Using Equity Market Reactions to Infer Exposure to Trade Liberalization [*]

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Abstract

We outline a method for using asset prices to identify firm exposure to changes in policy. We highlight the benefits of this approach for studying trade agreements and apply it to two US trade liberalizations, with China and Canada. We find that abnormal equity returns during key events associated with these liberalizations are correlated with standard measures of import competition, vary across firms even within industries, predict subsequent firm outcomes, and provide a more complete view of distributional implications. In both cases, predicted relative increases in operating profit among the very largest firms dwarf the relative losses of smaller firms.

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1 Introduction

We propose a new method for measuring firm exposure to changes in policy. Our approach is based on financial markets' reactions to key events associated with the new regime, such as the legislative votes during which it becomes law, and assumes that all new information relevant for firm value is fully reflected in its stock price. Hence, by measuring firms' average abnormal returns (AARs) relative to the market during these events, we leverage the "wisdom of the crowd" to obtain traders' assessment of the impact of the policy change on firm value.

We demonstrate the usefulness of our approach by estimating US firms' exposure to two US trade liberalizations, with China and Canada. Our primary focus is perhaps the most substantial US trade liberalization in the last few decades, the US granting of Permanent Normal Trade Relations (PNTR) to China in October 2000. In most of the empirical research focused on this liberalization, as well as studies of the distributional implications of trade more broadly, exposure to trade is defined in terms of import competition, measured via changes in tariffs or import volumes among the set of goods a worker, firm or region produces.[1] This standard approach has three disadvantages. First, by concentrating on import competition, it ignores other, potentially offsetting channels of exposure, for example the greater availability of low-cost foreign inputs that may allow users of these inputs to expand (Antràs et al. (2017); Bernard et al. (2018)), or general equilibrium effects. Second, because changes in trade barriers and import volumes are not easily observed for service firms, the standard approach generally ignores firms outside goods-producing industries, which often account for the vast majority of national employment. Such firms can be exposed to trade liberalization directly, via the terms of the agreement, or indirectly via customers, suppliers, and local labor markets. Finally, the usual approach may not be possible for trade liberalizations that focus on non-tariff barriers – for example, national treatment, the establishment of product standards or changes to intellectual property protections – which are not easily convertible into tariff equivalents.

Our approach addresses all of these limitations: using readily available stock price data, it captures the expected *net* impact of all avenues of exposure, it yields estimates for firms in all sectors of the economy with publicly traded firms, and it can be used to study any liberalization, so long as it can be associated with an event. Furthermore, it can provide a direct assessment of how changes in trade policy affect the return to capital, an important but under-studied dimension of the distributional implications of trade.[2]

PNTR, the first target of our method, was a non-traditional trade liberalization in that it substantially reduced *expected*, rather than *applied* US import tariffs on many Chinese goods. Moreover, as the most important component of China's entry into the World Trade Organization, it also eliminated substantial uncertainty about US-China relations.[3] We compute US firms' AARs

[1] See, for example, Bernard et al. (2006), Topalova (2010), Autor et al. (2014), Dix-Carneiro (2014), and Hakobyan and McLaren (2016).

[2] Grossman and Levinsohn (1989) find that firms' stock prices respond positively to import prices. Tello-Trillo (2015) and Keller and Olney (2017) document a link between between globalization and executive compensation.

[3] Handley and Limão (2017) estimate that the reduction in trade policy uncertainty associated with PNTR is

across the five legislative events required for PNTR's 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.

We find that US firms' PNTR AARs, hereafter AAR^{PNTR}, exhibit substantial heterogeneity, even across firms within narrowly defined industries. Among computer manufacturers, for example, Apple and Dell, which made extensive use of Chinese suppliers, have positive AAR^{PNTR}, while those of Gateway, a PC maker whose production was focused in the United States, are negative. AAR^{PNTR} also vary as expected across three, more formal validation exercises. *Contemporaneously*, we show that AAR^{PNTR} are negatively related to the policy's mandated decline in expected tariffs across the business segments in which firms operate. *Ex post*, we find a similarly negative correlation between firms' AAR^{PNTR} and subsequent import growth from China in those segments. Finally, for *external* validation, we demonstrate that AAR^{PNTR} exhibit a negative relationship with comparably constructed abnormal returns in the days following NATO's accidental bombing of the Chinese embassy in Belgrade in 1999. This association is in accord with expectations at the time that the bombing might derail US-China relations.

Consistent with the assumptions underlying our method – that PNTR is an important change in US policy and that, under market efficiency, AAR^{PNTR} are predictive of changes in firm value – we find that AAR^{PNTR} are positively related to subsequent profitability in terms of both survival and operating profit. These relationships are evident among both service firms and goods producers and, lending further support to the idea that exposure to PNTR transcends import competition, they persist after controlling for standard measures of such competition. Further, we find that these relationships are large relative to those estimated using AARs computed on randomly chosen dates in 2000, suggesting PNTR had an outsized impact on firms' cash flows, or represented a more persistent shock than those occurring on other dates.

An important contribution of our method is the ability to evaluate exposure across a wider range of industries, and to measure heterogeneous exposure within those industries. This breadth offers a more complete picture of the distributional implications of PNTR than prior studies in at least two ways. First, we find that while the vast majority of firms have negative predicted relative operating profit after the liberalization, a small group of very large goods and service firms with positive AAR^{PNTR} are predicted to have substantial relative gains, enough to dwarf smaller firms' relative losses. Furthermore, because these large firms are less labor-intensive than the smaller firms with negative AAR^{PNTR}, the cumulative predicted relative change in employment across all firms is negative, forecasting a relative increase in labor productivity. This increase suggests that at least part of the substantial rise in labor productivity in US manufacturing observed during this period (Fort et al. (2018)) may be driven by a reallocation of activity across firms. The relative decline of small firms' operating profit and employment highlights trade as a potential explanation for the

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.

rise of "superstar" firms in Decker et al. (2014) and Autor et al. (2017). Our findings also relate to recent research by Gutierrez and Philippon (2017), who show that industry "leaders" invest more in response to rising import competition from China than their followers.

A second benefit of our approach is its ability to examine exposure among service providers. While the heterogeneity of responses described above holds for manufacturing, predicted relative growth in operating profit is more uniform across firms in other sectors. In Wholesale and Retail, for example, almost all firms are predicted to shrink in relative terms. This outcome is consistent with Wall Street analysts' expectations at the time 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 also resembles the relationship between the increasing "toughness" of competition and declining markups following trade liberalization developed in Melitz and Ottaviano (2008).

In the final section of the paper, we apply our method to the 1989 Canada-United States Free Trade Agreement (CUSFTA). This liberalization is another good candidate for our method as it can be associated with a salient event – the 1988 Canadian federal election – and includes both tariff reductions and a substantial loosening of restrictions on services trade, which can be difficult to capture using standard measures of exposure. As with PNTR, we find that AAR^{CUSFTA} are validated by objective measures of these liberalizations: for US goods producing firms, they rise with Canadian tariff reductions and fall with US tariffs reductions, while for service providers they are substantially higher for firms in industries explicitly covered by national treatment. Here, too, we find that AAR^{CUSFTA} predict future outcomes. In contrast to our findings with PNTR, however, this result is confined to services firms, perhaps because the subsequent implementation of the North American Free Trade Agreement changed outcomes for goods firms in ways that investors during CUSFTA did not anticipate.

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] While this approach is not widely used in international economics, existing research does examine the relationship between stock returns and cross-sectional exposure to trade liberalization. Breinlich (2014) and Thompson (1993) show that abnormal returns associated with CUSFTA are higher for firms and industries which *ex ante* were thought to be positively affected by it, while Moser and Rose (2014) find that firms' returns rise with regional trade agreements the greater the intensity of their pre-existing trade with the proposed partners. More recently, Huang et al. (2018) find a negative relationship between firms' previous sales to China and their abnormal returns following President Trump's March 22, 2018 memorandum signifying a potential "trade war" between the US and China.[5] Bianconi et al. (2018) show that industries with greater reductions in tariff rate uncertainty after PNTR exhibit relatively lower stock returns.

