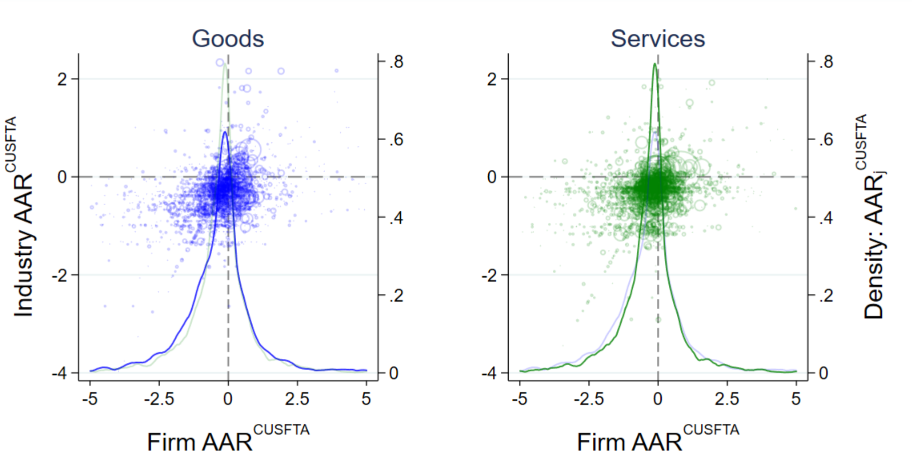


Figure 6: Firm- versus Industry-Level Average Abnormal Returns

Source: CRSP, COMPUSTAT and authors' calculations. Figure compares firms' AAR_j^{CUSFTA} to the unweighted average industry AAR_i^{CUSFTA} of their primary 4-digit SIC industry. Values below -5 and above 5 percent are dropped to improve readability. Each point's size is scaled to the firm's market capitalization in 1988.

1 we explore the relationship between tariff changes and AARs among goods producers. For each US firm j, we compute the weighted average change in Canadian ($\Delta\tau_j^{Can}$) and US ($\Delta\tau_j^{USA}$) tariffs, using the firms' sales across its goods-producing business segments as weights.[41]

The results in the column indicate that a one standard deviation reduction in Canadian tariffs corresponds to an *increase* in US AAR_j^{CUSFTA} of 0.048 standard deviations, while a commensurate reduction in US tariffs corresponds to 0.061 standard deviation *reduction* in US AAR_j^{CUSFTA}. These relationships are intuitive: US firms facing reduced Canadian tariffs are expected to benefit from increased market access, while those in industries in which the US is lowering tariffs are expected to suffer from increased import competition.

In the second column of Table 8 we perform a similar exercise including both goods firms and service firms, for which tariffs are not defined, by regressing their AAR_j^{CUSFTA} on an indicator variable which takes the value of 1 for service industries covered by a change in national treatment as well as a separate dummy variable for goods firms.[42] As indicated in

[41]Sales are as of 1978 or the first year in which the firm appears in our sample. Business segments are recorded according to 4-digit SIC industries. All variables have been divided by their standard deviations.

[42]These industries are listed in Section 14, Annex 1408 of the CUSFTA. Transportation, basic telecom-

Table 8: US Firms' AAR_j^{CUSFTA} versus Tariff Changes and Firm Attributes

	(1) AAR_j^{CUSFTA}	(2) AAR_j^{CUSFTA}
$\Delta\tau_j^{Can}$	-0.048	
	(0.021)	
$\Delta\tau_j^{USA}$	0.061	
	(0.024)	
National Treatment Change_j		0.107
		(0.049)
Ln(PPE per $\text{Worker})_j$	-0.012	0.040
	(0.037)	(0.020)
Ln(Mkt $\text{Cap})_j$	0.024	0.018
	(0.025)	(0.018)
$\frac{CashFlows}{Assets}\text{j}$	0.103	0.085
	(0.036)	(0.027)
Book Leverage_j	0.044	-0.013
	(0.031)	(0.019)
Tobins Q_j	0.003	-0.020
	(0.034)	(0.018)
$\text{I}(Goods_j)$		0.021
		(0.044)
Constant	-0.036	-0.051
	(0.023)	(0.038)
Observations	2065	3938
R^2	0.017	0.012

Source: CRSP, COMPUSTAT, Trefler (2004) and authors' calculations. Table presents firm-level OLS regressions of AAR_j^{CUSFTA} on US and Canadian tariff changes between 1988 and 1996 and a series of 1988 firm accounting attributes that are winsorized at the 1 percent level. Tariffs are defined at the 4-digit SIC level, and are weighted by segment sales within firms. All covariates are de-meaned and divided by their standard deviation. Standard errors are reported below coefficient estimates and are clustered by 3-digit SIC industries.

the table, we find that AAR_j^{CUSFTA} are on average 0.1 standard deviations greater for firms in sectors experiencing a change in national treatment than those service firms operating in non-covered service sectors.

4.3 AAR_j^{CUSFTA} and Subsequent Firm Outcomes

We now explore the relationship between firms' AAR_j^{CUSFTA} and subsequent firm outcomes. We estimes these relationships from 1978 to 1993 using the baseline difference-in-differences specification discussed in Section 3, and outlined in equation (12). The post period in this setting is defined as 1989 to 1993. Suppressed for space, we include the same controls as in

munications, doctors, dentists, lawyers, childcare, and government-provided services were not included.

our PNTR application, measured in 1978 and interacted with a post dummy.[43] Results are reported separately in Table 9 for all firms, goods producers, and service firms.

Table 9: AAR_i^{CUSFTA} and Firm Sales, COGS and Operating Profit

	Ln(Sales$_j$)	Ln(COGS$_j$)	Ln(Operating Profit$_j$)	Ln(Employment$_j$)	Ln(PPE$_j$)
			Panel A: All Firms		
Post*AAR_j^{CUSFTA}	0.030	0.024	0.028	0.026	0.017
	(0.021)	(0.020)	(0.017)	(0.016)	(0.017)
R^2	.937	.937	.925	.939	.951
Observations	47386	47397	45905	46980	47403
Unique Firms	4144	4146	4068	4144	4155
			Panel B: Goods Producers		
Post*AAR_j^{CUSFTA}	-0.015	-0.015	-0.001	0.007	-0.011
	(0.021)	(0.021)	(0.019)	(0.020)	(0.019)
R^2	.945	.945	.933	.952	.955
Observations	27202	27212	26393	27099	27349
Unique Firms	2256	2256	2210	2266	2269
			Panel C: Service Firms		
Post*AAR_j^{CUSFTA}	0.092	0.078	0.067	0.047	0.059
	(0.032)	(0.034)	(0.026)	(0.027)	(0.031)
R^2	.924	.924	.913	.921	.946
Observations	20184	20185	19512	19881	20054
Unique Firms	1888	1890	1858	1878	1886

Source: CRSP, COMPUSTAT and authors' calculations. Table presents firm-level OLS DID panel regressions of noted US firm outcomes on firms' CUSFTA average abnormal returns (AAR_j^{CUSFTA}) and a series of 1978 firm accounting attributes that are winsorized at the 1 percent level. Sample period is 1978 to 1993. All covariates are de-meaned and divided by their standard deviation. Standard errors are reported below coefficient estimates and are clustered by 3-digit SIC industries.

Two trends stand out. First, we find no statistically significant relationship between AAR_j^{CUSFTA} and outcomes overall or among goods-producing firms. To understand this result, note that AAR_j^{CUSFTA} reflect the effects of both Canadian and US tariff changes on firms' value. This result suggests that the two channels potentially offset one another. Consistent with this idea, we show in Figure 7 that the US and Canadian tariff cuts exhibit a strong positive correlation. With few exceptions firms expected to benefit from increased Canadian market access were similarly exposed to the pro-competitive effects of reduced US tariffs in their segments.

[43]These are PPE per Worker, Log Market Capitalization, Cash Flows to Assets, Book Leverage, and Tobins Q. In contrast to our results for PNTR, we do not report results for intangible capital as those data, from Peters and Taylor (2017), are not available during the CUSFTA sample period.

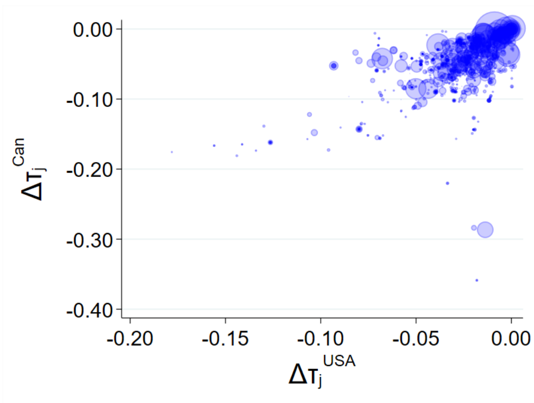


Figure 7: Exposure to US and Canadian Tariff Cuts

Source: CRSP, COMPUSTAT and authors' calculations. Figure compares firms' sales-weighted average US and Canadian tariff cut exposure during CUSFTA. Averages are based on firms major 4-digit sic segments. Each point's size is scaled to the firm's market capitalization in 1988.

Further, in Table A.11 of the Appendix, we show that $\Delta\tau_j^{Canada}$ and $\Delta\tau_j^{US}$ also fail to predict subsequent firm outcomes among goods producers. That neither AAR_j^{CUSFTA} nor bilateral tariff changes explain subsequent economic outcomes for these firms suggests that the cumulative effects of CUSFTA on manufacturing firms were small, or that any such effects take place outside of our period of analysis.[44]

By contrast, the final panel of Table 9 shows that the sales and operating profit of service firms do exhibit a strong relationship with AAR_j^{CUSFTA}. This relationship is consistent with the agreement's provisions with respect to national treatment of services noted above, as well as US comparative advantage in services more generally (Fort et al., 2018; Ding et al., 2019). Together, the results for goods and service firms suggest that a standard analysis of CUSFTA focused on manufacturing and relying on tariff-based metrics of exposure offers an incomplete picture of this liberalization.

[44] US and Canadian tariff reductions were to be phased in over ten years, and there is some evidence that most of the change in trade associated with the agreement occurred in the later years (Besedes et al., 2020). Assessment of post CUSFTA trends (after 1993), however, is complicated by the fact that during the CUSFTA phase-in period, the United States, Canada and Mexico negotiated and implemented the North American Free Trade Agreement (NAFTA).

4.4 Distributional Implications

In this section we use the procedure outlined in Section 3.4 to examine the impact of CUSFTA across firms. As in that section, we compute firms' cumulative relative predicted change in operating profit and employment using the (non-standardized) baseline DID coefficients from the last section, and plot these predictions against firms' market capitalization.[45] As indicated in Figure 8 (versus Figures 3 and 4), we find that while the reaction of operating profit to CUSFTA is qualitatively similar to that found for PNTR, the employment response differs starkly. In both liberalizations, cumulative relative predicted operating profit declines with market capitalization, in this case up to a threshold of about 1 billion. Employment also declines, up to a market capitalization of about 5 billion, but then begins *increasing*, as the largest firms' predicted relative employment turns positive.

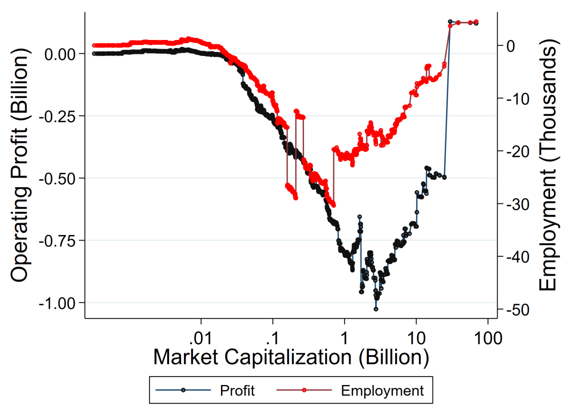


Figure 8: Cumulative Relative Change in Operating Profit and Employment
Source: CRSP, COMPUSTAT, and authors' calculations. Figure displays the predicted cumulative relative change in goods versus service firms' operating profit implied by the baseline difference-in-differences estimates in Table 6.

Some intuition for this difference can be found in Figure 9, which compares firms ' labor productivity during the two liberalizations. As illustrated in the figure, the largest firms during CUSFTA exhibit relatively high levels of employment per operating profit than the largest firms during PNTR. Given this difference, the largest firms' expansion of operating

[45]We focus on these outcomes because we find no statistically significant relationship with respect to physical capital. A version of this figure separately identifying goods versus service firms – indicating that the largest relative gains are experienced by service firms – is available upon request.

expansion may have required relatively more employment after CUSFTA than after PNTR.

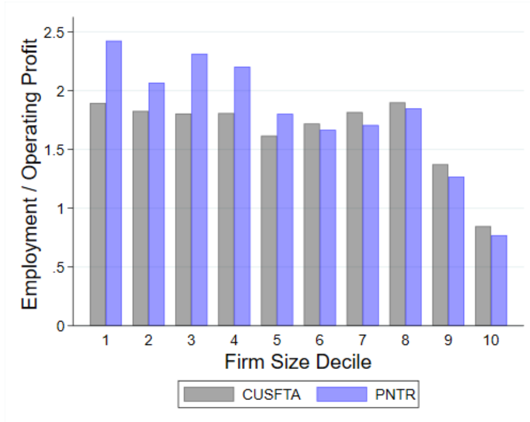


Figure 9: Distribution of $\frac{Employment}{OperatingProfit}$ by Firm Size Decile

Source: CRSP, COMPUSTAT, and authors' calculations. Figure displays the share of operating profit over employment accounted for by firms in each decile of firm size during CUSFTA and PNTR respectively. Firm size is the market capitalization of the firm prior to the relevant liberalization.

Figure 10, analogous to Figure 5 for PNTR, reports the cumulative relative change in operating profit and employment by groups of 2-digit SIC sectors for which we observe a large number of firms. Here, too, sectors vary substantially in their predicted relative changes, with firms in Telecommunications (48), particularly AT&T, exhibiting large relative increases in predicted employment and operating profit, consistent with the agreement's national treatment provisions. Reactions in manufacturing, by contrast, are very modest.

5 Comparing Liberalizations

The DID coefficients presented in Tables 6 and 9 represent elasticities between abnormal returns and relative firm outcomes in the post-period. As discussed formally in Appendix D, these elasticities can vary across liberalizations due to underlying heterogeneity in the speed at which policies' effects are realized, their persistence, the extent to which they impact cash flows versus discount rates, and the degree to which the realized effects align with *ex ante* expectations.