[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] Similarly, in an additional validity test in Section D of the Appendix we find a negative and statistically significant relationship between industry-level AAR_i^{PNTR} and similarly constructed returns in the seven days following the election of President Donald Trump. This association is consistent with Trump's anti-China campaign rhetoric.

While the above studies seek to rationalize equity prices movements during policy events, we propose using such movements *as "all in" measures of policy exposure* in order to predict subsequent firm outcomes. In this respect, our aim is similar to that of researchers outside the event study literature that seek to identify the multiple channels by which firms might be exposed to globalization. A number of papers, for example, examine the impact of trade liberalization on downstream firms' intermediate input costs and productivity (Amiti and Konings (2007); Fernandes (2007); Goldberg et al. (2010); Topalova and Khandelwal (2011)). Others emphasize liberalization's effect on investment, product scope and innovation (Bernard et al. (2006); Bustos (2011); Bloom et al. (2016); Pierce and Schott (2017); Autor et al. (2017); Gutierrez and Phillipon (2017)) or the transmission of labor demand shocks through supply chains and exports (Acemoglu et al. (2016); Feenstra et al. (2017); Feenstra and Sasahara (2017); Wang et al. (2018)). A virtue of our approach is that it identifies the *net* impact of all of these forces without requiring any information about firms' actual supply chains, innovative activity or labor market relationships. Beyond the international trade literature, our approach is most similar to Mobarak and Purbasari (2006) and Kogan et al. (2017), who use equity event studies to identify politically connected firms in Indonesia and the value of new patents among innovating firms, respectively. Fisman and Zitzewitz (2019) use a similar method to assess firms' potential sensitivity to the 2016 Presidential election and the Brexit referendum by constructing long-short portfolios based on firm's stock-price reactions to those event.

The method we propose has two caveats worth noting. First, because it is based on equity market reactions, it can be implemented only for firms whose shares are traded publicly. Second, firm AARs surrounding sweeping changes in policy must be interpreted with care, as they may ignore a portion of the overall systematic impact of the change in policy on the market, e.g., via changes in interest rates or exchange rates. To account for confounding macroeconomic shocks, firm AARs measure event price reactions relative to observed market returns. To the extent that the policy event has a systematic component, that part of its effect on the firm is not captured by AARs. Nevertheless, we demonstrate that our primary results are not sensitive to re-incorporation of plausible aggregate effects of the policy.

The paper proceeds as follows. In Section 2 we outline the theory behind our approach, deferring details to the Appendix. Sections 3, 4 and 5 validate and apply our method to PNTR. Section 6 applies our method to the Canada-US Free Trade Agreement. Section 7 concludes.

2 Theory

In this section we 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. As with all event studies, 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. To keep our discussion concise, we defer a more detailed description of asset pricing theory to Section A of the Appendix.

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. interest rate changes).[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 Section 5.

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, 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.

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

[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.

literature, a statistical 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.

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 $AR_{j,\tau} = AR^*_{j,\tau}$.

Mitigating $\epsilon^X_{j,\tau} \neq 0$: In our estimations below, we follow the event study literature in using short windows around the policy event and in excluding firms experiencing significant confounding events during the event window, to increase the likelihood that $\epsilon^X_{j,\tau} = 0$.

Mitigating $\hat{\beta}_j F^e_\tau \neq 0$: Avoiding the bias induced by the effect of the event on systematic factors is more challenging. While the assumption that $\hat{\beta}_j F^e_\tau$ is close to zero is reasonable for firm-specific

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

events (e.g., a patent grant or an earnings announcement), it is more tenuous for changes in policy 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).[9] This approach might be reasonable if, for example, one is certain that the entire impact of a policy is absorbed by the market in a very short time window – on the order of minutes rather than days – during which it is unlikely any other meaningful macroeconomic shock has taken place. On the other hand, it has the corresponding drawback that it assumes that all information about the event is incorporated within that narrow window. In this spirit, we explore the robustness of our results to narrower event windows in Section 5, where we also re-incorporate plausible values of F^e_τ into our estimates of AR^*.

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.

3.1 Policy Background

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.[10]

[9] Amiti et al. (2020), 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.

[10] 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

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 FDI (Hu, 1999). The AARs computed in the next section are designed to aggregate investors' expectations regarding the impact of all of such channels.

3.2 Computing 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.[11] The substantial gap between cloture and the vote in the Senate is due to that body's August recess.

The salience of these events was noted among Wall Street analysts and in newspaper articles at the time.[12] 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, imposes the market portfolio return $R_{m,t}$ as the only systematic factor in equation (2):

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

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).

[11] The full text of HR 4444 is available at `https://www.congress.gov`.

[12] 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.

We separately estimate this regression for every firm in our sample over all available dates in 1999. 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.[13] 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).[14]

In order to capture any anticipatory movements prior to each event, as well as any lagged response over the subsequent days, we use a five-day window surrounding each of the legislative events mentioned above, for a total of 25 days. 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 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 in our event windows.[15]

Our procedure yields AAR_j^{PNTR} for 5,378 firms that are present during 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. 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 1 reports the distributions of these returns.[16] The market-capitalization weighted average abnormal return across all firms is mean zero by definition. The left skewness in Figure 1, therefore indicates a positive correlation between market capitalization and AAR_j^{PNTR}.

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.[17] 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). Non-goods (or "service") producers are defined as firms whose segments do not include these sectors. In 2000, our sample consists of 2,385 goods producers and 2,993 service firms. As illustrated in Figure 2, we find that the AAR_i^{PNTR} of goods-producing firms is more

[13] 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 H.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.

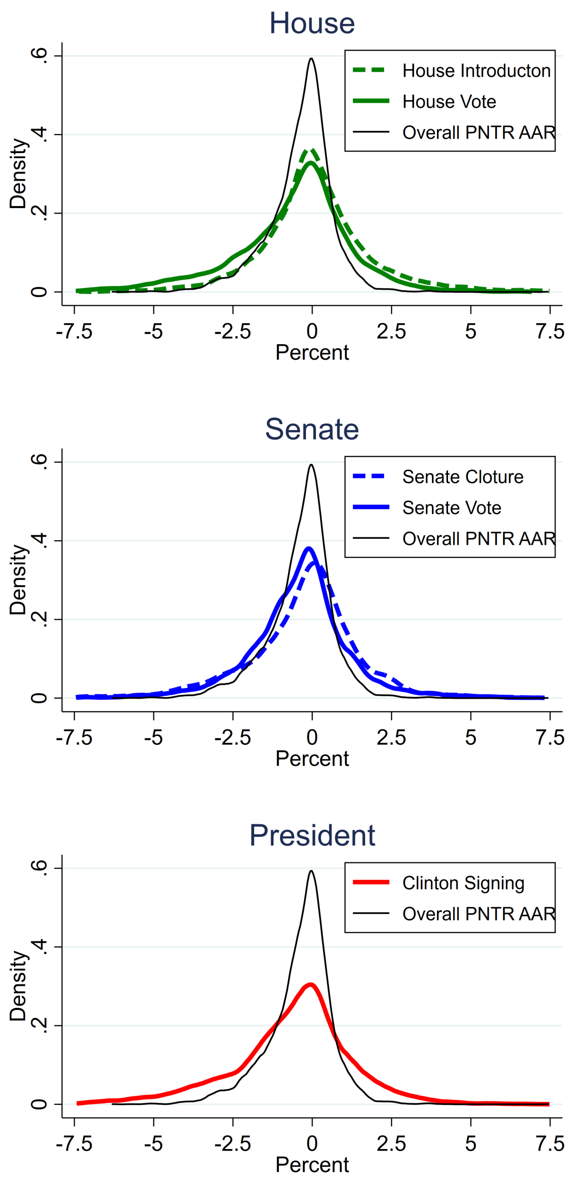
[14] Following convention, $R_{j,t}$ and $R_{m,t}$ are excess returns with respect to the risk-free rate, i.e., the one-month T-bill. Data on the daily market return and the risk-free rate are taken from Kenneth French's website. The market return is the value-weighted return for all firms meeting the criteria noted in the main text.

[15] By averaging across events, we treat each day as an independent draw from the distribution of returns. In Appendix Section H.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.

[16] Appendix Figures A.2 and A.3 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.

[17] 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.

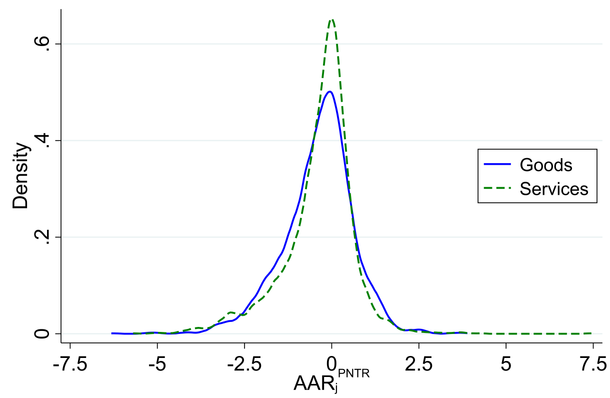
Figure 1: PNTR Average Abnormal Returns, By Event



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.

left-skewed than service firms. This outcome is consistent with the fact that goods-producing firms were directly exposed to increased import competition from China following PNTR, while service firms were not. 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.

Figure 2: 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 and standard deviations for the two groups of firms are -0.38 and 1.00 percent and -0.35 and 1.06 percent respectively.

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.[18] 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 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 by, for example, selling more in foreign markets or offshoring (Melitz, 2003; Breinlich, 2014; Antràs et al., 2017; Bernard et al., 2018).

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

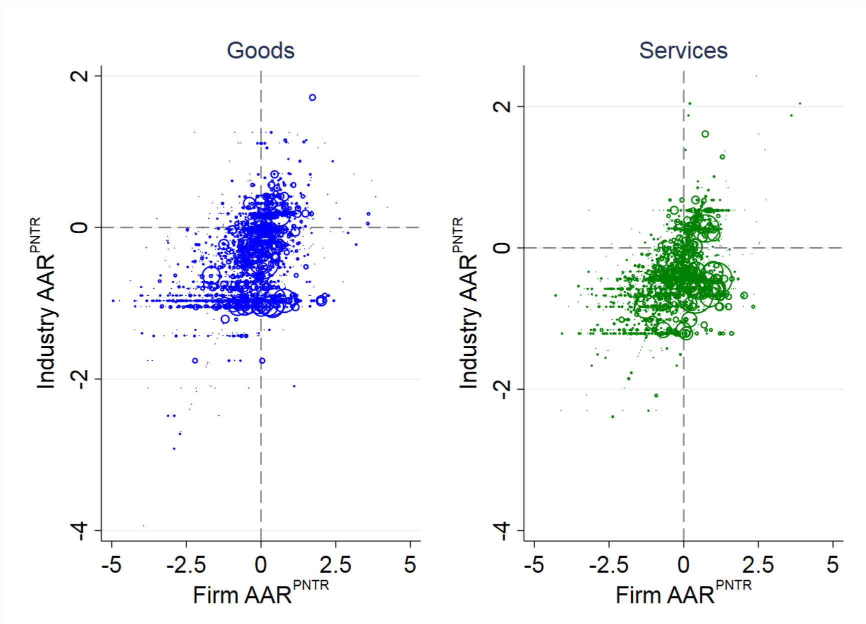
Table 1: $AAR_j^{PNTR} > 0$ Size Premia

	(1) All	(2) Goods	(3) Services
Sales	0.497***	0.758***	0.333***
	(0.134)	(0.230)	(0.127)
COGS	0.371***	0.607***	0.226*
	(0.108)	(0.168)	(0.115)
Operating Profit	0.458***	0.655***	0.346***
	(0.117)	(0.195)	(0.123)
Employment	0.421***	0.599***	0.314***
	(0.102)	(0.185)	(0.098)
PPE	0.513***	0.666***	0.370**
	(0.128)	(0.212)	(0.143)
Intangibles	0.374***	0.509***	0.284***
	(0.092)	(0.137)	(0.102)
Market Capitalization	0.712***	0.877***	0.602***
	(0.145)	(0.199)	(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. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

Finally, we find that firms' AAR_j^{PNTR} vary widely even within 6-digit NAICS industries. Figure 3 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.

Figure 3: 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.

"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 focused on producing computers within the United States, shrank in the early 2000s before closing its US operations in favor of contract manufacturers in Taiwan.[19]

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

3.3 Validity of AAR_j^{PNTR}

To the extent that correlates of the impact of the change in policy are observable, they can be used to validate the abnormal return measures described in the previous section. In this section we establish the *contemporaneous*, *ex post* and *external* validity of our approach by demonstrating that AAR_j^{PNTR} is correlated with objective measures of the change in policy available at the time, subsequent outcomes, and abnormal returns during an unrelated event in US-China relations.

Contemporaneous validity: We establish the contemporaneous validity of our measure, i.e., validity *vis a vis* observed objective attributes of the policy, by examining the relationship between AAR_j^{PNTR} and changes in expected US import tariffs, known in the literature as "NTR gaps". These gaps are defined as the difference between the higher non-NTR rate to which 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).[20] Their mean and standard deviation are 0.29 and 0.15. We summarize their distribution visually in Appendix Figure A.4.

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.[21]

To explore potential supply-chain linkages, we follow Pierce and Schott (2016) in computing firms' up- and downstream NTR gaps, $NTR\,Gap_j^{Up3}$ and $NTR\,Gap_j^{Down3}$. For each industry i, we

[20] 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).

[21] In Table A.1 of Section C 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) est4
NTR Gap_{j}	-0.202***	-0.244***	-0.139***	-0.076**
	(0.054)	(0.057)	(0.046)	(0.032)
NTR $\text{Gap}_{\text{j}}{}^{Up3}$		0.114**	0.075	0.088**
		(0.052)	(0.047)	(0.034)
NTR $\text{Gap}_{\text{j}}{}^{Down3}$		-0.038	-0.028	-0.086***
		(0.040)	(0.042)	(0.029)
MFA Exposure_j^{2006}			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 $\text{Tariffs}_{\text{j}}$			-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 $\text{Leverage}_{\text{j}}$				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. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

compute weighted averages of the NTR gaps across i's up- and downstream industries, using the 1997 US input-output total-use coefficients constructed by the US Bureau of Labor Statistics as weights.[22] For firms with multiple segments, we compute $NTR\,Gap_j^{Up3}$ and $NTR\,Gap_j^{Down3}$ as the sales weighted average of the respective industry-level gaps across segments. To the 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 $NTR\,Gap_j^{Up3}$ to be positive and the one with $NTR\,Gap_j^{Down3}$ to be negative, i.e., 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.

Estimates in column 2 are consistent with these expectations: the association between AAR_j^{PNTR} and own-industry exposure is negative, while the point estimate for $NTR\,Gap_j^{Up3}$ is positive, and both are statistically significant. The point estimate for $NTR\,Gap_j^{Down3}$ has the expected sign but is not statistically significant at conventional levels.[23]

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).[24] 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.

Finally, the fourth column of Table 2 includes a set of firm attributes, based on accounting variables, 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

[22] Given the the high correlation between an industry's own $NTR\,Gap_i$ and those of other industries within the same sector, we omit all industries within industry i's 3-digit NAICS root before computing the weighted averages, yielding $NTRGap_i^{Up3}$ and $NTRGap_j^{Down3}$. The "3" in the superscripts call attention to the omission of these sectors. 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 for correlations with $NTR\,Gap_i^{Up3}$ and $NTR\,Gap_j^{Down3}$ are 0.38 and -0.01.