In this section we take advantage of an additional benefit of our approach – its ability

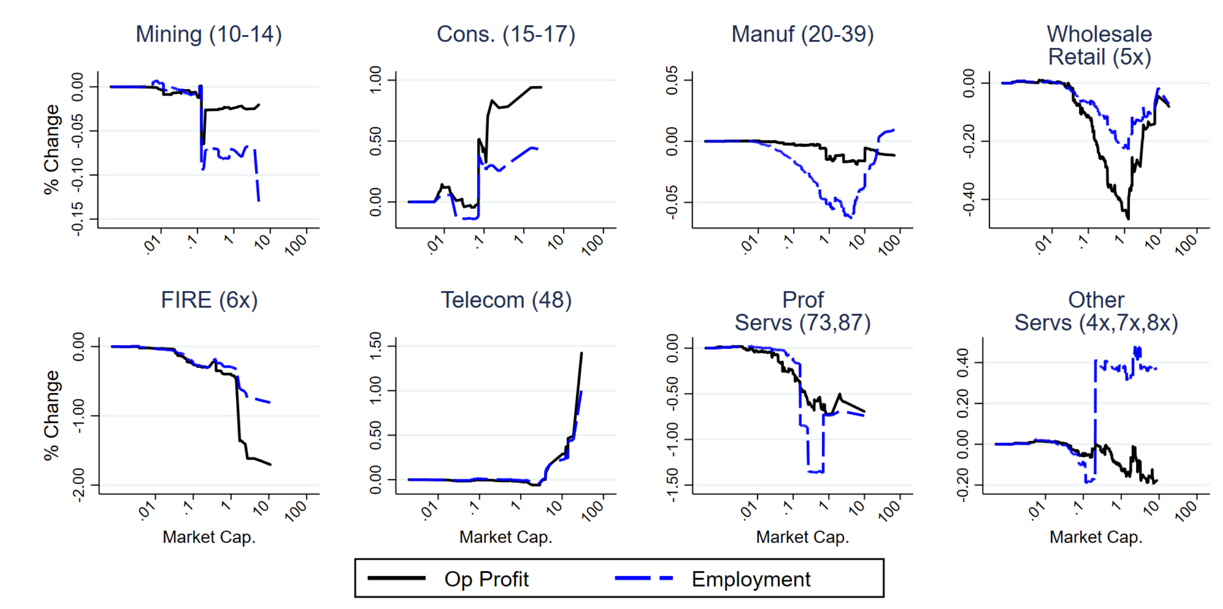


Figure 10: Cumulative Relative Changes by Sector

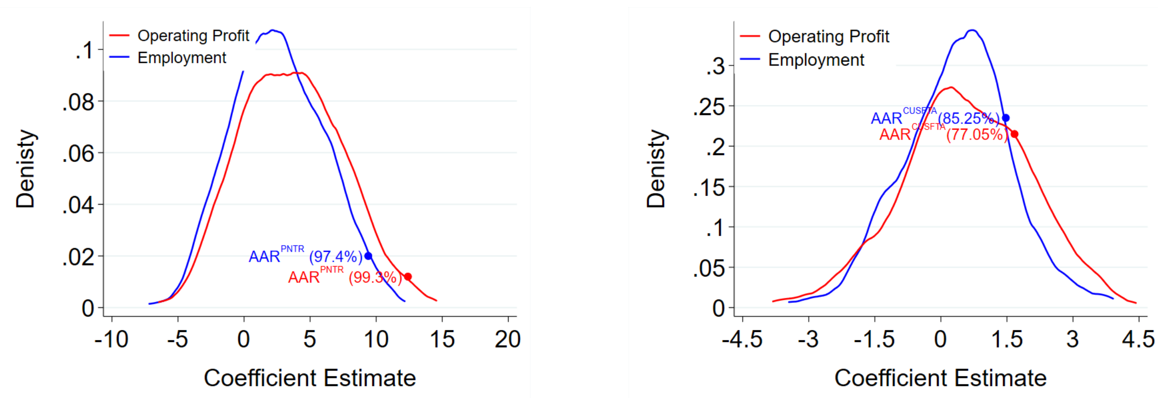
Source: CRSP, COMPUSTAT, and authors' calculations. Figure displays the predicted cumulative relative change in 2 firm outcomes implied by the baseline difference-in-differences estimates in Table 9 by noted 2-digit SIC sectors. Y-axis reports the cumulative predicted relative change as a share of the initial total of each outcome across firms in 1988, prior to CUSFTA. Each firm appears only in one panel, according to the SIC code of largest business segment in Compustat. Firms' market capitalization is calculated from CRSP immediately preceding our event window on used in construction of AAR for CUSFTA. Note that y-axes vary across panels.

to compare different trade liberalizations using a common metric – to explore potential explanations for PNTR's relatively strong impact on US outcomes *vis à vis* CUSFTA. We first show that the disparity in the two policies' impacts remains after controlling for potential variation in macroeconomic trends at the time of each policy change, as well as for potential market anticipation of PNTR's ultimate passage prior to the first legislative event. We then demonstrate that PNTR's impact was more immediate, and more durable, than that of CUSFTA. Finally, we explore whether differences in the policies' DID estimates might have been driven by greater-than-anticipated Chinese growth.

DID coefficients for PNTR and CUSFTA can be compared more directly by assessing their respective relationship to "benchmark" DID coefficients, denoted $\widehat{\delta}^{Benchmark}$, that capture expected positive relationships between abnormal returns and future firm performance on any day. To compute $\widehat{\delta}^{Benchmark}$ for PNTR, we repeat the following three steps 1000 times:

(i) draw five random non-PNTR trading days in 2000; (ii) compute average abnormal returns from 2 days before until 2 days after these dates (25 days in all); and (iii) substitute these AAR_j^{Random} in place of AAR_j^{PNTR} in our baseline DID regressions to estimate $\widehat{\delta}^{Benchmark}$ for operating profit and employment.[46] For CUSFTA, we use an analogous procedure befitting that liberalization, i.e., we sample dates from 1988 and compute abnormal returns in the 5 day window centered on each date.

The left and right panels of Figure 11 plot the actual versus benchmark DID estimates for each liberalization.[47] As expected, $\widehat{\delta}^{Benchmark}$ are predominantly positive: on average, higher AARs are associated with relative expansion of both operating and employment under both changes in policy, though the PNTR distribution spans a wider range of positive outcomes.



(a) PNTR **(b)** CUSFTA

Figure 11: Benchmark AAR_j^{Random} Estimates vs $AAR_j^{Liberalizations}$

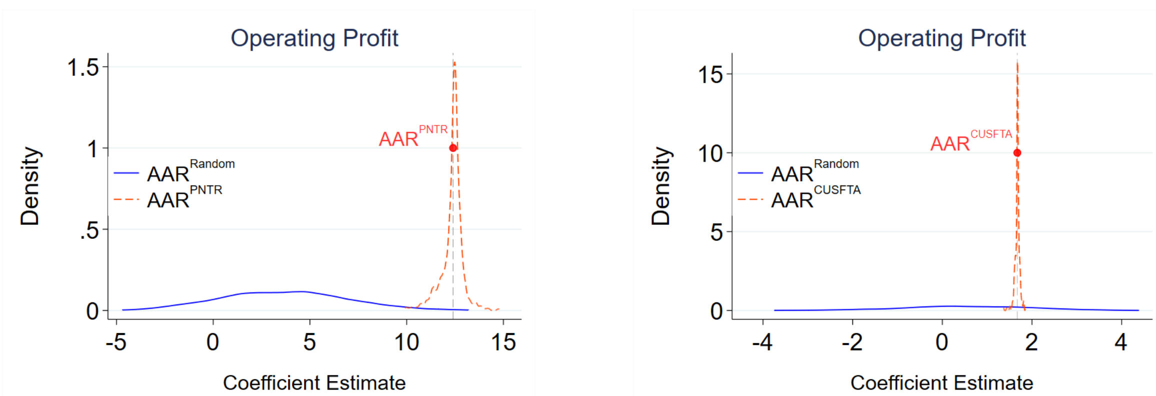
Source: CRSP, COMPUSTAT and authors' calculations. The figure presents the distribution of (non-standardized) operating profit and employment DID coefficient estimates from equation (12), where AAR_j^{Random} are used in place of AAR_j^{PNTR}. The highlighted points indicate the (non-standardized) baseline results, and the percentiles at which they would fall in the benchmark coefficient distribution. The means and standard deviations of operating profit are 3.6 and 3.8 for PNTR and 0.57 and 1.44 for CUSFTA. The means and standard deviations for employment are 2.5 and 3.47 for PNTR and 0.37 and 1.22 for CUSFTA. The highlighted point and vertical line note the position of the non-standardized version of the coefficient estimate obtained in our baseline results (Tables 6 and 9 respectively).

[46] We sample dates so that none of the resulting event windows overlap those used to calculate AAR_j^{PNTR}.

[47] In contrast to the results reported in Section 3.3.2, the DID coefficients displayed in Figure 11 are derived from *non-standardized* covariates. This switch is necessary for an apples-to-apples comparison of the two sets of DID coefficients, since a one standard deviation increase in AAR on days with a greater variance would represents a larger increase in AAR *in levels* than a 1 standard deviation increase on days with lower variance. As a result, the DID coefficients in the figure should be interpreted as the impact of a 1 percent increase in AAR.

A striking feature of Figure 11 is that the actual DID coefficients for PNTR lie further to the right of their $\widehat{\delta}^{Benchmark}$ distribution than those for CUSFTA, at the 97^{th} and 99^{th} percentiles versus the 85^{th} and 77^{th} percentiles. This difference implies that while the market expected operating profit and employment growth in response to both trade liberalizations, the magnitude of these responses *per percent* change in firm value was stronger during PNTR.

In Figure 12, we show that these differences cannot be explained by the confounding effects of other shocks which may have occurred during each period, e.g. the bursting of the tech bubble in 1999, by amending our DID specification (equation 12) to include *both* the AARs of interest and their respective AAR_j^{Random}. We run these specifications 1000 times, one for each AAR_j^{Random}, and, in the figure, display the distributions of the DID coefficients of interest alongside those of the added control. As indicated in the figure, the former are stable and very close to the baseline estimates in Tables 6 and 9, while the latter are diffuse over a broad range of generally smaller values. We interpret these findings as an indication that our DID coefficients of interest, and differences between them, do not reflect firms' exposure to differential macroeconomic trends.



(a) PNTR **(b)** CUSFTA

Figure 12: AAR - Operating Profit Estimate Stability

Source: CRSP, COMPUSTAT and authors' calculations. Figure plots the distribution of (non-standardized) operating profit DID coefficient estimates from an amended version of equation (12) which includes both AAR_j^{Random} and $AAR_j^{Liberalization}$ for each liberalization separately. The distribution of coefficient estimates for $PNTR$ are in panel 12a while those estimated for $CUSFTA$ are presented in panel 12b.

Another factor that can affect the relative size of our PNTR and CUSFTA DID coefficients is partial anticipation of each policy's ultimate passage *prior* to our event windows, leading to underestimations of their true effects and thereby higher estimated DID coefficients. For PNTR we are able to estimate the market's beliefs about the probability that PNTR would ultimately pass prior to the first event using options pricing data in the manner developed by Langer and Lemoine (2019), discussed in detail in Appendix F. (Unfortunately, unavailability of call option data as far back as CUSFTA prevents us from performing an analogous computation for that liberalization.) We find that the market assigned a 12 percent probability to PNTR's passage prior to the introduction of the bill in the House. We can account for this anticipation by deflating our PNTR DID coefficients for operating profit and employment in Table 6 and 7 respectively by (1/(1-.12)), from 0.129 and 0.098 to 0.113 and 0.086. While these adjustments are not trivial, they merely fall to the 98.6 and 95.9 percentiles of the benchmark distributions displayed in Figure 10, still above those for CUSFTA.

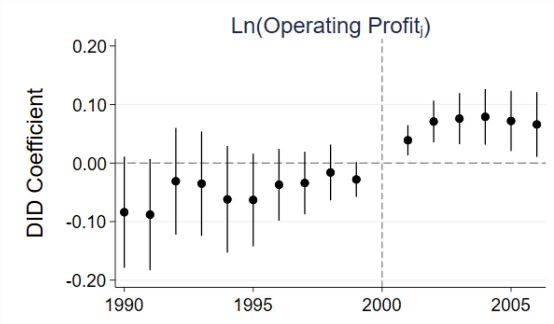
We compare the two policies' speed of onset and duration using "annual" specifications that replace the single DID term in equation (12) with interactions of AAR_j^{PNTR} and a full set of year dummies:

$$ln(Outcome_{j,t}) = \sum_{y=1990}^{2006} \delta_y \times 1\{t=y\} \times AAR_j^{PNTR} + \sum_{y=1990}^{2006} 1\{t=y\} \times \mathbf{X_j}\gamma_\mathbf{y} + \alpha_j + \alpha_t + \epsilon_{j,t}.$$

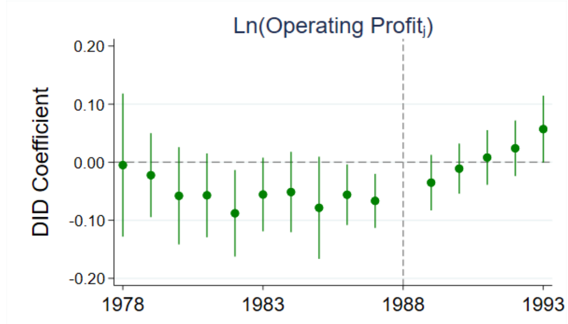
Results for operating profit are displayed in Figure 13 where, for PNTR, we report the results for all firms and for CUSFTA we focus on service firms, as the baseline estimates for goods-producing firms are statistically insignificant.[48] As indicated in the figure, we find that PNTR affects firms' relative operating profit both more quickly and more durably than CUSFTA, consistent with the sharp and persistent impact of Chinese imports on US industries and regions noted by Pierce and Schott (2016) and Autor et al. (2021).

A plausible explanation for the relatively sharp reaction of US firms to PNTR displayed

[48]Figures for all other outcomes may be found in Figures A.8 and A.9. Results are qualitatively similar when including NAICS-2 by year fixed effects or additional controls.



(a) PNTR



(b) CUSFTA

Figure 13: Operating Profits and AAR: Annual Specification

Source: CRSP, COMPUSTAT and authors' calculations. Figure displays a series of 95 percent confidence intervals for the difference-in-difference term of interest in equation (13). Each panel is from a separate, firm-level OLS regression of noted firm outcome on PNTR average abnormal returns (AAR_j^{PNTR}) interacted with a full set of year dummy variables as well as a series of initial (1990) firm accounting attributes, also interacted with year dummy variables and winsorized at the 1 percent level. Sample period is 1990 to 2006. Effects of CUSFTA are analogously estimated from 1978 to 1994. All covariates are de-meaned and divided by their standard deviations. The covariates for the year of the policy change are omitted. Standard errors used to construct confidence intervals are clustered at the 4-digit NAICS level and 3-digit SIC respectively

in Figure 13 is relative under-estimation of trade liberalization with China compared to Canada. This under-estimation might be driven by the relative difficulty of predicting a change in tariff rate uncertainty versus tariffs or national treatment (Handley and Limão, 2017), or the fact that China's unprecedented growth in the years after PNTR outpaced even the most informed forecasts. With respect to the latter, Figure 14 reports the persistent gap between China's actual growth in real GDP as estimated by the IMF and World Bank versus one-year-ahead forecasts made by the IMF, from 1999 to 2007. If the anticipated effects of PNTR on firms relied on such forecasts, then the realized effects of PNTR on firms' operating profit and employment would have been more extreme than were priced in at the time of the change in policy. This explanation need not imply market inefficiency or uninformed market participants, but rather imperfect foresight. It receives further support from Bombardini et al. (2020), who find that US politicians underestimated the magnitude of PNTR at the time of its passage, a potential factor in the subsequent political backlash documented by Rodrik (2021), Che et al. (2016) and Autor et al. (2017).

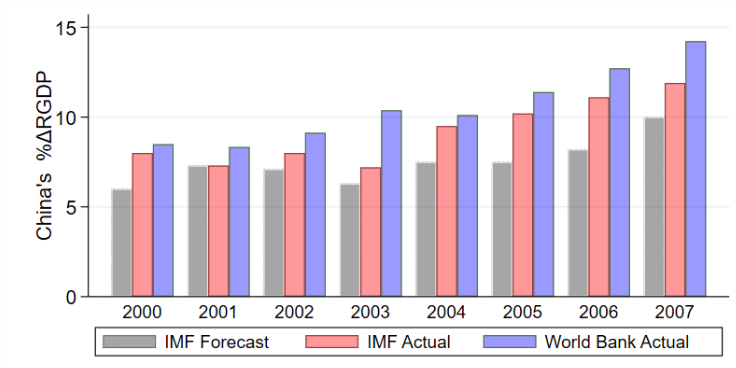


Figure 14: Forecasted vs Realized Chinese RGDP Growth

Source: Forecasts are one-year forecasted RGDP growth for the indicated year taken from the IMF World Economic Outlook annual reports. Adjacent bars indicate realized RGDP growth calculated by the IMF and World bank respectively for the indicated year.[49]

6 Robustness Exercises

Our results for PNTR and CUSFTA are robust to a broad range of alternative specifications and assumptions. For the sake of brevity, we relegate these tests to the Online Appendix and briefly describe them here. In Section F we include a formal discussion of the effect of partial anticipation of PNTR events on AARs and show that such anticipation does not affect our main results. In Section G we demonstrate that our baseline difference-in-differences estimates are robust to a number of changes in estimation strategy, including: (1) re-estimation of equation (12) for each of our five policy events separately; (2) weighting each regression by the 1990 level of the dependent variable; (3) including 2-digit NAICS-by-year fixed effects; (4) using a one-day $[-1, 1]$ rather than two-day window around each event in computing AAR_j^{PNTR}; (5) estimating AAR_j^{PNTR} using a popular alternative to the CAPM, the Fama and French (1993) three-factor model; (6) eliminating observations in our event windows that occur at the same time as earnings, dividend announcements, mergers and acquisitions (M&A), stock repurchases, and seasoned equity offering (SEO) announcements; (7) using buy-and-hold abnormal returns rather than average abnormal returns; (8) using bootstrapping to address sampling error in firms' estimated factor loading in the CAPM, $\hat{\beta}_j$s; and (9) allowing for non-zero systematic effects of PNTR on market returns.