[23] 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.

[24] 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 B 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.

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.[25] To reduce the influence of outliers, these accounting variables are winsorized at the 1 percent level, i.e., observations below the first percentile and above the ninety-ninth percentile are replaced with the observations 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.

Together, the results in Table 2 suggest that firms' abnormal returns during the key votes associated with PNTR are related to aspects of the upcoming changes in policy known at the time, including but not limited to the NTR gap. As a result, in exploring firm outcomes in Section 4 we use AAR_j^{PNTR} as the sole measure of firms' exposure to the change in policy.

Ex Post validity: Table 3 examines the link between firms' AAR_j^{PNTR} and US import growth from China, an outcome not knowable in 2000, but useful for assessing the validity of AAR_j^{PNTR} *ex post*. For each firm, we calculate weighted average US import growth across observed business segments in 2000. Given that imports are not observed for service firms, 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, 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.

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 an additional covariate. The coefficient for import growth between 2000 and 2006 remains the same in terms of magnitude and significance, while the coefficient for import growth in the prior period is close to zero and statistically insignificant. These results suggest that investors' reactions during passage of PNTR anticipated an increase in import competition from China relative to the 1990s, and that this increase is not the continuation of a prior trend.

Results in column 3 reveal that these relationships are robust to inclusion of firm attributes noted in the previous section. As indicated in the table, coefficient estimates for the changes in Chinese imports retain the same sign and statistical significance pattern as in column 2. The coefficient estimate on post-2000 import growth from China, -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. This corresponds to a loss in market value of about 2.4

[25]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.

percent.[26]

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. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

External validity: As discussed in more detail in Pierce and Schott (2016), several events in US-China relations during the 1990s likely increased uncertainty regarding annual renewal of China's NTR status in the United States. One of the more prominent of these events was the accidental NATO bombing of the Chinese embassy in Belgrade, Yugoslavia on May 7, 1999. 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.[27] We establish the external validity of AAR_j^{PNTR} by examining how it relates to firms' average abnormal returns in the seven trading days after the bombing occurred, $AAR_j^{Belgrade}$.[28] A virtue of this external validity check, relative to the results reported above, is that it can be

[26]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.

[27]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).

[28]We employ an asymmetric, longer event window for the bombing given that it was unanticipated and that information about it unfolded slowly.

performed for both goods-producing and service firms.[29]

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 for all firms, as well as for goods-producing and service firms separately. We find that the relationship between the AARs is *negative* and statistically significant at conventional levels in all three columns, 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. Interestingly, the magnitude and statistical significance of the relationship is larger for service firms.

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

	(1) $\mathrm{AAR_j}^{PNTR}$	(2) $\mathrm{AAR_j}^{PNTR}$	(3) $\mathrm{AAR_j}^{PNTR}$
$\mathrm{AAR_j}^{Belgrade}$	-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. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

4 Using AAR_j^{PNTR} to Predict Firm Outcomes

Standard event studies in the finance literature focus on determining if 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 can be used as an explanatory variable for firm outcomes, including exit, operating profit and employment. We consider each in turn.

[29] Across goods firms, we find the expected *positive* relationship between the $AAR_j^{Belgrade}$ and the $NTR\ Gap_j$ in Section C of the Appendix.

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

4.1 Firm Survival

Exit from our sample signifies de-listing from the firm's stock exchange. We group exits into three categories based on the de-listing codes provided by CRSP: (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		
$\text{AAR}_j{}^{PNTR}$		-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	0.17	0.204	0.041
Δ Prob.	0.028	-0.154	0.054	-0.036
Pseudo R^2	.122	.122	.122	.122
Observations	4377	4377	4377	4377
		Panel B: Goods Only		
$\text{AAR}_j{}^{PNTR}$		-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	0.633	0.148	0.18	0.039
Δ Prob.	-0.01	-0.122	0.152	-0.078
Pseudo R^2	.128	.128	.128	.128
Observations	2266	2266	2266	2266
		Panel C: Service Only		
$\text{AAR}_j{}^{PNTR}$		-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	0.229	0.043
Δ Prob.	0.057	-0.175	0.007	0.034
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. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

We investigate the relationship between PNTR and exit in Table 5, which presents results from

[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.

the estimation of a multinomial logit regression,

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

where $Pr(Y_j = d)$ is the probability that firm j exits between 2000 and 2006 due to de-listing category d.[32]

The fundamental attributes of firms that govern success or failure during trade liberalization may affect firm 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. As a result, the regressions in this and subsequent sections of the paper continue to include as covariates the accounting variables employed in Table 2 above, represented here by $\mathbf{X}_j^{2000}$.[33]

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 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 percentage 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 firms. In terms of marginal effects, for goods producers we find that higher AAR_j^{PNTR} are negatively associated with the likelihood of exit via bankruptcy and contraction, as well as for other causes, though the magnitude of the latter is small. We find a positive association with respect to de-listing as a result of merger, which may indicate the relative attractiveness of firms with a "China strategy." Further research into such an explanation is warranted. Among service firms, we find a positive relationship between AAR_j^{PNTR} and survival, and a negative relationship between AAR_j^{PNTR} and exit via bankruptcy and contraction.

This last result provides additional support for our approach, as it suggests investors anticipated a link between the change in trade policy and firms' future profits. The greater overall importance of AAR_j^{PNTR} in explaining service firm survival may be due to service firms' thinner profit margins.[34]

[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.

[33]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.

[34]This difference is displayed in Appendix Figure A.5, which plots the distribution of both types of firms' prof-

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.

4.2 Relative Growth in Operating Profit, Employment and Capital

In this section we explore the relationship between AAR_j^{PNTR} and measures of profitability among surviving firms using a generalized difference-in-differences specification,

$$\begin{aligned} ln(OperatingProfit_{j,t}) &= \delta Post \times AAR_j^{PNTR} + \gamma Post \times \mathbf{X_j^{1990}} \\ &\quad +\alpha_j + \alpha_t + \epsilon_{j,t}. \end{aligned} \tag{12}$$

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 represents the vector of winsorized initial (here 1990) firm accounting attributes that may influence profitability through channels unrelated to PNTR, as described above.[35] 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

itability, as measured by the log of the firm's operating profit divided by the book value of its assets.

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

Table 6: 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***
	(0.026)	(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
Cluster	NAICS-4	NAICS-4	NAICS-4	NAICS-4	NAICS-4	NAICS-4	NAICS-4	NAICS-4	NAICS-4
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. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

profit are larger for goods firms, while the opposite is true for COGS.[36]

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 – than goods firms – 8.6 log points. We return to the implications of this result in Section 4.3 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 may be an indication of 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) and Bloom et al. (2016).

Our results with respect to capital also relate to recent research showing mixed relationships between trade liberalization and both innovation and investment in physical and intangible capital. Autor et al. (2016), for example, find that increases in Chinese import penetration negatively affect patenting, while Gutierrez and Philippon (2017) find relative increases in intangible investment and innovation among industry leaders in response to PNTR. Using US Census data, Pierce and Schott (2017) find similar results among US manufacturing establishments using US Census data.

Benchmarking results: Given the forward-looking nature of financial markets, abnormal returns might be expected to predict subsequent firm operating profit even on days unrelated to PNTR. As we discuss in detail in Section E of the Appendix, log gross abnormal returns at any time t can be expressed as changes in expectations regarding the entire future stream of firm profits, as well as differences in the sequence of future discount rates. As a result, the estimated magnitude of $\widehat{\delta}$ is a function of three forces: how PNTR affects firms' cash flows and discount rates, the timing of its impact on these cash flows, and PNTR's persistence in terms of the rate at which its impact on firm profits decays over time.

[36] In Appendix Table A.5 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 the Senate vote. Appendix Tables A.6 and A.7 demonstrate that we find similar results when we add $NTRGap_j$, $NTR\,Gap_j^{Up3}$ and $NTR\,Gap_j^{Down3}$ as additional covariates to the baseline specification, suggesting that AAR_j^{PNTR} captures the effects of PNTR through channels beyond direct import competition.

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
Cluster	NAICS-4	NAICS-4	NAICS-4	NAICS-4	NAICS-4	NAICS-4	NAICS-4	NAICS-4	NAICS-4
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. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

For context, we benchmark the predictive power of AAR_j^{PNTR} to analogous estimates, AAR_j^{Random}, derived from randomly chosen non-PNTR dates during our sample period. Specifically, we repeat the following three steps 1000 times: (i) draw five random trading days in 2000; (ii) compute average abnormal returns for the 5-day windows around these dates; and (iii) use these AAR_j^{Random} in our baseline DID specification.[37] This procedure yields a "benchmark" distribution of $\widehat{\delta}^{Random}$ coefficients to which our baseline PNTR estimates, referred to as $\widehat{\delta}^{PNTR}$ for the remainder of this section, can be compared.

The two coefficient distributions are plotted in Figure 4.[38] The highlighted point on each indicates the location of $\widehat{\delta}^{PNTR}$. Two results stand out. First, the mean of the "benchmark" distributions for both operating profit and employment are positive, indicating that higher AARs are, on average, associated with subsequent relative expansion. Second, the equivalent estimates for our baseline results lie in the far right tails of the distributions. As noted above, this outcome suggests that the effects of PNTR are more persistent than the shocks on randomly chosen days, that they are more of a cash-flow shock than a discount-rate shock, or that they are more front-loaded. We leave disentangling the relative contributions of these forces to future research.[39] Of course, it is possible that subsequent shocks magnified the effects of PNTR, such that firms with positive AAR_j^{PNTR} benefited more than anticipated, while firms with negative AAR_j^{PNTR} were hurt more than anticipated. Such an outcome would have the effect of inflating the estimated difference-in-differences coefficients. However, this issue would not be unique to our measure of exposure versus standard approaches; it is a consideration in any study of policy change.

4.3 The Distributional Implications of PNTR

A large body of recent research has focused on the distributional implications of trade liberalization with China across US workers and regions. In this section we use our baseline DID estimates to examine the distributional implications of PNTR across firms. As with all DID exercises, this analysis provides an estimate of the *relative* gains and losses among firms *vis a vis* the market, before versus after PNTR.[40] An important advantage of our use of publicly traded data is the ability to examine distributional implications with respect to operating profit as well as other outcomes, such as employment.

For each firm j, we compute the predicted relative operating profit for 2001 to 2006 using

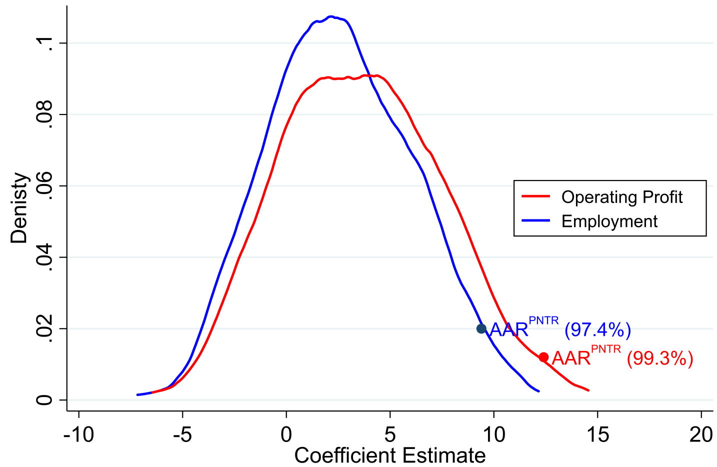
[37]We sample dates so that none of the resulting event windows overlap those used to calculate AAR_j^{PNTR}.

[38]In contrast to our baseline results, we use *non-standardized* covariates to generate the coefficients displayed in Figure 4. As a result, they should be interpreted as the impact of a 1 percent increase in AAR_j^{Random} or AAR_j^{PNTR}. This switch is necessary for an apples-to-apples comparison, 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.

[39]We note that the relationship between stock returns and subsequent firm outcomes, and how such relationships vary across time and market conditions, is largely unexplored. We intend to pursue these topics further in complementary research.

[40]The trends here can be interpreted as level effects only under the very strong assumptions noted in Section 2. Alternatively, level effects can be estimated via other approaches, such as structural general equilibrium modeling (e..g, Dix-Carneiro (2014); Caliendo et al. (2015)).

Figure 4: Benchmark AAR_j^{Random} Estimates vs AAR_j^{PNTR}



Source: CRSP, COMPUSTAT and authors' calculations. Figure presents the distribution of (non-standardized) DID coefficient estimate from equation (12) using AAR_j^{Random} in place of AAR_j^{PNTR}. The colored points indicate the non-standardized version of the coefficient estimates obtained in our baseline results (Tables 6 and 7), and the percentiles at which they would fall in the benchmark coefficient distribution.

the coefficient $\hat{\delta}$ from a DID specification analogous to equation (12), but estimated using non-standardized covariates:

$$\widehat{Op\ Profit_j^{Post\ Period}} = \Big(exp(\hat{\delta} \times AAR_j^{PNTR}) - 1 \Big) \times Op\ Profit_j^{2000} \tag{13}$$

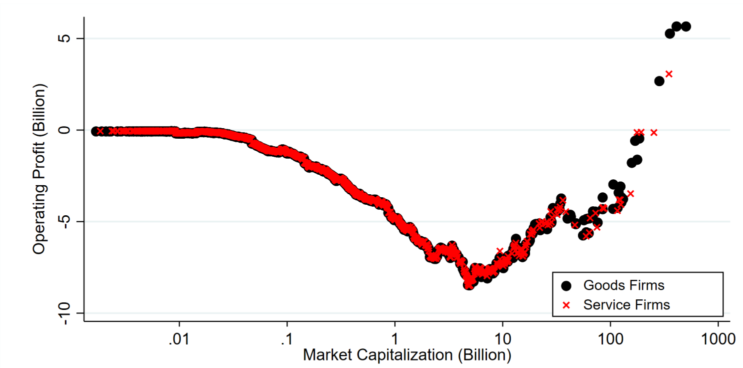
The product of $\hat{\delta}$ and AAR_j^{PNTR} is the predicted growth in operating profit in the post-PNTR period relative to the pre-PNTR period, in log points. It is exponentiated and reduced by 1 to convert it into percentage terms, and then multiplied by operating profit in 2000 to convert it into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

Figure 5 plots the cumulative predicted relative operating profit in the post period, calculated by summing the fitted value from equation (13) along the firm size distribution, against the market capitalization, ordering firms by size. Goods producers are represented by large black dots, while service firms are indicated by the small red x's. Cumulative profit generally declines with firm size until market capitalization reaches approximately 10 billion dollars. Firms larger than that 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 primarily by goods producers: while both goods and service firms populate lower levels of market capitalization, the balance shifts toward goods firms as firm size rises. Above 20 billion dollars, 57 percent of firms are goods producers. Above 50 and 100 billion dollars, their share is two-thirds.[41]

[41] As discussed further in Section F of the Appendix, large firms' size as well as their generally positive AAR_j^{PNTR}

Overall, the differential expected relative growth of large firms suggests a potential role for trade liberalization in the rising share of economic activity attributed to large, old (i.e., "superstar") firms documented in Decker et al. (2014) and Autor et al. (2017).

Figure 5: 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 is from 2000, prior to PNTR.