7 Conclusion

We introduce a method for gauging firms' exposure to changes in trade policy based on abnormal equity returns, and use this method to measure US firms' exposure to trade liberalizations with China and Canada. With respect to China, we find that firms' average abnormal returns surrounding key legislative milestones associated with the liberalization vary widely within industries, that they are correlated with standard variables used to assess import competition, and that they provide explanatory power beyond these standard measures. Among both service and goods-producing firms, we find a strong relationship between firm size and predicted relative gains in operating profit, employment and capital. We also find stark differences in traders' assessment of subsequent relative operating profit across broad 2-digit NAICS sectors. For CUSFTA, we demonstrate that goods firms' average abnormal returns are correlated with US and Canadian tariff changes, while for service firms they are higher in industries subject to national treatment. For service firms, we also find that firms' average abnormal returns predict future operating profit, underscoring our method's ability to evaluate the removal of trade restrictions outside the manufacturing sector.

Our study highlights several important advantages to using equity market reactions to assess the impact of changes in trade policy. First, these reactions capture direct as well as indirect channels of exposure. Second, they are readily available for firms in all sectors of the economy in which firms are publicly traded. Finally, they can be used to quantify the effect of non-tariff barriers, which are notoriously difficult to capture using standard measures of exposure (Goldberg and Pavcnik, 2016). We hope use of the measure of exposure we propose will prove useful for further extending international trade research into these areas, and in examining impacts of policy exposure more broadly, e.g., in understanding firm responses to changes in the minimum wage.

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Online Appendix (Not for Publication)

This Online Appendix contains additional empirical results as well as more detailed explanations of data and methods used in the main text.

A The End of the Global Multi-Fiber Arrangement

During the Uruguay Round of trade negotiations, the United States, the EU and Canada agreed to eliminate quotas on developing country textile and clothing exports in four phases starting in 1995 (Brambilla et al., 2010). While the first three phases of quota expirations took place as of January 1 of 1995, 1998 and 2002, imports from China remained under quota until its accession to the WTO. Upon entering the WTO on December 31, 2001, quotas were eliminated on U.S. imports from China of products covered by the first three phases. Quotas on Phase IV products were eliminated on schedule on January 1, 2005. As discussed in Brambilla et al. (2010), the distribution of textile and clothing goods across phases was not random: the United States, like other countries, reserved their more import-sensitive product categories for the final phase.

As noted in the main text, we follow Pierce and Schott (2016) in controlling for expiration of MFA quotas on US imports from China using a time-varying measure that reflects the import-weighted fill rates of the quotas, where fill rates are defined as actual divided by allowable imports. These measures capture both the timing of the different phase of quota expirations as well as how restrictive the quotas had been prior to removal.

We construct these measures using 10-digit HS-level (HS10) data from Ahn et al. (2011) that identify the products covered by the MFA, their phase of quota expiration and their tariff fill rate by year. These HS10 data are then aggregated to industries using the concordance in Pierce and Schott (2016). For each industry, the measure is set to the import-weighted fill rate of the matching HS10 products in the year prior to tariff removal. For China, these measures are set to zero (i.e., no exposure to MFA quota reductions) prior to 2002. For Phase I, II and III products, beginning in 2002, the measures are set to the import-weighted fill rates observed in 2001. For Phase IV products, beginning in 2005, the measures are set to the import-weighted fill rates observed in 2004. A higher value indicates greater exposure to MFA quota reductions.

We then use the firm's sales at the segments level from 1990 to 1997 to calculate the average share of sales coming from any segment in the pre-MFA period. These shares were then used as the weights to calculate the time varying exposure discussed above.

B AAR_j^{PNTR}, $AAR_j^{Belgrade}$ and the NTR Gap

We investigate the relationship between firms' average abnormal returns during each legislative event e and the sales-weighted average NTR gap of their major segments ($NTR\,Gap_j$) using an OLS specification of the form

$$AAR_j^e = \delta NTR\,Gap_j + \epsilon_{ji}. \tag{A.1}$$

Results are reported in Table A.1. We find negative and statistically significant relationships between $NTR\,Gap_j$ and average abnormal returns for three of the five legislative events, with the exceptions being the introduction of the bill in the House of Representatives and the Senate vote. The sign for these two events is also negative, though the magnitudes are small. Column 6 reveals that this negative relationship also holds for AAR_j^{PNTR}, the average abnormal return across all five events. The coefficient estimate in that column implies that the relationship is also economically significant, with a one standard deviation increase in $NTR\,Gap_j$ associated with a 0.200 standard deviation decline in AAR_j^{PNTR}. This drop is equivalent to a 5 percent decline in market value, or about 167 million dollars.[50]

We investigate the link between $AAR_i^{Belgrade}$ and the NTR gap via the OLS regression,

$$AAR_j^{Belgrade} = \delta NTR\,Gap_j + X_j\gamma + \epsilon_i, \tag{A.2}$$

where X_j represents firm attributes in 2000 and, as in the main text, all variables have been de-meaned and divided by their standard deviations. Results, reported in Table A.2, indicate that firms' own-industry NTR gaps exhibit a *positive* relationship with $AAR_j^{Belgrade}$, while their upstream gaps exhibit a *negative* relationship, both in a simple bi-variate regression and when the additional controls are included. The relationships for the own NTR gap is consistent with the idea that firms that receive greater protection from pre-PNTR US trade policy towards China might benefit in terms of relative market value from a breakdown in US-China relations due to the bombing, e.g., if protests in China prompt the US Congress to reject China's temporary NTR status. Likewise, the result for the upstream gap suggests that firms that rely on suppliers that might receive greater protection are associated with declines in relative market value. The negative relationship between $AAR_j^{Belgrade}$ and the

[50] Multiplying the coefficient of -0.200 by the standard deviation of AAR_j^{PNTR} (1.03 percent) yields a reduction in market value of about 5.15 percent over 25 days. The average market value of a firm in 2000 in our sample is 3.25 billion dollars.

market capitalization in Column 3 suggests that larger firms' market value declined relatively more following the bombing. This is also consistent with tables in the main text which find that larger firms exhibit higher AAR_j^{PNTR}.

C PNTR and the 2016 Presidential Election

During his campaign for President, Donald Trump emphasized his intent to overturn what he perceived to be "bad deals" in international trade, particularly those with respect to China and the North American Free Trade Agreement.[51] As a consequence, his surprise victory offers another opportunity to examine the external validity of AAR_j^{PNTR}. Here, however, we conduct the analysis at the industry level given the degree of firm attrition and industry-switching that occurs between 2000 and 2016. We compare the market capitalization weighted average AAR_j^{PNTR} across firms' major industries, AAR_i^{PNTR}, to similarly constructed returns in the seven days[52] following the election, AAR_i^{Trump}, using an OLS specification of the form

$$AAR_i^{Trump} = \delta AAR_i^{PNTR} + \epsilon_i. \tag{A.3}$$

As above, i indexes 6-digit NAICS industries, all variables are de-meaned and divided by their standard deviations, and standard errors are clustered at the 4-digit NAICS level.[53]

Results, reported in Table A.3, are consistent with the idea that industries whose expected profits might rise with PNTR are those whose profits might fall with Trump's election. That is, we find a negative and statistically significant relationship between AAR_i^{PNTR} and AAR_i^{Trump}, where the coefficient estimate in the first column implies that a one standard deviation increase in AAR_i^{PNTR} is associated with a 0.128 standard deviation decrease in AAR_i^{Trump}. Results in the second column reveal that this relationship is also statistically

[51]For example, in a 2016 campaign rally in Staten Island, NY, Trump stated, "China's upset because of the way Donald Trump is talking about trade with China. They're ripping us off, folks, it's time. I'm so happy they're upset." Similarly, when discussing NAFTA, Trump stated, "NAFTA is the worst trade deal maybe ever signed anywhere, but certainly ever signed in this country Wagner et al. (2018)," shows that firms' abnormal returns in the days surrounding Donald Trump's election are negatively correlated with their exposure to international markets, and that more internationally exposed sectors exhibit declines relative to more domestically oriented sectors.

[52]We choose this window to reflect the unexpected nature of his election and uncertainty over how he might react in the first few days after election. At the beginning of the Trump campaign in 2015, betting markets were offering 25:1 odds against his success. These odds never became shorter than 5:1, even on the day before the election (`http://fortune.com/2016/11/09/donald-trump-president-gamble/`).

[53]These attributes are for 2000 and are drawn from COMPUSTAT. They represent market capitalization weighted averages of each attribute across firms within each six-digit NAICS industry. As before, all accounting ratios derived from COMPUSTAT are winsorized at the 1 percent level.

and economically significant among goods producing firms. The relationship, while negative, is insignificant among service firms.

D Interpreting DID Point Estimates

Following Vuolteenaho (2002) and omitting firm subscripts, we can write abnormal returns as:

$$r_t - E_{t-1}[r_t] = (E_t - E_{t-1})[\sum_{s=0}^{\infty} \rho^s (g_{t+s} - f_{t+s})] - (E_t - E_{t-1})[\sum_{s=0}^{\infty} \rho^s r_{t+s}] + k_t \tag{A.4}$$

where $r_t = log(1 + R_t + R_t^f)$, $f_t = log(1 + R_t^f)$, $g_t = log(1 + ROE_t)$, and ROE_t is net income divided by lagged book value of equity in year t. In this expression, k_t is an approximation error and ρ is an approximating constant close to, but smaller than 1.[54] Equation (A.4) is an accounting identity that requires only the standard assumption that the change in firms' book value of equity equals their net income minus dividend payments. It reveals that abnormal returns relate linearly to news about both cash flows (the first term on the right-hand side) and discount rates (the second term on the right-hand side).

More broadly, it illustrates that the estimated magnitude of our difference-in-differences coefficients, $\widehat{\delta}$ (see equation 12), is a function of three forces. First, it will depend on the extent to which our shock is predominantly a cash flow shock or a discount rate shock. Specifically, because our dependent variable is operating profit, shocks with a more predominant cash flow component (i.e. the first term on the right-hand side of equation (A.4) is significantly larger than the second, discount rate, term) will have a higher $\widehat{\delta}$. Second, the $\widehat{\delta}$ coefficient, will depend on the persistence of the PNTR shock. If the change in policy were subsequently reversed, for example, one would expect $\widehat{\delta}$ to be zero.[55] Finally, $\hat{\delta}$ depends on the timing of PNTR's impact on firms' cash flows. Because our regressions use data on operating profits only up to five years in the future, the $\widehat{\delta}$ coefficient will be higher the more front-loaded the effects of the shock considered. While we leave disentangling the relative

[54] E.g., Voulteenaho (2002) finds and optimal value of $\rho = 0.967$

[55] One might be tempted to believe that a more persistent shock would simply result in higher abnormal returns in absolute value rather than a larger δ. This outcome is true only if investors know the persistence parameter for the shock process. If, instead, investors learn about the persistence of shocks in a Bayesian process, changes in expectations after each shock, and hence abnormal returns, will depend on both the persistent component and the transitory component of the shock (adjusted for the perceived signal to noise ratio). By contrast, realized profitability will depend only on the persistent component of the shock, as the transitory component, by definition, averages out to zero. Hence, for shocks that are more transitory in nature, the coefficient in equation (12) will be smaller than for shocks of a more persistent nature.

contributions of these forces to future research, we emphasize that $\hat{\delta}$ does not represent a simple mechanical relationship between current expectations and future realizations.

E Distributional Effect Counterfactuals

As noted in Section 3.4 of the main text, large firms' size as well as their AAR_j^{PNTR} contribute to their predicted relative growth *vis a vis* small firms in Figure 3. Two simple counterfactual predictions, plotted in Appendix Figure A.7, provide insight into the relative importance of these two margins. The first, represented by the blue, long-dashed line, plots the cumulative predicted relative change in operating profit across all firms using firms' actual operating profit in 2000, but substituting the median AAR_j^{PNTR} across all firms for their actual AAR_j^{PNTR}. The second, traced out by the red, short-dashed line, uses firms' actual AAR_j^{PNTR} in combination with the median operating profit across all firms. The relative height of the latter (red) compared to the former (blue) reveals that while the largest firms' AAR_j^{PNTR} generally are positive, it is their size rather than the magnitude of their AARs that is most influential in determining the magnitude of their relative gains.

F Using Call Options to Estimate *Ex Ante* Event Probabilities

One concern regarding the use of event studies to estimate the impact of a policy change is that such changes are generally discussed in the public arena prior to passage, often for a prolonged period of time. As a result, anticipatory trading may lead stock returns measured in the days following the event to understate the true effect of the policy. In this section we formally characterize this "partial anticipation" bias and show that it does not affect our main results.

We assume a single event to simplify exposition, but note that we generalize the approach to multiple events in our implementation below. For every firm j, the effect of the policy event on the firm's stock price is given by $P^Y_{j,\tau-1} - P^N_{j,\tau-1}$, where $P^Y_{j,\tau-1}$ is the price that we would observe immediately prior to the event if investors were certain that the policy would be approved at τ, and $P^N_{j,\tau-1}$ is the price we would observe if investors believed that the policy would be rejected. Neither is observed. Instead, we have only realized prices $P_{j,\tau-1}$ and $P_{j,\tau}$.

We construct an approximation for $P^Y_{j,\tau-1} - P^N_{j,\tau-1}$ from observed prices. The observed price immediately prior to the event can be written as

$$P_{j,\tau-1} = \pi^Y_{\tau-1} P^Y_{j,\tau-1} + (1-\pi^Y_{\tau-1}) P^N_{j,\tau-1}, \tag{A.5}$$

where $\pi^Y_{\tau-1}$ is the time $\tau-1$ probability that the policy will be approved at τ. Re-arranging and adding $P^Y_{j,\tau-1}$ to both sides, we obtain

$$P^Y_{j,\tau-1} - P_{j,\tau-1} = (1-\pi^Y_{\tau-1})(P^Y_{j,\tau-1} - P^N_{j,\tau-1}) \tag{A.6}$$

If the policy is approved at time τ, the realized price immediately after the event $P_{j,\tau}$ equals $P^Y_{j,\tau}$ by definition. Hence, by adding $P_{j,\tau} - P^Y_{j,\tau}$ to the left-hand side, we can rewrite equation (A.6) as

$$(P_{j,\tau} - P_{j,\tau-1}) - (P^Y_{j,\tau} - P^Y_{j,\tau-1}) = (1-\pi^Y_{\tau-1})(P^Y_{j,\tau-1} - P^N_{j,\tau-1}). \tag{A.7}$$

Dividing both sides by the realized price prior to the event recasts this equation in terms of returns:

$$\frac{P_{j,\tau} - P_{j,\tau-1}}{P_{j,\tau-1}} - \frac{P^Y_{j,\tau} - P^Y_{j,\tau-1}}{P_{j,\tau-1}} = (1-\pi^Y_{\tau-1})\frac{P^Y_{j,\tau-1} - P^N_{j,\tau-1}}{P_{j,\tau-1}}, \tag{A.8}$$

$$R_{j,\tau} - E(R_{j,\tau}|X_\tau) = (1-\pi^Y_{\tau-1}) AR^*_{j,\tau} \tag{A.9}$$

Going from equation (A.8) to equation (A.9), we use the notation introduced in Section 2 and the understanding that $(P^Y_{j,\tau} - P^Y_{j,\tau-1})/P_{j,\tau-1}$ captures the return we would expect if only the non-event state variables change, from $X_{\tau-1}$ to X_τ. This is equivalent to the expected "normal" returns term $E(R_{j,\tau}|X_\tau)$. Equation (A.9) shows that $AR_{j,\tau} = R_{j,\tau} - E(R_{j,\tau}|X_\tau)$ is an unbiased estimate of $AR^*_{j,\tau}$ only if the event is completely unanticipated – that is, if $\pi^Y_{\tau-1} = 0$.

Equation (A.9) makes clear that partial anticipation bias, even if it exists, does not affect our difference-in-differences or distributional results: dividing AAR^{PNTR}_j by $(1-\pi^Y_{\tau-1})$ leads to a simple rescaling of our DID coefficient of interest, $\hat{\delta}$ (equation 12), while our computation of predicted relative operating profit (equation 12) is invariant to a rescaling of AAR^{PNTR}_j. Nevertheless, in the remainder of this section, we outline and implement a procedure for estimating *ex ante* event probabilities, and find that, under the assumption that no relevant information was released *between* our events, the partial anticipation bias in our AAR^{PNTR}_j measure is quite low: investors' *ex ante* assessment of the ultimate passage of PNTR was about 12 percent prior to the introduction of the bill in the House. While we are unaware of any events whose stature is equivalent to those we study, we speculate that this partial anticipation may reflect investors' reactions to various comments about the bill made by influential legislators or the President prior to the start of the formal legislative process.

To estimate *ex ante* event probabilities we follow Langer and Lemoine (2019) who show that the *ex ante* probability of an event, $\pi^Y_{\tau-1}$, can be estimated using deep-out-of-the-money call options. The intuition is straightforward: if investors' beliefs about the impact of the change in policy do not change during the event window, increases in the prices of deep-out-of-the-money call options for firms standing to benefit from PNTR correspond to increases in investors' assessment of the probability of its final passage. As explained in greater detail below, the calculation of an *ex-ante* event probability requires knowledge of the *ex-post* event probability. This *ex-post* probability is known for the last event, the Clinton signing: it is 1. For the rest of the events, we assume the *ex post* event probability is equal to the *ex ante* probability of the subsequent event.