As we discuss in Section 2, a potential complication of our approach is that large changes in policy 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 (13) reveals that this bias affects firms' predicted relative operating profit through both AAR_j^{PNTR} and, consequently, through the estimated difference-in-differences 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 characterize the qualitative impact such an adjustment would have by considering a range of plausible values for F_τ^e. For each value, we adjust AAR_j^{PNTR}, re-estimate $\hat{\delta}$, and compute predicted relative changes in firms' operating profit given these new estimates. As shown in Figure A.9 of the Appendix, the distributional implications are largely unchanged by these adjustments. Specifically, we show that for values of F_τ^e between -1.5 and 1.5 percent, the finding that relative declines in operating profit among smaller firms are dwarfed by relative increases among the largest firms is unchanged.[42]

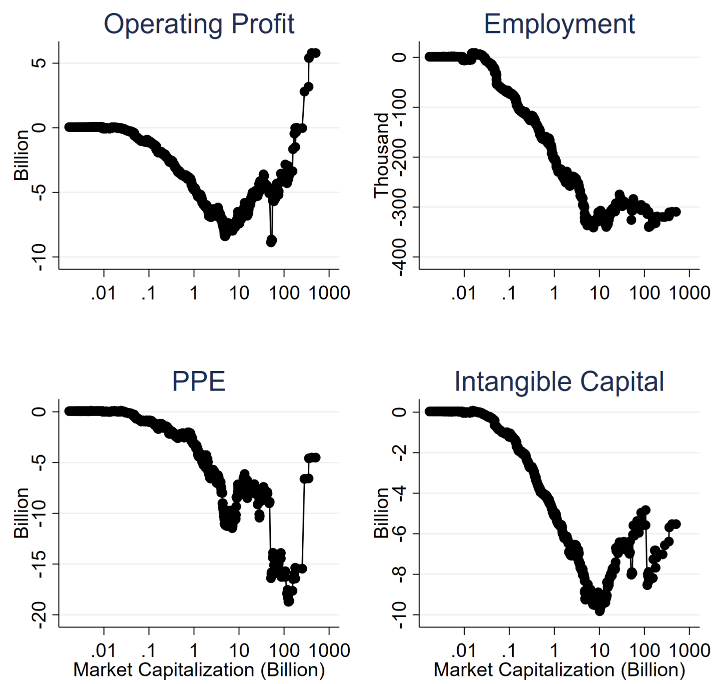
We do not find similarly large increases among the largest firms' predicted relative growth in employment. As illustrated in the top right panel of Figure 6, which combines goods producers and service firms for legibility, relative growth in employment is zero or moderately negative among the largest firms, implying a positive relationship between firm size and predicted relative growth in labor productivity. Physical and intangible capital, displayed in the bottom two panels of Figure 6, by contrast, more closely resemble the distribution of outcomes observed for operating profit, with predicted relative increases in physical capital among large firms being rarer than for operating

contribute to their predicted relative growth *vis a vis* small firms in Figure 5.

[42]For context, we note that the market, i.e., the market capitalization weighted average return during our five event windows is 0.98, -0.6, -0.6, -0.54, and -1.7 percent.

profit, but more common for intangible capital. The latter result is consistent with recent research by Gutierrez and Philippon (2017), who show that industry "leaders" invest more in response to rising import competition from China than their followers.

Figure 6: Cumulative Relative Change in Firm Outcomes



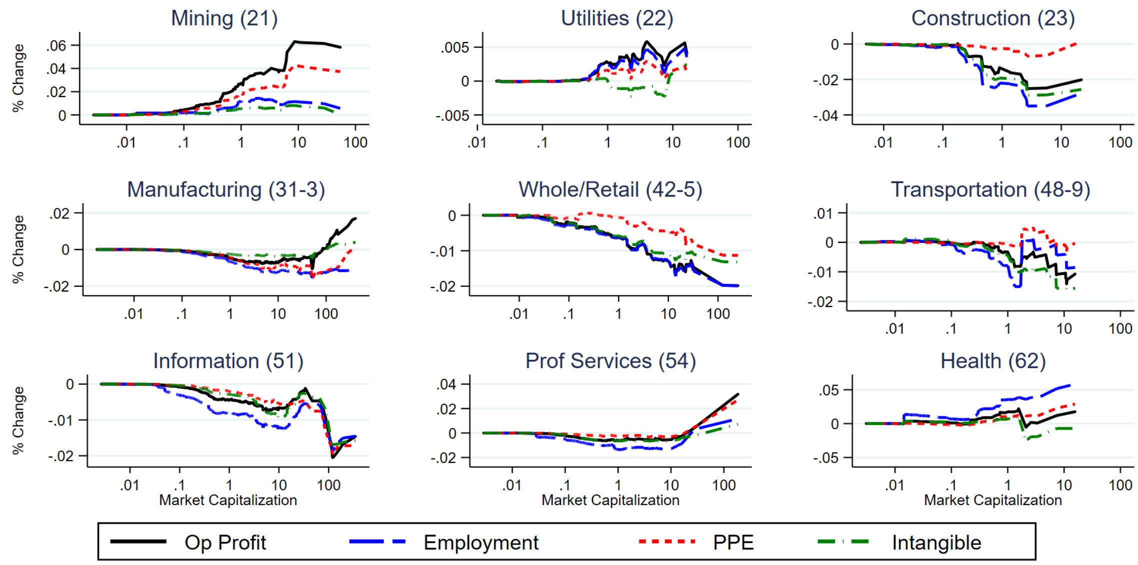
Source: CRSP, COMPUSTAT, and authors' calculations. Figure displays the predicted cumulative relative change in four firm outcomes implied by the baseline difference-in-differences estimates in Table 6. Firms' market capitalization is from 2000, prior to PNTR.

Figure 7 reports the cumulative relative change in each outcome for 2-digit NAICS sectors 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 is consistent 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.[43]

Two other sectors of note in Figure 7 are Professional Services and Information. Professional Services, which includes business services such as accounting and law as well as engineering and research and development, exhibit a large cumulative relative gain. This increase may be driven

[43]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).

Figure 7: 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.

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 AARs 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.[44] 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, this liberalization 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.[45] 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.

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

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

5 PNTR Robustness Exercises

In this section we examine the robustness of the results presented above in several ways. First, we re-estimate our findings using a more flexible difference-in-differences strategy to search for pre-trends. Second, we discuss concerns related to partial anticipation of the event and describe several approaches to mitigating these concerns. Finally, we summarize the results of a number of additional robustness tests described in greater detail in the Appendix.

5.1 Annual Specifications

If changes in firm outcomes are attributable to PNTR, abnormal returns should be correlated with firm outcomes after passage of PNTR but not before. To determine whether such a pattern does exist, we replace the single difference-in-differences term in equation (12) with interactions of AAR_j^{PNTR} and a full set of year dummies. We also include the interaction of firms' initial (1990) attributes, similarly interacted with a full set of year dummies:

$$\begin{aligned} ln(Outcome_{j,t}) \quad &= \quad \sum_{y=1990}^{2006} \delta_y \times 1\{t=y\} \times AAR_j^{PNTR} + \sum_{y=1990}^{2006} 1\{t=y\} \times \mathbf{X_j} \gamma_\mathbf{y} \\ &\quad + \alpha_j + \alpha_t + \epsilon_{j,t}. \end{aligned} \tag{14}$$

In all other respects, the estimation of equation (14) resembles that of equation (12).[46]

Results are reported in Figure 8, where, to conserve space, we focus on four of the outcomes discussed in the previous section – operating profit, employment and physical and intangible capital – and the sample of all firms. Within each panel, a series of 95 percent confidence intervals traces out the sequence of δ_t from 1990 to 2006, with 2000 omitted. As indicated in the figure, we find that estimates are not statistically significant prior to 2000, but positive and generally statistically significant afterwards.