Let $C_{j,\tau-1,T}(P_{j,\tau-1},K)$ be the price at time $\tau-1$ of a call option on stock j with strike price K and expiration $T>\tau$. This price can be written

$$C_{j,\tau-1,T}(P_{j,\tau-1},K)=\pi^Y_{\tau-1}C_{j,\tau-1,T}(P^Y_{j,\tau-1},K)+(1-\pi^Y_{\tau-1})C_{j,\tau-1,T}(P^N_{j,\tau-1},K) \tag{A.10}$$

where $\pi^Y_{\tau-1}$, $P^Y_{j,\tau-1}$, and $P^N_{j,\tau-1}$ are defined above.

$\pi^Y_{\tau-1}$ can be estimated for firms meeting two criteria: (i) the effect of the policy on the their stock price is large and positive; and (ii) at $\tau-1$, there exist call options written on these firms that are deep-out-of-the-money (i.e. the call option strike price is significantly higher than the current stock price). These options derive most of their value from the states of the world in which the policy is approved (i.e. $C_{j,\tau-1,T}(P^N_{j,\tau-1},K)\approx 0$), and equation (A.10) is reasonably approximated by

$$C_{j,\tau-1,T}(P_{j,\tau-1},K)\approx\pi^Y_{\tau-1}C_{j,\tau-1,T}(P^Y_{j,\tau-1},K), \tag{A.11}$$

which implies

$$\pi^Y_{\tau-1}\approx\frac{C_{j,\tau-1,T}(P_{j,\tau-1},K)}{C_{j,\tau-1,T}(P^Y_{j,\tau-1},K)}. \tag{A.12}$$

Note that $C_{j,\tau-1,T}(P^Y_{j,\tau-1},K)$ is not observed but can be approximated by the realized call option price after the event $(C_{j,\tau,T}(P_\tau,K))$, under the standard event-study assumption that we can control for all changes in non-event state variables (from $X_{\tau-1}$ to X_τ). Hence, we can obtain an approximation for the call-option price ratio on the right-hand side of equation (A.12) as

$$\pi^Y_{\tau-1}\approx\frac{C_{j,\tau-1,T}(P_{j,\tau-1},K)}{C_{j,\tau,T}(P_{j,\tau},K)}-E\left[\frac{C_{j,\tau-1,T}(P_{j,\tau-1},K)}{C_{j,\tau,T}(P_{j,\tau},K)}|X_\tau\right] \tag{A.13}$$

where the expectation term on the right-hand side of the equation measures the expected effect on the call-price ratio caused by non-event state variables (X_τ).

We aim to estimate not only the probability of PNTR right before the Clinton signing, but also before each of the other four events we consider in our empirical analysis. To this end, note that the arguments above can easily be generalized to show that the ratio of deep-out-of-the-money call option prices around each of our events provides an estimate for the ratio of perceived PNTR probabilities around those events. Hence, for each of our five events $i = 1, ..., 5$, we estimate:

$$CR_i = \frac{\pi^Y_{\tau_i - 2}}{\pi^Y_{\tau_i + 2}} \approx \widehat{\frac{C_{j,\tau_i-2,T}(P_{\tau_i-2}, K)}{C_{j,\tau_i+2,T}(P_{\tau_i+2}, K)}} \tag{A.14}$$

Note that we use five-day windows around each of our events to remain consistent with the baseline results in our analysis. While, technically, only one call option is required to obtain the above estimate for each event, this relies on the assumption that we have correctly identified a firm which stands to substantially benefit from PNTR, and a call option on that firm which is so deep-out-of-the-money that it is worth virtually 0 if PNTR does not pass. Since we have no clear way to make sure we can satisfy this assumption, we use several firms in our tests, and we estimate the CR_i terms by using a panel regression for each event i:

$$log\left(\frac{C_{j,t-2,T}(P_{t-2}, K)}{C_{j,t+2,T}(P_{t+2}, K)}\right) = \alpha_j + \beta_i I_{\tau_i-2,\tau_i+2} + X_{j,t} + \epsilon_{j,t} \tag{A.15}$$

Here, j indexes firms, t indexes time (in days), and α_j is a firm fixed effect. For each event, the above regression uses dates from 100 days before event i to seven days before the expiration (T) of the call option C (excluding the dates that occur during the event windows of any of the other four events). We attempt to identify firms that stand to benefit from PNTR by restricting the sample to firms that have positive abnormal returns for all five events. The term I_{τ_i-2,τ_i+2} is a dummy variable that equals one in the five-day event window around event i. $X_{j,t}$ is a vector of six dummy variables, one for each of the confounding events used in our analysis above (announcements of dividends, earnings, repurchases, SEO's, acquisitions, and being acquired). We include these dummy variables to control for any other changes that may have had a confounding effect on call prices.

Data on call option prices comes from OptionMetrics. For each event i, for each firm, we keep only the call options that, for all days of the event window, are out-of-the-money, have positive bid price, and positive volume. Of the remaining options, we select the ones with the closest expiration date to the event, but not closer than 7 days to it. Of the remaining set of options, we pick the one with the highest strike price (i.e. the most out-of-the-money one), and this is the option C_j we use in equation (A.15). We use the β_i coefficient from this regression to obtain an estimate of CR_i in equation (A.14):

$$CR_i = \frac{\pi^Y_{\tau_i-2}}{\pi^Y_{\tau_i+2}} \approx e^{\beta_i}$$

Since, by definition, the probability of PNTR after the Clinton signing ($i = 5$) is 1, the above equation implies the probability prior to the signing is $\pi^Y_{\tau_5-2} = e^{\beta_5}$. As mentioned above, we assume the *ex post* probability for each event is equal to the *ex ante* probability of the subsequent event. This implies that $\pi^Y_{\tau_i+2} = \pi^Y_{\tau_{i+1}-2}$ for all $i = 1, ..., 4$. Using this result, we can recursively back out the remaining four probabilities as $\pi^Y_{\tau_4-2} = e^{\beta_5+\beta_4}$ and so on until $\pi^Y_{\tau_1-2} = e^{\beta_5+\beta_4+...+\beta_1}$. To allow for cross-correlation between the five equations in (A.15), we estimate them jointly as a system of equations to obtain our β_i estimates and then use them to calculate the ex-ante event probabilities $\pi^Y_{\tau_i-2}$ as explained above.

The results are reported in Table A.5. The coefficient reported in each column represents the estimated *ex ante* probability of PNTR's ultimate passage, i.e., the probability at the start of the noted five-day window. The first interesting message in Table A.5 is that there is an increase in the probability of PNTR's ultimate passage after each event of around 10 to 30 percent, with the largest occurring with the conclusion of the legislative process, the vote in the Senate.[56] The second interesting message in Table A.5 is that passage of PNTR seems to have been anticipated prior to the first event, with probability 0.118. While this estimate is only statistically different from 0 at the 10 percent level, it nevertheless suggests a modest amount of partial anticipation bias, and that there may have been one or more earlier events that were influential in changing investors' expectations regarding PNTR. While we are unaware of any such events whose stature is equivalent to those we study, we speculate that investors may have reacted to various comments about the bill made by influential legislators or the President leading up to the start of the formal legislative process.

G Additional Robustness Exercises

In this section we examine the robustness of the results presented in our study in several ways. First, we test for the existence of pre-trends in our main DID specifications by estimating the predictive effect of AAR^{PNTR}_j separately for each year in our sample. Second, we explore the robustness of our primary findings to alternative weighting strategies and a more restrictive set of fixed effects. Third, we address issues specific to financial market analysis, including alternative asset pricing models, potentially confounding events, and event window size.

[56]The high likelihood of PNTR passing immediately prior to the Clinton signing is not surprising given the President's public support for the bill throughout the process.

Fourth, we re-estimate our results using a bootstrap to account for sampling error associated with estimation of firms' $\hat{\beta}_j$s. Finally, we perform a sensitivity analysis which shows that the distributional effects we document in section 3.4 are largely unchanged if we allow PNTR to have a systematic effect on market returns.

G.1 Sector-Year Fixed Effects and Weighting

In this section we consider two extensions of our baseline DID specifications. First, we re-estimate equation (12) for each outcome, weighting each regression by the 1990 level of the dependent variable. Results are displayed in the upper three panels of Figure A.10 for all, goods-producing and service firms, respectively. To conserve space, we report only the DID coefficients of interest and their 95 percent confidence intervals. As indicated in the figure, the sign pattern and statistical significance are similar to the baseline estimates reported in Tables 6 and 7, though we now find that the relationships between AAR_j^{PNTR} and both forms of capital are statistically significant among service firms, while the relationships between AAR_j^{PNTR} and both COGS and intangible capital are less precisely estimated among goods producers.

Second, while our baseline specification employs firm and year fixed effects, one may be concerned that these estimates do not sufficiently control for broad trends such as the collapse of the tech bubble in 2000. To account for such sector-year-specific outcomes, we include 2-digit NAICS by year fixed effects. Results are displayed in the bottom three panels of Figure A.10. As indicated in the figure, coefficient estimates are generally smaller in magnitude, but remain statistically significant, save for intangible capital among service firms.

G.2 Financial Market Concerns

In this section we re-estimate our baseline specifications employing alternative event windows, using a different asset pricing model, omitting firms with potentially confounding announcements during the relevant event windows, and using buy-and-hold (rather than average) abnormal return.

Reduced Event Windows: Thus far we have assumed that PNTR-based information enters equity markets in the five-day trading day window surrounding each legislative event. To the extent that markets responded within a narrower window, our baseline regressions are mis-specified. Here, we re-estimate our baseline findings using a $[-1, 1]$ window around each event. As in the main text, we report only the DID coefficients of interest and their 95 percent confidence intervals to conserve space. The top panel of Figure A.11 reveals that the sign and statistical significance patterns of the coefficient estimates are broadly similar to those in our baseline specification.

The shortened event window also yields similar results with respect to PNTR's distributional implications. This outcome can be seen in Figure A.12, which also contains results for two additional exercises: (1) restricting the event window to the day of the event; and (2) imposing the same restriction but using raw returns rather than abnormal returns to generate cumulative predicted relative operating profit. As indicated in the figure, all three exercises yield similar distributional implications, though the predicted relative losses of small firms are more muted when using raw returns.

Alternate Asset Pricing Model: The asset pricing literature proposes a number of asset pricing models beyond the CAPM which question the prediction that the market portfolio captures all sources of systematic risk. Here, we examine the robustness of our results to using a popular alternative to the CAPM: the 3-factor model proposed by Fama and French (1993). This model augments CAPM with two additional risk factors: Small Minus Big (SMB), which measures the return difference between small firms and large firms, and High Minus Low (HML) which measures the return difference between firms with high versus low book-to-market value of equity.[57] Exposures to these two new factors, as well as to the market portfolio can be estimated using the following statistical model:

$$(R_{j,t} - R_{ft}) = \alpha_j + \beta_j(R_{mkt,t} - R_{ft}) + \beta_j^{SMB} SMB_t + \beta_j^{HML} HML_t + \epsilon_{j,t}. \tag{A.16}$$

As before, the returns on these portfolios are taken from Kenneth French's website.[58] We estimate this model separately for each firm using the full set of trading days in 1999 and calculate abnormal returns as before, defining $\widetilde{AAR}_j^{PNTR}$ as the average abnormal return based on equation (A.16).[59] As illustrated in the second panel of Figure A.11, results are similar to those in our baseline specifications.

Potentially Confounding Announcements: Our estimates of AAR_j^{PNTR} may include changes in stock prices driven by unrelated occurrences that coincidentally take place during our event windows. The corporate finance literature has focused on five types of such events: earnings announcements, dividend announcements, mergers and acquisitions (M&A), stock

[57]The motivation behind these factors is the empirical observation that, even when accounting for their exposure to the market, small firms have significantly higher average returns than large firms and high book-to-market firms have significantly higher average returns than low book-to-market firms. This suggests that these two return differentials must constitute compensation for exposure to systematic risk factors that are not captured by firms' exposure to the market.

[58]To the extent that firm size is related to firms' ability to benefit from globalization, as is assumed in many models of international trade (Melitz, 2003), using the Fama and French (1993) model would strip abnormal returns of their exposure to this policy as captured by the SMB factor.

[59]The simple correlation between $\widetilde{AAR}_j^{PNTR}$ and AAR_j^{PNTR} is over 0.96.

repurchases, and seasoned equity offerings (SEOs).

To examine the sensitivity of our results to the potential impact of such announcements, we identify all occurrences of each of the above events for all firms in our sample. Earnings announcement dates are obtained from the COMPUSTAT quarterly dataset, while M&A, SEO and repurchase announcements are obtained from the Securities Data Corporation (SDC) Platinum database. We re-calculate AAR_j^{PNTR}, omitting any PNTR legislative event for which a firm has any of the aforementioned announcements within 10 trading-days of that event. For example, for a firm with an earnings announcement 9 trading-days before or after the House vote, we would calculate AAR_j^{PNTR} as the average abnormal return among the remaining legislative dates. As discussed previously, using AAR versus cumulative abnormal returns (CAR) allows us to make this adjustment without altering our sample size substantially.

Results based on these re-calculated AAR_j^{PNTR} are reported in the final panel of Figure A.11. As indicated in the figure, the estimates of the relationship between AAR_j^{PNTR} and subsequent firm outcomes are robust to the exclusion of these event dates. [60]

Buy-and-hold abnormal returns: Finally, we examine if our main baseline results are robust to using buy-and-hold returns ($BHAR$s) rather than average returns (AARs) as an alternative method of aggregating pricing information over multi-day event windows. $BHAR$s are calculated by compounding daily abnormal returns across all days in our five event windows for which we have non-missing abnormal returns. We find that the results reported in the main text using AAR_j^{PNTR} are very similar to those using $BHAR_j^{PNTR}$. To preserve space, we focus on our main distributional result with respect to cumulative predicted relative operating profit. Figure A.13 shows that the relative predicted growth of large firms when using $BHAR$s ("Average Buy-and-Hold") is similar to the one using AARs ("Baseline"), albeit slightly more muted.

G.3 Generated Regressors

Thus far we have ignored the sampling error associated with a key input to the calculation of AAR_j^{PNTR}, the firms' $\hat{\beta}_j$s. Failing to account for this error can give rise to a classic generated-regressor problem where standard errors are biased downwards by an amount which is an increasing function of the sampling error in $\hat{\beta}_j$. In this section, we address this issue using a bootstrap. To allow standard errors to be clustered by 4-digit NAICS industry, we employ a clustered bootstrap as follows. First, we construct 1000 sets of $\hat{\beta}_j$ by drawing the requisite number of trading days, with replacement, in the pre-period for each firm. Second, we

[60] In unreported results, we also re-estimate column 1 of Table 2 in where we find that each of these alternate calculations of AAR_j^{PNTR} are similarly correlated with $NTRGap_j$.

sample the requisite number of 4-digit NAICS industries, with replacement, from the full set of industries in our data. Third, we re-estimate equation (12) using this draw. Steps 2 and 3 are repeated 1000 times, each time using a different set of $\hat{\beta}_j$s (from step 1) to construct the AAR_j^{PNTR} to account for the sampling error.

Appendix Tables A.9 and A.10 report a re-estimation of the results in Tables 6 and 7 using this procedure. For each covariate, the first line reports the baseline coefficient, the second line reports the bootstrap standard error, and the third line reports the average bootstrap coefficient, e.g., $\overline{Post * AAR_j^{PNTR}}$ for the DID term of interest. Comparison of the bootstrap estimates to the baseline indicate that the bootstrap standard errors are very similar, suggesting that the sampling errors in firms' $\hat{\beta}_j$ are likely quite small. The average bootstrap coefficients also are very close to the baseline coefficients, suggesting that the sampling errors in firms' $\hat{\beta}_j$ do not induce significant attenuation bias in our results, though it is important to note that bootstrap bias estimates can have a very large variance.

G.4 Netting Out the Market Return

As discussed in Section 2, a potential complication of using abnormal returns to measure exposure to changes in policy is that some policies may affect the market return. In that case, AAR_j^{PNTR} are underestimated if the policy affects the market positively ($F_\tau^e > 0$), and over-estimated if the impact is negative ($F_\tau^e < 0$).

Equation (12) reveals that this bias affects firms' predicted relative operating profit through both AAR_j^{PNTR} and, consequently, through the estimated DID coefficients $\hat{\delta}$. As we do not observe F_τ^e separately from F_τ^X, we are unable to correct for this bias directly. Nevertheless, we can use sensitivity analysis to characterize the qualitative impact such an adjustment might have if F_τ^e is allowed to range over a series of plausible values. Here, we choose F_τ^e values between -1.5 and 1.5 percent, which seems reasonable given that the realized returns on the market during our five event windows are 0.98, -0.6, -0.6, -0.54, and -1.7 percent.[61]

For each value, we adjust AAR_j^{PNTR} by that amount, re-estimate $\hat{\delta}$, and re-compute the predicted relative changes in firms' operating profit given these new estimates. As shown in Figure A.14, the distributional implications are largely unchanged by these adjustments. In each case, the relative declines in operating profit among smaller firms remain dwarfed by the relative increases of the largest firms.

[61] The historical average annual return across calendar years is about 8 percent, implying a 25-day compounded return of 0.77 percent. Our -1.5 to 1.5 percent range of values thus allows for twice that magnitude to occur during our windows in either direction.

Table A.1: AAR_j^e versus the NTR Gap

	(1) $\text{AAR}_j^{HouseIntro}$	(2) $\text{AAR}_j^{HouseVote}$	(3) $\text{AAR}_j^{SenateCloture}$	(4) $\text{AAR}_j^{SenateVote}$	(5) $\text{AAR}_j^{Clinton}$	(6) AAR_j^{PNTR}
NTR Gap_j	-0.017	-0.133	-0.125	-0.020	-0.192	-0.200
	(0.039)	(0.048)	(0.030)	(0.024)	(0.048)	(0.053)
Constant	0.113	-0.080	-0.055	-0.010	-0.005	-0.021
	(0.035)	(0.063)	(0.045)	(0.024)	(0.043)	(0.058)
Observations	2315	2315	2315	2315	2315	2315
R^2	0.000	0.018	0.017	0.000	0.036	0.044

Source: CRSP and authors' calculations. This table presents firm-level OLS regressions of average abnormal returns during five PNTR legislative milestones on $NTR\,Gap_j$. The regression sample is restricted to firms in goods-producing industries,i.e., NAICS sectors 11, 21 and 3X. All variables are de-meaned and divided by their standard deviation. Standard errors are reported below coefficient estimates and are clustered by 4-digit NAICS industries.

Table A.2: $AAR_j^{Belgrade}$ versus the NTR Gap

	(1) $\text{AAR}_\text{j}{}^{Belgrade}$	(2) $\text{AAR}_\text{j}{}^{Belgrade}$	(3) $\text{AAR}_\text{j}{}^{Belgrade}$
NTR Gap_j	0.076	0.105	0.073
	(0.031)	(0.033)	(0.032)
NTR $\text{Gap}_\text{j}{}^{Up}$		-0.080	-0.080
		(0.029)	(0.028)
NTR $\text{Gap}_\text{j}{}^{Down}$		-0.073	-0.063
		(0.033)	(0.031)
Ln(PPE per $\text{Worker})_\text{j}$			-0.019
			(0.035)
Ln(Mkt $\text{Cap})_\text{j}$			-0.123
			(0.035)
$\frac{CashFlows}{Assets}{}_\text{j}$			0.013
			(0.027)
Book Leverage_j			-0.030
			(0.025)
Tobins Q_j			0.149
			(0.048)
Constant	0.002	0.054	0.078
	(0.043)	(0.044)	(0.037)
Observations	2222	2222	2222
R^2	0.005	0.014	0.028

Source: CRSP and authors' calculations. This table presents firm-level OLS regressions of $AAR_j^{Belgrade}$ on the $NTR\,Gap_j$ and a a series of 1990 firm accounting attributes that are winsorized at the 1 percent level. Sample period is 1990 to 2006. All covariates are de-meaned and divided by their standard deviation. Goods firms have a business segment active in NAICS sectors 11, 21 and 3X. Service firms have no business segments in these sectors. Standard errors are reported below coefficient estimates and are clustered by 4-digit NAICS industries

Table A.3: AAR_i^{PNTR} versus AAR_i^{Trump}

	(1) $\mathrm{AAR_i}^{Trump}$	(2) $\mathrm{AAR_i}^{Trump}$	(3) $\mathrm{AAR_i}^{Trump}$
$\mathrm{AAR_i}^{PNTR}$	-0.165	-0.350	-0.063
	(0.060)	(0.100)	(0.046)
Constant	0.014	0.022	0.022
	(0.059)	(0.085)	(0.077)
Observations	379	204	175
R^2	0.026	0.069	0.006
Firm Type	All	Goods	Services

Source: CRSP, COMPUSTAT and authors' calculations. Table presents 6-digit-NAICS-level OLS estimates from regressing average abnormal returns surrounding the 2016 Presidential election (AAR_i^{Trump}) on average abnormal returns during key legislative events associated with PNTR (AAR_i^{PNTR}). All covariates are de-meaned and divided by their standard deviation. Goods firms have a business segment active in NAICS sectors 11, 21 and 3X. Service firms have no business segments in these sectors. Standard errors are clustered at the NAICS 4-digit level and are reported below coefficient estimates.

Table A.4: CRSP De-Listing Codes

Code	Description	Category	N
450	Issue liquidated, final distribution verified, issue closed to further research.	Contraction/Bankruptcy	2
470	Issue liquidated, no final distribution is verified, issue pending further research.	Contraction/Bankruptcy	2
550	Delisted by current exchange - insufficient number of market makers.	Contraction/Bankruptcy	3
551	Delisted by current exchange - insufficient number of shareholders.	Contraction/Bankruptcy	8
560	Delisted by current exchange - insufficient capital, surplus, and/or equity.	Contraction/Bankruptcy	61
580	Delisted by current exchange - delinquent in filing, non-payment of fees.	Contraction/Bankruptcy	61
561	Delisted by current exchange - insufficient (or non-compliance with rules of) float or assets.	Contraction/Bankruptcy	67
574	Delisted by current exchange - bankruptcy, declared insolvent.	Contraction/Bankruptcy	105
584	Delisted by current exchange - does not meet exchange's financial guidelines for continued listing.	Contraction/Bankruptcy	199
552	Delisted by current exchange - price fell below acceptable level.	Contraction/Bankruptcy	235
232	When merged, shareholders primarily receive common stock or ADRs.	Merger	1
252	When merged, shareholders primarily receive common stock or ADRs, preferred stock, warrants, rights, debentures, or notes.	Merger	1
251	When merged, shareholders primarily receive common stock or ADRs and cash.	Merger	1
261	When merged, shareholders primarily receive cash and preferred stock, or warrants, or rights, or debentures, or notes.	Merger	2
243	When merged, shareholders primarily receive common stock, issue on CRSP file and other property, issue on CRSP file.	Merger	2
241	When merged, shareholders primarily receive common stock and cash, issue on CRSP file.	Merger	93
231	When merged, shareholders primarily receive common stock or ADRs.	Merger	229
233	When merged, shareholders receive cash payments.	Merger	564
575	Delisted by current exchange - company request, offer rescinded, issue withdrawn by underwriter.	Other	1
500	Issue stopped trading on exchange - reason unavailable.	Other	1
583	Delisted by current exchange - denied temporary exception requirement.	Other	1
587	Delisted by current exchange - corporate governance violation.	Other	4
573	Delisted by current exchange - company request, deregistration (gone private).	Other	8
582	Delisted by current exchange - failure to meet exception or equity requirements.	Other	16
585	Delisted by current exchange - protection of investors and the public interest.	Other	22
520	Issue stopped trading current exchange - trading Over-the-Counter.	Other	60
570	Delisted by current exchange - company request (no reason given).	Other	65
-	-	Survivor	2563

Source: CRSP and authors' calculations. Table presents presents the CRSP de-listing codes used for categorizing the firm exits between 2000 and 2006 among the firms included in the exit regressions reported in Table 5.

Table A.5: Ex-Ante Probability of PNTR Passage

	(1) House Intro	(2) House Vote	(3) Senate Cloture	(4) Senate Vote	(5) Clinton Signing
Probability	0.118	0.266	0.447	0.620	0.928
	(0.060)	(0.108)	(0.140)	(0.184)	(0.221)
FE	Firm	Firm	Firm	Firm	Firm
Cluster	Firm	Firm	Firm	Firm	Firm
Observations	2512	2512	2512	2512	2512

This table reports the call-option implied probability – estimated before each of our five events – that PNTR will pass. We assume that these probabilities do not change in the time before the five events. For example, the estimates in the first two columns suggest that prior to the introduction of the bill in the House, the probability that PNTR will pass was 11.8 percent, and right after the introduction, the probability had increased to 26.6 percent.

Table A.6: AAR_j^e and Operating Profit

	House Intro	House Vote	Senate Cloture	Senate Vote	Clinton Signing	PNTR
	Panel A: Ln(Operating Profit) – All Firms					
$\mathrm{AAR_j}$	0.141	3.170	3.381	1.291	3.752	12.471
	(0.096)	(0.856)	(0.704)	(0.730)	(0.893)	(2.472)
R^2	.913	.913	.913	.912	.913	.913
Observations	48486	48463	48465	48311	48259	48551
Unique Firms	4353	4351	4347	4325	4317	4360
	Panel B: Ln(Operating Profit) – Goods Producers					
$\mathrm{AAR_j}$	0.138	3.507	2.674	0.236	5.152	13.804
	(0.112)	(1.092)	(0.801)	(0.829)	(1.135)	(2.519)
R^2	.919	.919	.919	.919	.92	.92
Observations	26912	26901	26894	26804	26784	26928
Unique Firms	2235	2234	2232	2222	2219	2237
	Panel C: Ln(Operating Profit) – Service Firms					
$\mathrm{AAR_j}$	0.114	2.465	3.554	2.475	1.765	9.418
	(0.131)	(1.224)	(1.113)	(1.101)	(0.851)	(3.461)
R^2	.906	.906	.906	.906	.906	.906
Observations	21574	21562	21571	21507	21475	21623
Unique Firms	2118	2117	2115	2103	2098	2123

Source: CRSP, COMPUSTAT and authors' calculations. Table presents firm-level OLS DID panel regressions of firm operating profit on the abnormal returns associated with each legislative event (AAR_j^e) and a series of 1990 firm accounting attributes that are winsorized at the 1 percent level. In contrast to the results reported in the main text, variables are not standardized, e.g., the coefficients indicate the log-point impact on operating profit of a 1 percentage point increase in AAR_j^e. AAR for the individual events have been divided by the change in probability associated with PNTR's passage which are estimated as described in section F and reported in table A.5. Results for variables other than AAR_j^e are suppressed. Sample period is 1990 to 2006. Standard errors are reported below coefficient estimates and are clustered by 4-digit NAICS industries.

Table A.7: Explanatory Power of AAR_j^{PNTR} versus NTR Gap – Goods Producers

	Ln(Sales$_j$)	Ln(COGS$_j$)	Ln(Profit$_j^{OP.}$)	Ln(Employment$_j$)	Ln(PPE$_j$)	Ln(K$_j^{Int.}$)
	Panel A: NTR Gaps Only					
Post*NTR Gap$_j$	-0.068	-0.073	-0.066	-0.021	-0.078	0.024
	(0.025)	(0.022)	(0.032)	(0.019)	(0.029)	(0.025)
Post*NTR Gap$_j^{Up}$	0.011	0.019	-0.036	0.004	-0.043	-0.068
	(0.019)	(0.021)	(0.036)	(0.019)	(0.026)	(0.030)
Post*NTR Gap$_j^{Down}$	-0.081	-0.054	-0.139	-0.058	-0.064	-0.048
	(0.019)	(0.020)	(0.031)	(0.020)	(0.027)	(0.023)
R^2	.926	.93	.92	.942	.948	.943
P-value (Gaps)	0	.001	0	.012	.001	.05
	Panel B: NTR Gaps and AARs					
Post*AAR$_j^{PNTR}$	0.136	0.083	0.111	0.079	0.098	0.055
	(0.039)	(0.023)	(0.025)	(0.025)	(0.025)	(0.019)
Post*NTR Gap$_j$	-0.046	-0.060	-0.052	-0.008	-0.062	0.033
	(0.023)	(0.021)	(0.030)	(0.020)	(0.028)	(0.025)
Post*NTR Gap$_j^{Up}$	-0.003	0.010	-0.042	-0.005	-0.053	-0.074
	(0.019)	(0.021)	(0.035)	(0.020)	(0.028)	(0.032)
Post*NTR Gap$_j^{Down}$	-0.069	-0.046	-0.125	-0.051	-0.055	-0.043
	(0.019)	(0.020)	(0.031)	(0.020)	(0.027)	(0.024)
R^2	.927	.93	.92	.942	.949	.943
P-value (Gaps)	0	.004	0	.046	.001	.063
Firm Type	Goods	Goods	Goods	Goods	Goods	Goods
Observations	28483	28563	26729	28566	28752	28582
Unique Firms	2317	2318	2215	2324	2324	2318

Source: CRSP, COMPUSTAT and authors' calculations. Table presents firm-level OLS DID panel regressions of noted firm outcomes on firms' PNTR average abnormal returns (AAR_j^{PNTR}), their NTR gaps, and a suppressed series of 1990 firm accounting attributes that are winsorized at the 1 percent level. Sample period is 1990 to 2006. All covariates are de-meaned and divided by their standard deviation. Goods firms have a business segment active in NAICS sectors 11, 21 and 3X. Standard errors are reported below coefficient estimates and are clustered by 4-digit NAICS industries.

Table A.8: Explanatory Power of AAR_j^{PNTR} versus NTR Gap – Service Firms

	Ln(Sales$_j$)	Ln(COGS$_j$)	Ln(Profit$_j{}^{OP.}$)	Ln(Employment$_j$)	Ln(PPE$_j$)	Ln(K$_j^{Int.}$)
	Panel A: NTR Gaps Only					
Post*NTR Gap$_j{}^{Up}$	0.057	0.041	0.029	0.008	0.057	0.100
	(0.044)	(0.038)	(0.062)	(0.042)	(0.059)	(0.074)
Post*NTR Gap$_j{}^{Down}$	-0.084	-0.072	-0.088	-0.051	-0.032	-0.012
	(0.020)	(0.023)	(0.027)	(0.019)	(0.023)	(0.023)
R^2	.921	.922	.907	.927	.939	.885
P-value (Gaps)	0	.007	.001	.015	.384	.399
	Panel B: NTR Gaps and AARs					
Post*AAR$_j{}^{PNTR}$	0.085	0.093	0.083	0.093	0.058	0.070
	(0.031)	(0.029)	(0.035)	(0.030)	(0.037)	(0.030)
Post*NTR Gap$_j{}^{Up}$	0.066	0.051	0.036	0.018	0.063	0.105
	(0.046)	(0.039)	(0.065)	(0.044)	(0.061)	(0.076)
Post*NTR Gap$_j{}^{Down}$	-0.075	-0.063	-0.079	-0.040	-0.025	-0.004
	(0.021)	(0.023)	(0.029)	(0.020)	(0.023)	(0.023)
R^2	.921	.923	.907	.927	.939	.886
P-value (Gaps)	.002	.027	.007	.116	.501	.36
Firm Type	Services	Services	Services	Services	Services	Services
Observations	21953	21953	21177	21747	21791	20209
Unique Firms	2134	2134	2082	2133	2134	2064

Source: CRSP, COMPUSTAT and authors' calculations. Table presents firm-level OLS DID panel regressions of noted firm outcomes on firms' PNTR average abnormal returns (AAR_j^{PNTR}), their NTR gaps, and a suppressed series of 1990 firm accounting attributes that are winsorized at the 1 percent level. Sample period is 1990 to 2006. All covariates are de-meaned and divided by their standard deviation. Service firms have no business segments in NAICS sectors 11, 21 and 3X. Standard errors are reported below coefficient estimates and are clustered by 4-digit NAICS industries.