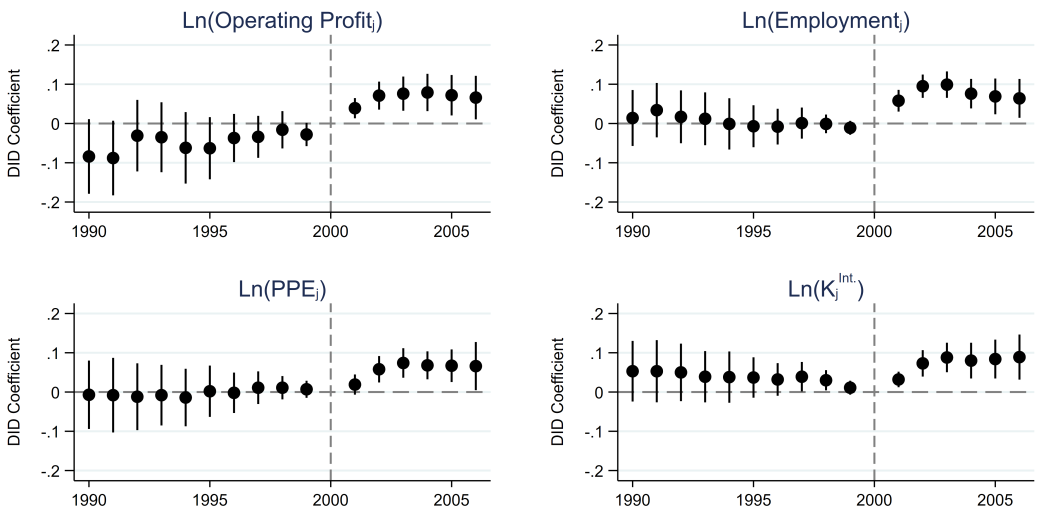
5.2 Controlling for Partial Anticipation of Events

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,

[46] Results are qualitatively similar when including NAICS-2 by year fixed effects or additional controls.

Figure 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 (14). 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.

and $P_{j,\tau-1}^N$ 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 $P_{j,\tau-1}^Y - P_{j,\tau-1}^N$ from observed prices. The observed price immediately prior to the event can be written as

$$P_{j,\tau-1} = \pi_{\tau-1}^Y P_{j,\tau-1}^Y + (1-\pi_{\tau-1}^Y) P_{j,\tau-1}^N, \tag{15}$$

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

$$P_{j,\tau-1}^Y - P_{j,\tau-1} = (1-\pi_{\tau-1}^Y)(P_{j,\tau-1}^Y - P_{j,\tau-1}^N) \tag{16}$$

If the policy is approved at time τ, the realized price immediately after the event $P_{j,\tau}$ equals $P_{j,\tau}^Y$ by definition. Hence, by adding $P_{j,\tau} - P_{j,\tau}^Y$ to the left-hand side, we can rewrite equation (16) as

$$(P_{j,\tau} - P_{j,\tau-1}) - (P_{j,\tau}^Y - P_{j,\tau-1}^Y) = (1-\pi_{\tau-1}^Y)(P_{j,\tau-1}^Y - P_{j,\tau-1}^N). \tag{17}$$

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

$$\frac{P_{j,\tau} - P_{j,\tau-1}}{P_{j,\tau-1}} - \frac{P_{j,\tau}^Y - P_{j,\tau-1}^Y}{P_{j,\tau-1}} = (1-\pi_{\tau-1}^Y)\frac{P_{j,\tau-1}^Y - P_{j,\tau-1}^N}{P_{j,\tau-1}}, \tag{18}$$

$$R_{j,\tau} - E(R_{j,\tau}|X_\tau) = (1-\pi_{\tau-1}^Y) AR_{j,\tau}^* \tag{19}$$

Going from equation (18) to equation (19), 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 (19) 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 (19) 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 (13)) is invariant to a rescaling of AAR^{PNTR}_j. Nevertheless, in Appendix G, 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.

5.3 Additional Robustness Tests

In Section H of the Appendix, we demonstrate that our baseline difference-in-differences estimates are robust to a number of changes in our 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^{PNTR}_j; (5) estimating AAR^{PNTR}_j 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; and (8) using bootstrapping to address sampling error in firms' estimated factor loading in the CAPM, $\hat{\beta}_j$s.

6 CUSFTA

We further assess the usefulness of our method by applying it to a second important liberalization: the 1989 Canada-US Free Trade Agreement (CUSFTA). CUSFTA eliminated most tariffs between the two countries over a ten-year period, and is an attractive target for our method because it was the largest bilateral trade agreement at its time, and because it explicitly targeted service sectors via the application of national treatment, which, unlike tariffs, is difficult to quantify.[47] It is also well studied: Trefler (2004), for example, 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 firms' and industries' *ex ante* characteristics.

We follow Breinlich (2014) in focusing on the November 21, 1988 Canadian federal election as the key event associated with ultimate passage of CUSFTA. This election revolved around the agreement, 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.[48]

We compute US firms' average abnormal CUSFTA returns, AAR_j^{CUSFTA}, around the Canadian election analogously to those calculated for PNTR. In Table 8 we perform a *contemporaneous* validation of these abnormal returns by comparing them to the agreement's terms using the same specification employed in Table 2 for PNTR. First, for each US firm j, we compute the weighted average change in Canadian ($\Delta\tau_j^{Canada}$) and US ($\Delta\tau_j^{US}$) tariffs, using the firms' sales across its goods-producing business segments as weights.[49] This validation exercise omits service firms. As indicated by the coefficient estimates in the first column of the table, we find 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 access, while those in industries in which the US is lowering tariffs are expected to suffer from increased import competition. Firms with substantial exposure to both tariff cuts might face significant, but offsetting, exposures. Indeed, we find that the correlation of the two sets of tariff changes within firms is 0.58. These relationships highlight AARs ability to capture multiple channels of exposure in a *single* measure.

In the second column of Table 8 we regress US service firms' AAR_j^{CUSFTA} on an indicator variable which takes the value of 1 for service industries covered by national treatment.[50] As indicated in the table, we find that AAR_j^{CUSFTA} are on average 0.92 standard deviations greater for firms in covered sectors than those for firms in non-covered sectors.

We estimate the relationships between US firms' outcomes from 1978 to 1993 and their AAR_j^{CUSFTA} using the baseline difference-in-differences specification discussed in Section 3, and outlined in equation (12). Results are reported in Table 9. To conserve space, we report only the difference-in-differences coefficients of interest. In contrast to our results for PNTR, we do not report results

[47] In this case, "national treatment" means that the US and Canada must treat the service firms in each others' countries symmetrically, for instance, with respect to professional licensing standards or access.

[48] We were not able to estimate the ex-ante probability of a Mulroney election using the method mentioned in Section 5.2 because, as detailed in Appendix G, this method uses stock option data, and these data are not available as far back as 1988.

[49] 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.

[50] These industries are listed in Section 14, Annex 1408 of the CUSFTA. Transportation, basic telecommunications, doctors, dentists, lawyers, childcare, and government-provided services were not included.

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

	(1) USA $\text{AAR}_j{}^{CUSFTA}$	(2) USA $\text{AAR}_j{}^{CUSFTA}$
$\Delta\tau_j^{CAN}$	-0.048**	
	(0.021)	
$\Delta\tau_j^{USA}$	0.061**	
	(0.024)	
Affected Service		0.092**
		(0.039)
$\text{Ln(PPE per Worker)}_j$	-0.012	0.039*
	(0.037)	(0.020)
Ln(Mkt Cap)_j	0.024	0.017
	(0.025)	(0.018)
$\frac{CashFlows}{Assets}{}_j$	0.103***	0.084***
	(0.036)	(0.027)
Book Leverage_j	0.044	-0.014
	(0.031)	(0.019)
Tobins Q_j	0.003	-0.021
	(0.034)	(0.018)
Constant	-0.036	-0.036*
	(0.023)	(0.020)
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 year-1978 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 4-digit NAICS industries. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

for intangible capital as those data, from Peters and Taylor (2017), are not available during the CUSFTA sample period.