Table A.9: Bootstrapped AAR_i^{PNTR} and Firm Sales, COGS and Operating Profit (Sales-COGS)

	Ln(Sales$_j$)			Ln(COGS$_j$)			Ln(Profit$_j{}^{OP.}$)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post*AAR$_j{}^{PNTR}$	0.130	0.150	0.095	0.105	0.097	0.103	0.129	0.143	0.098
	(0.025)	(0.034)	(0.033)	(0.019)	(0.023)	(0.027)	(0.026)	(0.029)	(0.037)
$\overline{Post * AAR_j{}^{PNTR}}$	0.098	0.104	0.076	0.079	0.063	0.084	0.090	0.091	0.072
Post*PPE per Worker$_j$	0.053	0.147	-0.015	0.046	0.129	-0.007	0.037	0.152	-0.040
	(0.040)	(0.062)	(0.030)	(0.036)	(0.057)	(0.024)	(0.046)	(0.063)	(0.031)
$\overline{Post * PPEperWorker_j}$	0.051	0.130	-0.015	0.043	0.112	-0.008	0.033	0.135	-0.036
Post*Ln(Mkt Cap)$_j$	-0.068	-0.091	-0.062	-0.076	-0.097	-0.072	-0.074	-0.105	-0.058
	(0.023)	(0.029)	(0.030)	(0.020)	(0.027)	(0.027)	(0.025)	(0.029)	(0.026)
$\overline{Post * Ln(MktCap)_j}$	-0.066	-0.079	-0.064	-0.074	-0.086	-0.073	-0.069	-0.093	-0.060
Post*$\frac{CashFlows}{Assets}$$_j$	-0.136	-0.198	-0.044	-0.060	-0.098	-0.012	-0.137	-0.212	-0.045
	(0.033)	(0.037)	(0.032)	(0.021)	(0.024)	(0.030)	(0.035)	(0.041)	(0.027)
$\overline{Post * \frac{CashFlows}{Assets}}$	-0.130	-0.191	-0.040	-0.056	-0.092	-0.009	-0.132	-0.204	-0.041
Post*Book Leverage$_j$	-0.037	-0.095	0.026	-0.027	-0.077	0.024	-0.033	-0.081	0.017
	(0.020)	(0.022)	(0.024)	(0.021)	(0.025)	(0.026)	(0.024)	(0.026)	(0.024)
$\overline{Post * BookLeverage_j}$	-0.038	-0.096	0.023	-0.027	-0.077	0.022	-0.033	-0.080	0.015
Post*Tobins Q$_j$	0.128	0.163	0.097	0.126	0.143	0.107	0.114	0.156	0.074
	(0.024)	(0.042)	(0.027)	(0.023)	(0.039)	(0.028)	(0.026)	(0.039)	(0.032)
$\overline{Post * TobinsQ_j}$	0.133	0.163	0.106	0.129	0.145	0.114	0.120	0.156	0.082
Observations	51121	28694	22427	51205	28778	22427	48551	26928	21623
Unique Firms	4516	2340	2176	4517	2341	2176	4360	2237	2123

Source: CRSP, COMPUSTAT and authors' calculations. Table presents bootstrapped firm-level OLS DID panel regressions of noted firm outcomes on firms' PNTR average abnormal returns (AAR_j^{PNTR}) and a series of 1990 firm accounting attributes that are winsorized at the 1 percent level. Sample period is 1990 to 2006. All covariates are de-meaned and divided by their standard deviation. Goods firms have a business segment active in NAICS sectors 11, 21 and 3X. Service firms have no business segments in these sectors. Bootstrapping procedure is detailed in section G.3. Reported bootstrapped standard errors are clustered at the NAICS 4-digit level and are reported below coefficient estimates. Average of the 1000 bootstrapped coefficients ($\overline{Post * AAR_j^{PNTR}}$) is reported below the standard error. Right-hand side variables also include firm and year fixed effects.

Table A.10: Bootstrapped AAR_i^{PNTR} and Employment, PPE, and Intangible Capital

	Ln(Employment$_j$)			Ln(PPE$_j$)			Ln(Intangibles$_j$)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post*AAR$_j{}^{PNTR}$	0.098	0.086	0.102	0.091	0.112	0.061	0.064	0.053	0.066
	(0.019)	(0.020)	(0.031)	(0.024)	(0.022)	(0.040)	(0.019)	(0.017)	(0.031)
$\overline{Post * AAR_j{}^{PNTR}}$	0.073	0.051	0.088	0.056	0.059	0.040	0.028	0.013	0.035
Post*PPE per Worker$_j$	0.036	0.102	-0.008	-0.062	0.012	-0.129	0.007	0.074	-0.021
	(0.021)	(0.026)	(0.028)	(0.045)	(0.073)	(0.026)	(0.026)	(0.032)	(0.030)
$\overline{Post * PPEperWorker_j}$	0.037	0.101	-0.006	-0.065	-0.010	-0.130	0.005	0.068	-0.020
Post*Ln(Mkt Cap)$_j$	-0.071	-0.091	-0.067	-0.076	-0.116	-0.037	-0.025	-0.059	0.004
	(0.016)	(0.019)	(0.025)	(0.025)	(0.032)	(0.027)	(0.020)	(0.017)	(0.039)
$\overline{Post * Ln(MktCap)_j}$	-0.070	-0.084	-0.069	-0.071	-0.099	-0.037	-0.021	-0.052	0.004
Post*$\frac{CashFlows}{Assets}{}_j$	-0.024	-0.056	0.033	-0.030	-0.044	-0.003	-0.037	-0.062	0.003
	(0.021)	(0.022)	(0.030)	(0.017)	(0.020)	(0.028)	(0.022)	(0.020)	(0.031)
$\overline{Post * \frac{CashFlows}{Assets}}$	-0.019	-0.048	0.034	-0.025	-0.037	0.001	-0.026	-0.049	0.009
Post*Book Leverage$_j$	-0.052	-0.092	-0.010	-0.050	-0.109	0.022	-0.056	-0.077	-0.043
	(0.019)	(0.021)	(0.026)	(0.022)	(0.026)	(0.024)	(0.017)	(0.022)	(0.025)
$\overline{Post * BookLeverage_j}$	-0.053	-0.092	-0.014	-0.049	-0.107	0.019	-0.054	-0.073	-0.042
Post*Tobins Q$_j$	0.119	0.166	0.084	0.169	0.227	0.130	0.189	0.232	0.146
	(0.016)	(0.031)	(0.020)	(0.028)	(0.046)	(0.030)	(0.034)	(0.032)	(0.048)
$\overline{Post * TobinsQ_j}$	0.122	0.171	0.089	0.173	0.231	0.139	0.193	0.234	0.151
Observations	51007	28779	22228	51227	28968	22259	49468	28782	20686
Unique Firms	4522	2347	2175	4523	2347	2176	4442	2337	2105

Source: CRSP, COMPUSTAT and authors' calculations. Table presents bootstrapped firm-level OLS DID panel regressions of noted firm outcomes on firms' PNTR average abnormal returns (AAR_j^{PNTR}) and a series of 1990 firm accounting attributes that are winsorized at the 1 percent level. Sample period is 1990 to 2006. All covariates are de-meaned and divided by their standard deviation. Goods firms have a business segment active in NAICS sectors 11, 21 and 3X. Service firms have no business segments in these sectors. Bootstrapping procedure is detailed in section G.3. Reported bootstrapped standard errors are clustered at the NAICS 4-digit level and are reported below coefficient estimates. Average of the 1000 bootstrapped coefficients ($\overline{Post * AAR_j^{PNTR}}$) is reported below the standard error. Right-hand side variables also include firm and year fixed effects.

Table A.11: τ_j^{CUSFTA} and Profit, Employment, PPE, and Intangible Capital

	Ln(Sales$_j$)	Ln(COGS$_j$)	Ln(Profit$_j^{OP.}$)	Ln(Employment$_j$)	Ln(PPE$_j$)
	Panel A: Bilateral Tariff Changes				
$\Delta\tau^{USA^{88,94}}$	0.006	0.020	-0.012	0.025	0.037
	(0.017)	(0.016)	(0.018)	(0.019)	(0.022)
$\Delta\tau^{Can^{88,94}}$	-0.019	-0.013	-0.030	-0.047	-0.035
	(0.021)	(0.021)	(0.022)	(0.023)	(0.024)
R^2	.947	.949	.934	.948	.958
Observations	23590	23601	22997	23483	23662
Unique Firms	1956	1956	1917	1959	1961
	Panel B: US Tariff Changes Only				
$\Delta\tau^{USA^{88,94}}$	-0.005	0.012	-0.030	-0.003	0.016
	(0.014)	(0.014)	(0.015)	(0.015)	(0.017)
R^2	.947	.949	.934	.948	.958
Observations	23590	23601	22997	23483	23662
Unique Firms	1956	1956	1917	1959	1961
	Panel C: Canadian Tariff Changes Only				
$\Delta\tau^{Can^{88,94}}$	-0.015	-0.001	-0.036	-0.033	-0.014
	(0.017)	(0.018)	(0.018)	(0.018)	(0.020)
R^2	.947	.949	.934	.948	.958
Observations	23590	23601	22997	23483	23662
Unique Firms	1956	1956	1917	1959	1961

Source: CRSP, COMPUSTAT and authors' calculations. Table presents firm-level OLS DID panel regressions of noted firm outcomes on firms' CUSFTA tariff change exposure. Tariff changes and a series of 1978 firm accounting attributes that are winsorized at the 1 percent level. Sample period is 1978 to 1993. All covariates are de-meaned and divided by their standard deviation. Goods firms have a business segment active in NAICS sectors 11, 21 and 3X. Service firms have no business segments in these sectors. Right-hand side variables also include firm and year fixed effects. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

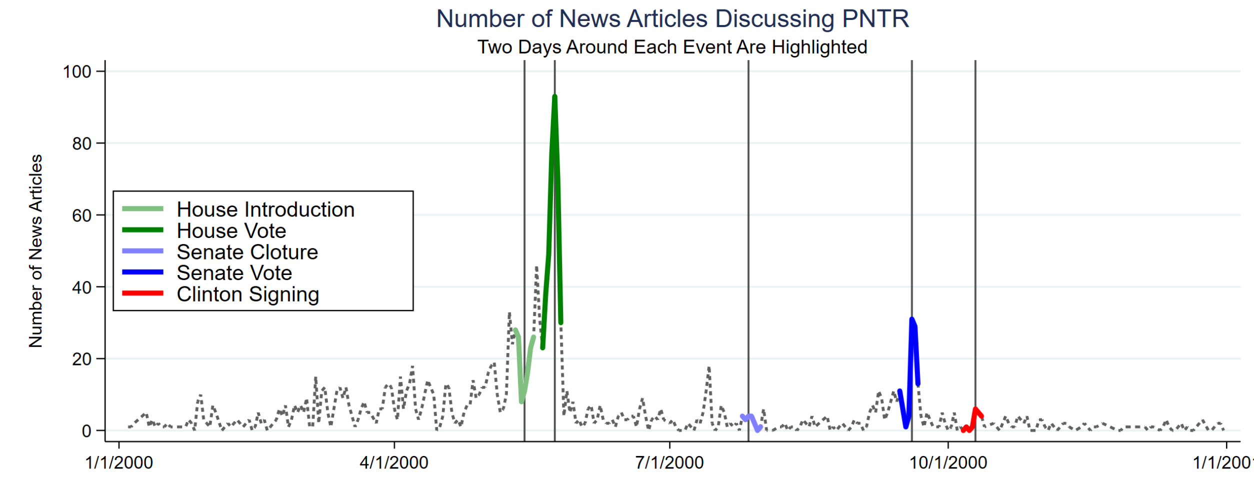

Figure A.1: Count of Articles Mentioning "Permanent Normal Trade Relations"

Source: Noted media outlets and authors' calculations. Figure reports the number of unique articles which mention PNTR during calendar year 2000 from the following sources: the Associated Press, BBC Monitoring International Reports, the Boston Globe, the Chicago Tribune, CNN Transcripts, the Financial Times, the Los Angeles Times, the New York Times, the Washington Post, PR Newswire and the Wall Street Journal. Segments in bold indicate the five legislative event windows considered in our analysis: the introduction of the bill in the House, the House vote, the Senate vote to bring the bill to the floor, the Senate vote and Clinton's signing, in that order.

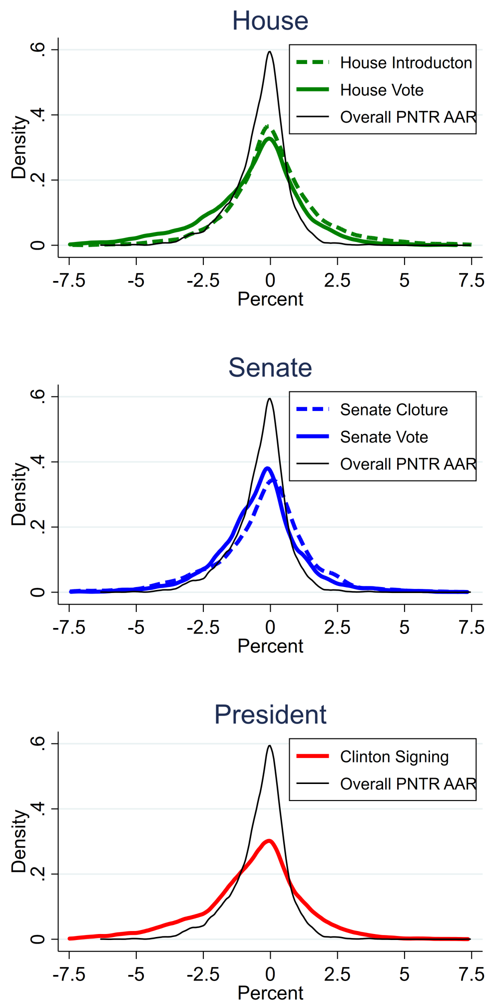

Figure A.2: PNTR Average Abnormal Returns, By Event

Source: CRSP and authors' calculations. Figure displays distributions of abnormal returns across 5 PNTR legislative events, and overall. Values below -7.5 and above 7.5 percent are dropped to improve readability. In chronological order, the means by event are 0.12, -0.65, -0.25, -0.40, and -0.68 percent, while standard deviations are 1.9, 2.1, 2.1, 1.8 and 2.2 percent.

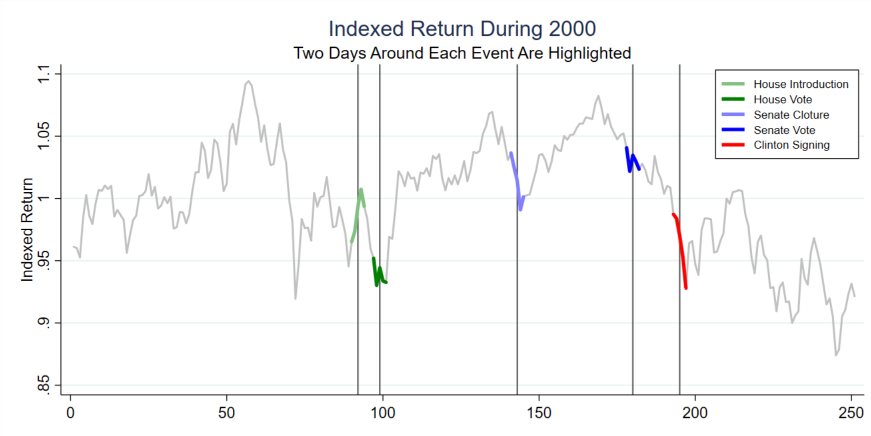

Figure A.3: Market Return During PNTR Windows

Source: CRSP and authors' calculations. Figure reports the daily market return during 2000. Segments in bold indicate the five legislative event windows considered in our analysis: the introduction of the bill in the House, the House vote, the Senate vote to bring the bill to the floor, the Senate vote and Clinton's signing, in that order.

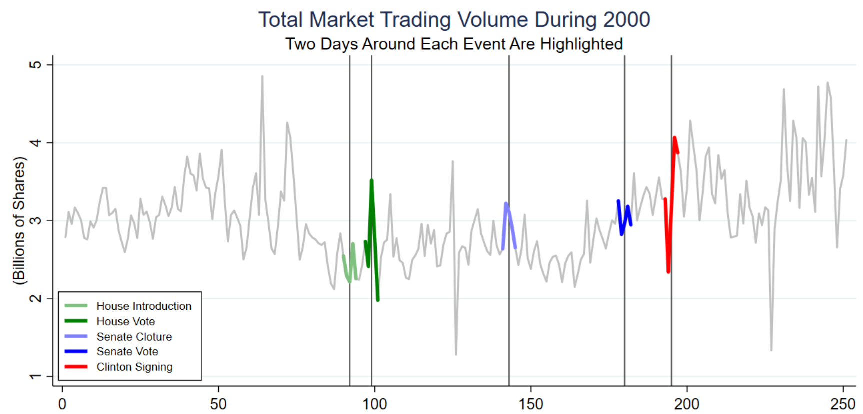

Figure A.4: Market Volume During PNTR Windows

Source: CRSP and authors' calculations. Figure reports the daily market volume during 2000. Segments in bold indicate the five legislative event windows considered in our analysis: the introduction of the bill in the House, the House vote, the Senate vote to bring the bill to the floor, the Senate vote and Clinton's signing, in that order.

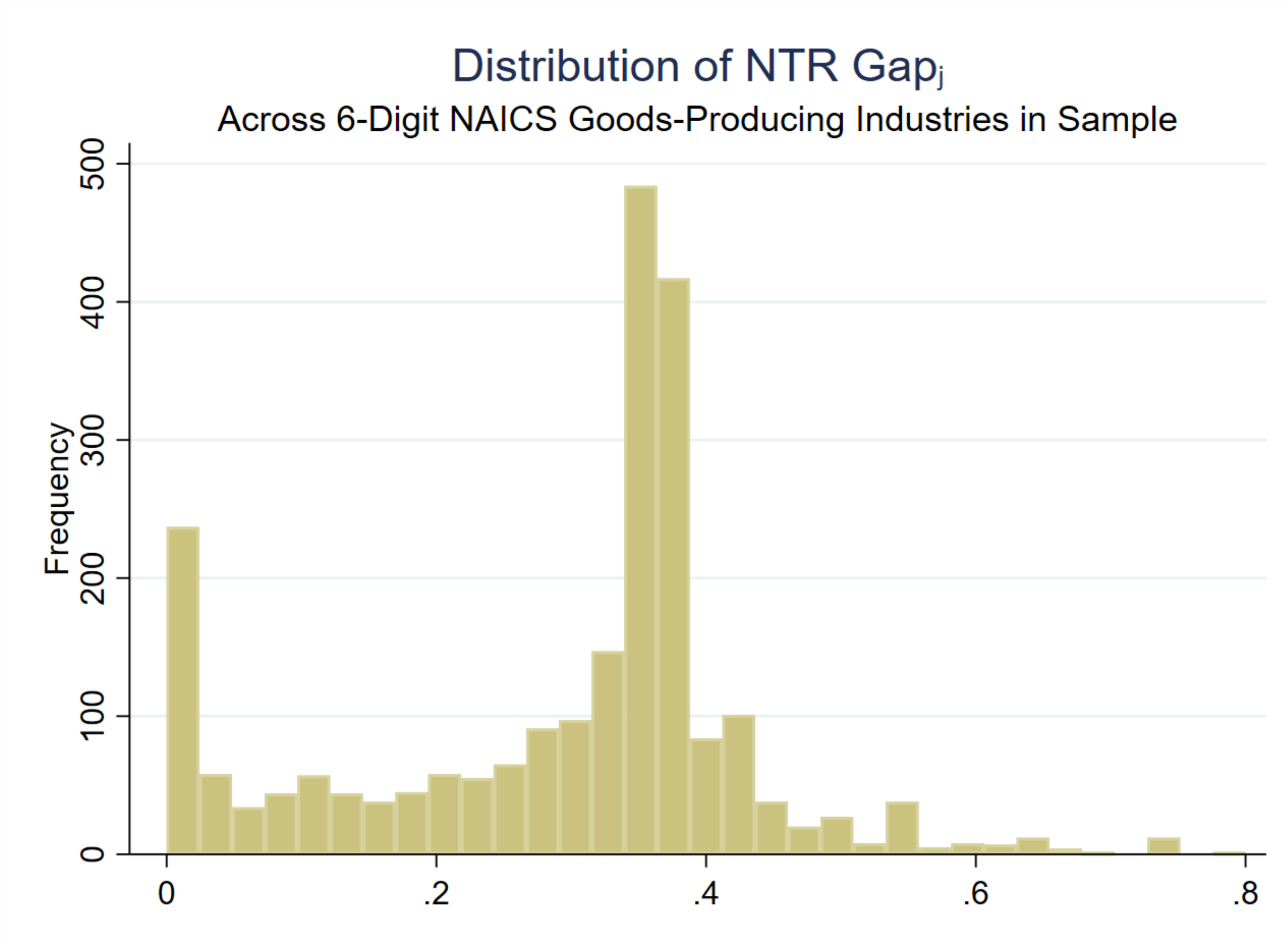

Figure A.5: Distribution of the NTR Gap

Source: Feenstra et al. (2002) and Pierce and Schott (2016). Figure displays the distribution of $NTR\,Gap_i^{Own}$ across goods-producing 6-digit manufacturing industries populated by firms in our sample. Goods-producing sectors are defined as: Manufacturing (NAICS 31-33), Mining (NAICS 21), and Agriculture, Forestry, Fishing and Hunting (NAICS 11).

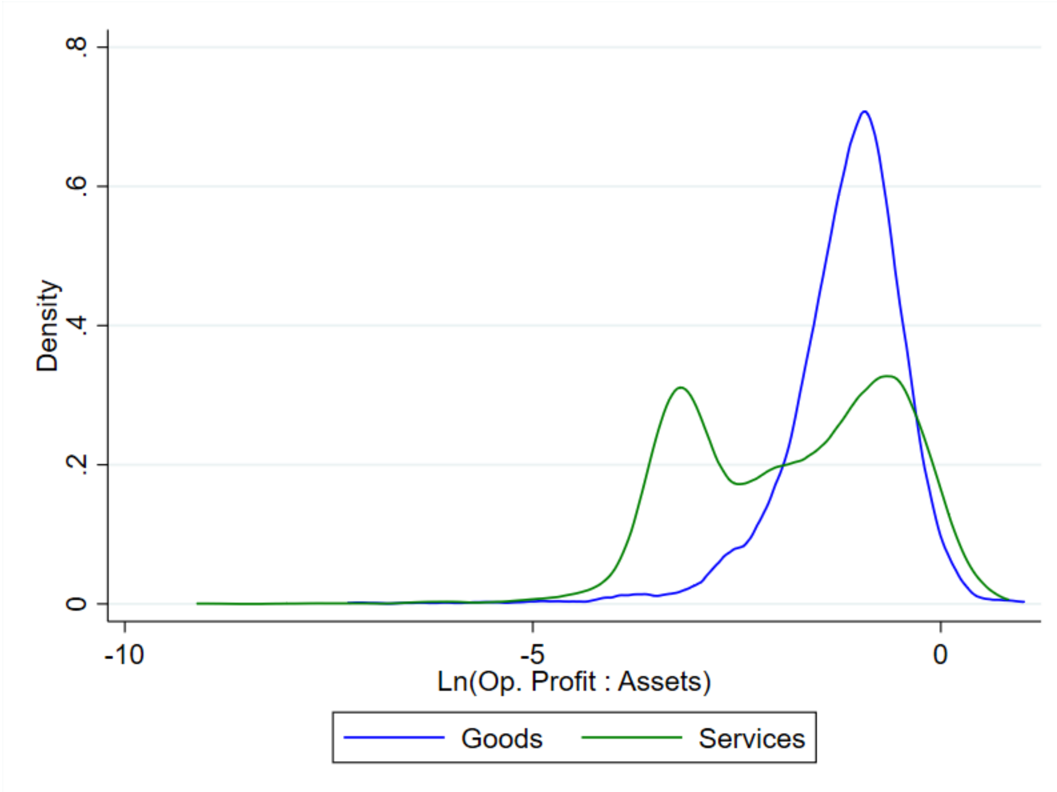

Figure A.6: Distribution of Ln($\frac{OperatingProfit}{Assets}$) by Firm Type in 2000

Source: CRSP, COMPUSTAT and authors' calculations. Figure displays the distribution of firm-level Ln($\frac{OperatingProfit}{Assets}$) among all goods and service producing firms in our sample in the year 2000. Goods firms have a business segment active in NAICS sectors 11, 21 and 3X. Service firms have no business segments in these sectors.

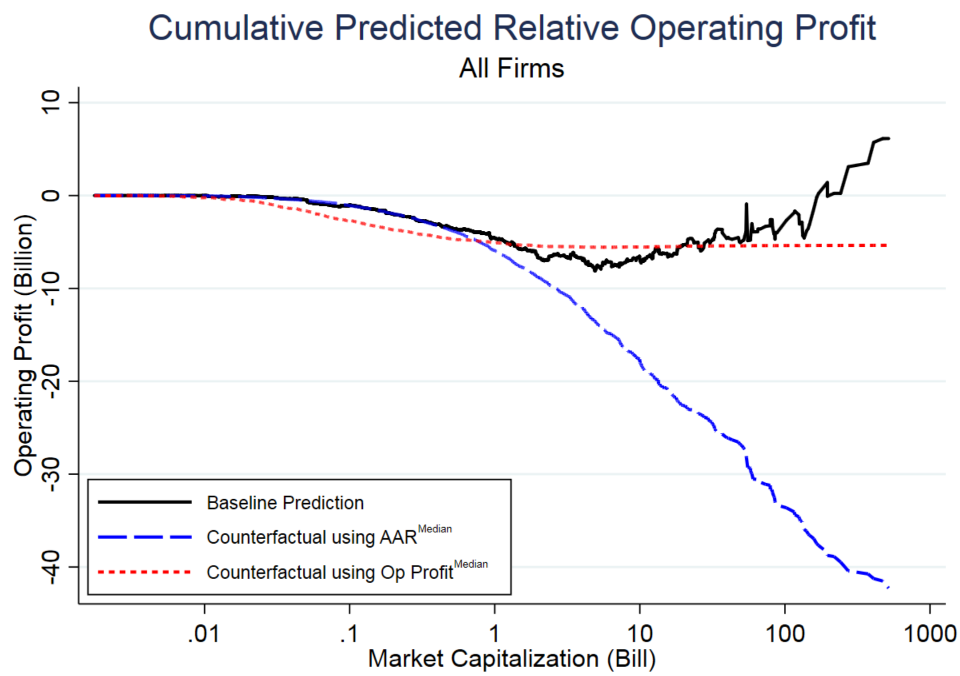

Figure A.7: Counterfactual Cumulative Relative Change in Operating Profit

Source: CRSP, COMPUSTAT, and authors' calculations. Figure displays the predicted cumulative relative change in firms' operating profit implied by the baseline difference-in-differences estimates in Table 6 along with two coarse counterfactuals. The first plots the cumulative predicted relative change in operating profit using firms' actual operating profit in 2000, but substituting the median across all firms for their actual AAR_j^{PNTR}. The second uses firms' actual AAR_j^{PNTR} in combination with the median operating profit across all firms in place of their actual initial operating profit in 2000. Firms' market capitalization is from 2000, prior to PNTR.

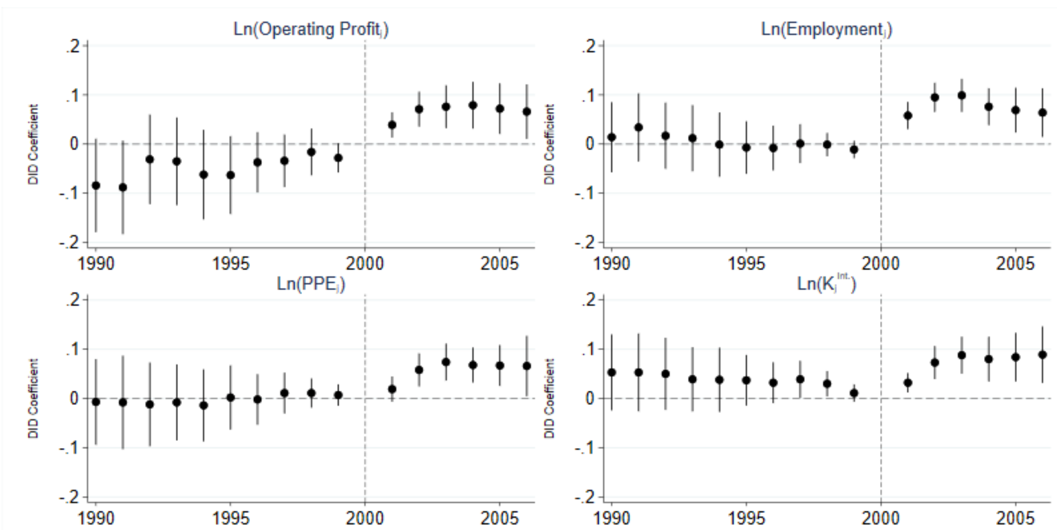

Figure A.8: AAR_j^{PNTR} and Firm Outcomes: Annual Specification

Source: CRSP, COMPUSTAT and authors' calculations. Figure displays a series of 95 percent confidence intervals for the difference-in-difference term of interest in equation (13). Each panel is from a separate, firm-level OLS regression of noted firm outcome on PNTR average abnormal returns (AAR_j^{PNTR}) interacted with a full set of year dummy variables as well as a series of initial (1990) firm accounting attributes, also interacted with year dummy variables and winsorized at the 1 percent level. Sample period is 1990 to 2006. Sample includes 4505 firms. All covariates are de-meaned and divided by their standard deviations. Standard errors used to construct confidence intervals are clustered at the 4-digit NAICS level.

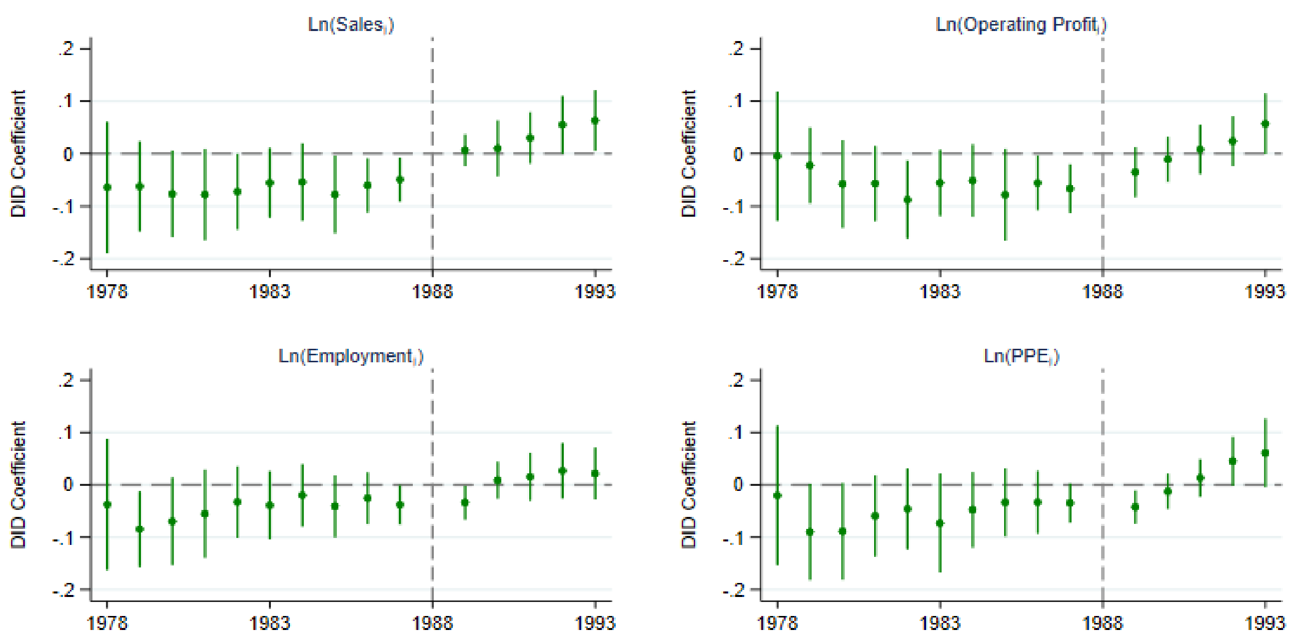

Figure A.9: AAR_j^{CUSFTA} and Firm Outcomes: Annual Specification

Source: CRSP, COMPUSTAT and authors' calculations. Figure displays a series of 95 percent confidence intervals for the difference-in-difference term of interest in equation (13). Each panel is from a separate, firm-level OLS regression of noted firm outcome on CUSFTA average abnormal returns (AAR_j^{CUSFTA}) interacted with a full set of year dummy variables as well as a series of initial (1990) firm accounting attributes, also interacted with year dummy variables and winsorized at the 1 percent level. Sample period is 1978 to 1994. All covariates are de-meaned and divided by their standard deviations. Standard errors used to construct confidence intervals are clustered at the 3-digit SIC level.

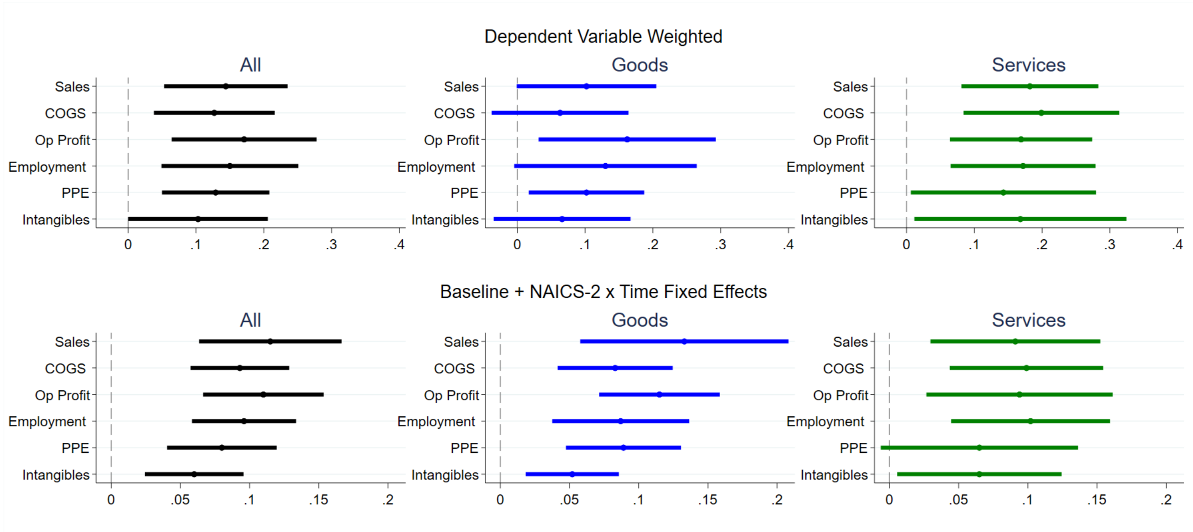

Figure A.10: AAR_j^{PNTR} and Firm Outcomes: Robustness Specifications

Source: CRSP, COMPUSTAT and authors' calculations. Figure displays a series of 95 percent confidence intervals for the difference-in-difference term of interest from equation (12). Each interval is from a separate regress. Top panel weights observations by firms' initial value of the dependent variable. Bottom panel includes 2-digit NAICS by year fixed effects reflecting firms' primary activity. All covariates are standardized by subtracting their means and dividing by their standard deviations. Sample period is 1990 to 2006. Sample includes up to 4517 firms, depending on year. Regression include initial firm accounting attributes, winsorized at the 1 percent level, interacted with *Post*. Standard errors used to construct confidence intervals are clustered at the 4-digit NAICS level.

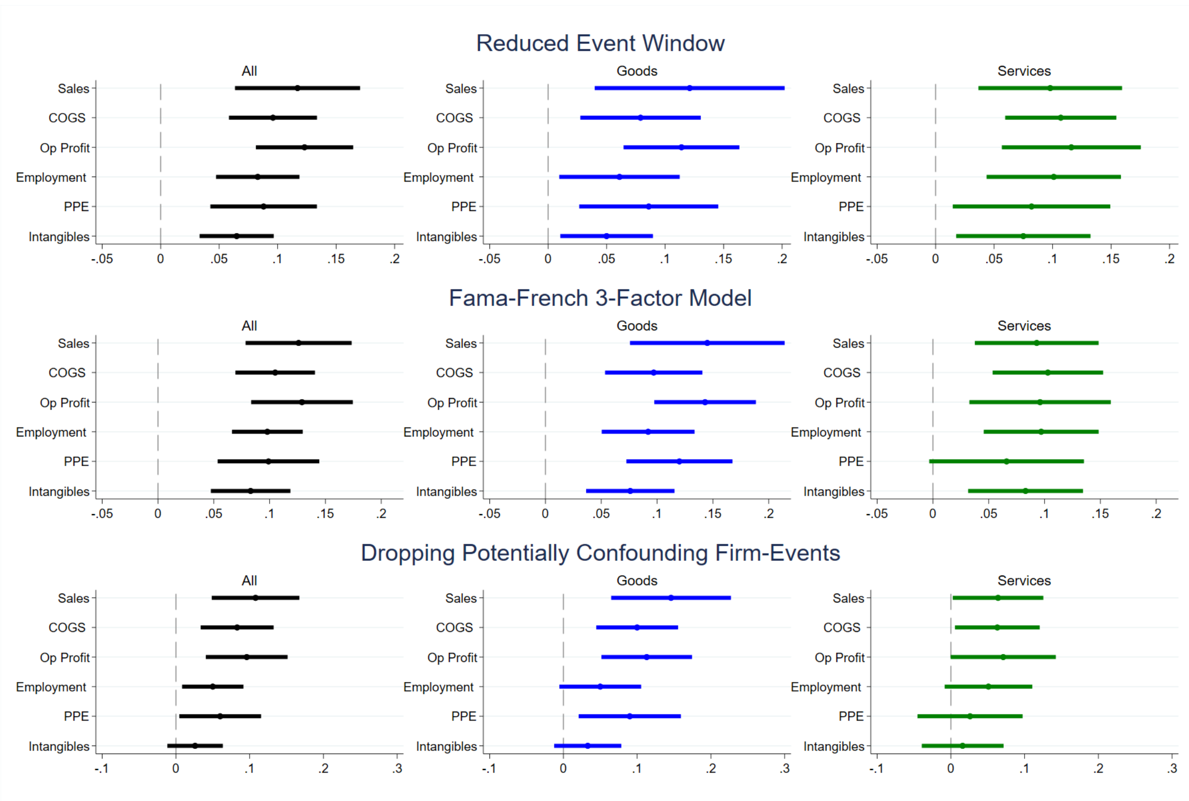

Figure A.11: AAR_j^{PNTR} and Firm Outcomes: Finance Robustness Specification
Source: CRSP, COMPUSTAT and authors' calculations. Figure displays a series of 95 percent confidence intervals for the difference-in-difference term of interest from equation (12). Each interval is from a separate regress. Top panel uses narrower event windows, middle panel uses Fama-French 3-Factor asset pricing model in place of CAPM, and bottom panel eliminates firms with confounding events during windows. All covariates are standardized by subtracting their means and dividing by their standard deviations. Sample period is 1990 to 2006. Sample includes up to 4517 firms, depending on year. Regression include initial firm accounting attributes, winsorized at the 1 percent level, interacted with *Post*. Standard errors used to construct confidence intervals are clustered at the 4-digit NAICS level.

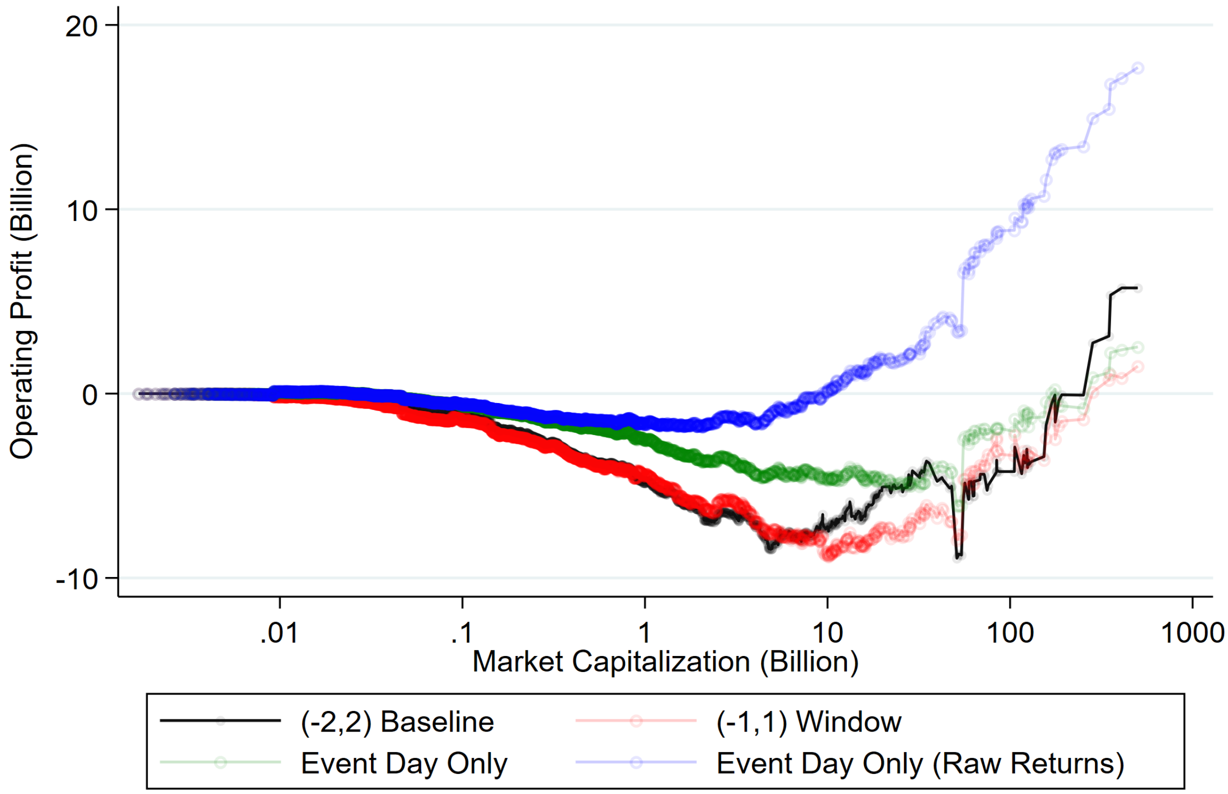

Figure A.12: Cumulative Relative Changes using Alternate Windows

Source: CRSP, COMPUSTAT, and authors' calculations. Figure displays the predicted cumulative relative change in firm operating profit implied by the baseline difference-in-differences estimates performed separately for three alternate measures of abnormal returns: (1) the baseline (-2,2) window; (2) a (-1,1) window; (3) a window consisting just of the day of the event and (4) the realized returns using only the day of each event. Y-axis reports the cumulative predicted relative change as a share of the initial level across firms in 2000, prior to PNTR. Firms' market capitalization is from 2000, prior to PNTR.

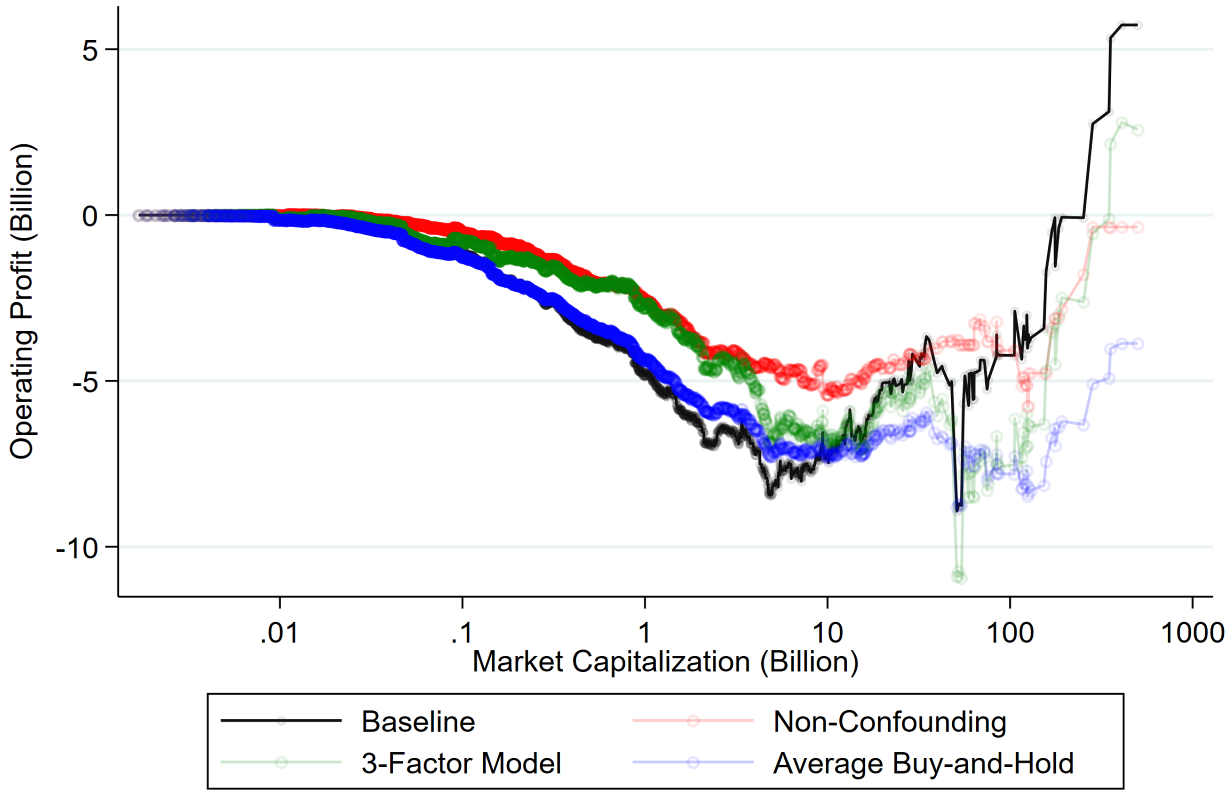

Figure A.13: Cumulative Relative Changes using Alternate $BHAR_j^{PNTR}$

Source: CRSP, COMPUSTAT, and authors' calculations. Figure displays the predicted cumulative relative change in firm operating profit implied by the baseline difference-in-differences estimates using alternate calculations of AAR_j^{PNTR}: (1) the baseline; (2) a version that omits events for firms if they encompass a dividend announcement, merger announcement, SEO, or repurchase announcement within 7 days of the event; (3) a version based on Fama and French (1993) 3-factor asset pricing model; and (4) a buy-and-hold return version. Y-axis reports the cumulative predicted relative change as a share of the initial level across firms in 2000, prior to PNTR. Firms' market capitalization is from 2000, prior to PNTR.

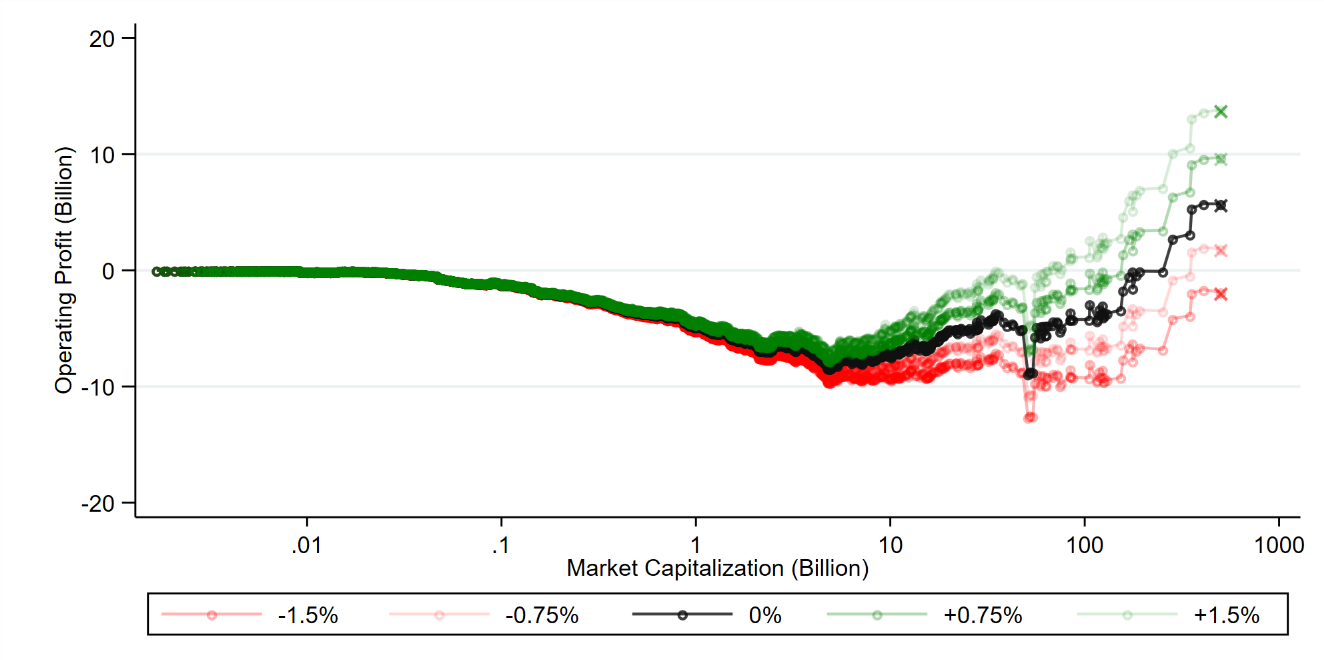

Figure A.14: Cumulative Relative Changes Using Different Aggregate Assumptions

Source: CRSP, COMPUSTAT, and authors' calculations. Figure displays the predicted cumulative relative change in firm operating profit implied by the difference-in-differences estimates performed by adding $\widehat{\beta}_j * F^e_\tau$ to AAR_j^{PNTR} where F^e_τ is the effect of PNTR on returns over the 25 days in our and takes on values ranging from -1.5% to 1.5%. The value 0.0% corresponds to our baseline assumption of no aggregate impact of the policy on the market. Y-axis reports the cumulative predicted relative change as a share of the initial level across firms in 2000, prior to PNTR. Firms' market capitalization is from 2000, prior to PNTR.