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

	Ln(Sales)	Ln(COGS)	Ln(Operating Profit)	Ln(Employment)	Ln(PPE)
			All Firms		
AAR_j^{CUSFTA}	0.019	0.011	0.025	0.022	0.012
	(0.019)	(0.019)	(0.016)	(0.016)	(0.017)
R2	.938	.939	.927	.942	.953
Observations	43954	43968	42492	43597	43976
Unique Firms	4143	4145	4066	4143	4153
			Goods Firms		
AAR_j^{CUSFTA}	-0.025	-0.022	-0.003	0.007	-0.009
	(0.022)	(0.021)	(0.019)	(0.021)	(0.021)
R2	.947	.946	.934	.954	.957
Observations	25134	25145	24335	25053	25283
Unique Firms	2255	2255	2208	2265	2267
			Service Firms		
AAR_j^{CUSFTA}	0.077***	0.055*	0.063**	0.036	0.042
	(0.028)	(0.029)	(0.025)	(0.026)	(0.030)
R2	.926	.928	.917	.925	.948
Observations	18820	18823	18157	18544	18693
Unique Firms	1888	1890	1858	1878	1886
FE	j&t	j&t	j&t	j&t	j&t
Cluster	SIC-3	SIC-3	SIC-3	SIC-3	SIC-3
Weights	Equal	Equal	Equal	Equal	Equal
Years	1978-1993	1978-1993	1978-1993	1978-1993	1978-1993

Source: CRSP, COMPUSTAT and authors' calculations. Table presents firm-level OLS DID panel regressions of noted 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 4-digit NAICS industries. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

Two trends stand out. First, as indicated in the first and second panels of the table, we find no relationship between AAR_j^{CUSFTA} and outcomes among goods-producing firms. This unexpected result may be due to CUSFTA's long time horizon, or to subsequent events. As noted in our discussion of the PNTR difference-in-differences regressions and Section E of the Appendix, the difference-in-differences term is a function of the future stream of firm profits and discount rates. 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, 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). Thus, it also is possible that any gains for US goods producers anticipated in 1989 were subsequently offset by NAFTA's provisions.[51] As

[51]NAFTA is another potentially attractive application for our approach. However, the primary source of uncertainty in NAFTA's passage – the November 17, 1993 vote in the House of Representatives – occurred the day after a Federal Open Market Committee (FOMC) meeting. FOMC meetings have been shown to play an outsized role in firm returns

discussed earlier, our approach's susceptibility to such reversals is not unique. In fact, in Table A.11 of the Appendix, we show that neither $\Delta\tau_j^{Canada}$ nor $\Delta\tau_j^{US}$ are predictive of subsequent operating profit. To the best of our knowledge, no other research has documented significant effects of CUSFTA on US manufacturing firms.

In contrast to the results for US goods producers, in the third panel of Table 9 we do find a positive and statistically significant relationship between AAR_j^{CUSFTA} and the subsequent sales, cost of goods sold, and operating profit of US service firms. This relationship is consistent with the agreement's provisions with respect to national treatment of services noted above. It also is in accord with US comparative advantage in services more generally (Fort, 2016; Fort et al., 2018; Ding et al., 2019). Together, the results for goods and service firms suggest that a standard analysis of CUSFTA which focuses on manufacturing and relies on tariffs to assess exposure, offers an incomplete picture of this liberalization.

Finally, we examine the distributional implications of CUSFTA across firms in Figure 9, which plots the cumulative relative change in operating profit and employment across US firms. The patterns are broadly similar to those displayed for PNTR: firms with smaller market capitalization exhibit relative declines in both outcomes, while larger firms exhibit relative increases. The most noticeable difference between Figure 9 and the analogous Figure 6 for PNTR is the substantial increase in relative employment among the largest firms following CUSFTA. As was the case with AAR_j^{PNTR}, firm size is positively correlated with AAR_j^{CUSFTA}. However, the relative employment among the largest firms was substantially higher during the CUSFTA period than during the PNTR period. Thus, employment growth among such firms had a much larger effect on cumulative employment growth.

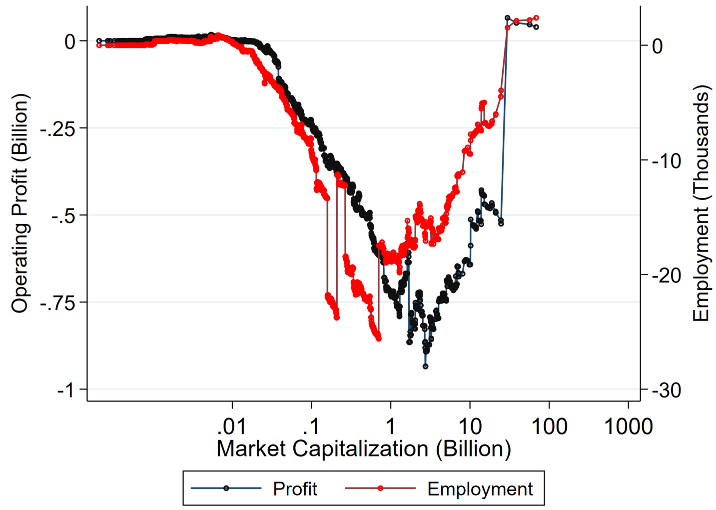
7 Conclusion

We introduce a method for gauging firms' exposure to changes in 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 during 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'

(e.g. Bernanke and Kuttner (2005), Lucca and Moench (2015)), and, as noted in Section 2, the existence of such a confounding event is problematic for our approach. While we currently are unable to separate the information revealed by the House vote from that of the FOMC meeting, we hope to address this issue in future research.

Figure 9: Cumulative Relative Change in Operating Profit and Employment: US Firms



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 is from 2000, prior to PNTR.

average abnormal returns predict future operating profit, accentuating 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)). More broadly, our approach may also prove useful for evaluating firm sensitivity to other policy shocks, such as changes in domestic labor laws, monetary policy surprises, or the introduction of new technologies. Using a wider set of assets, it is also amenable to studies beyond firms, e.g., using municipal bond prices to measure regional exposure to changes in policy. We are currently exploring applications along these lines.

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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 Basic Asset Pricing Framework

A stock is a claim to an infinite stream of uncertain future dividends $\{d_{t+s}\}_{s=1}^{\infty}$. The marginal investor prices this asset by maximizing his/her lifetime utility over the amount ξ of the asset purchased today (time t):

$$\max_{\xi} u(c_t) + \sum_{s=1}^{\infty} E_t[\delta^s u(c_{t+s})] \tag{A.1}$$

subject to the usual budget and market clearing constraints:

$$c_t = f_t - p_t \xi \tag{A.2}$$

$$\sum_{s=1}^{\infty} c_{t+s} = \sum_{s=1}^{\infty} (f_{t+s} + d_{t+s}\xi) \tag{A.3}$$

Here, u is the investor's increasing and concave utility function, δ accounts for investor impatience (intertemporal substitution), $\{c_{t+s}\}_{s=0}^{\infty}$ is the consumption stream after an amount ξ of the stock is purchased and $\{f_{t+s}\}_{s=0}^{\infty}$ is their consumption without the purchase. The investor's first order condition gives the price of the asset at time t (i.e. p_t):

$$p_t u'(c_t) = \sum_{s=1}^{\infty} E_t[\delta^s u'(c_{t+s}) d_{t+s}] \tag{A.4}$$

$$p_t = \sum_{s=1}^{\infty} E_t \left[\delta^s \frac{u'(c_{t+s})}{u'(c_t)} d_{t+s} \right] \tag{A.5}$$

The term multiplying dividends is often referred to as the stochastic discount factor, and is a function of the investor's willingness to substitute consumption across time and across states of nature:

$$m_{t,t+s} = \delta^s \frac{u'(c_{t+s})}{u'(c_t)} \tag{A.6}$$

This yields the familiar formula describing stock prices as the expected discounted value of their future dividends:

$$p_t = \sum_{s=1}^{\infty} E_t \left[m_{t,t+s} d_{t+s} \right] \tag{A.7}$$

Writing this formula for time $t+1$ prices, substituting it back into equation 7 and using the law of iterated expectations, we obtain the two-period pricing formula

$$p_t = E_t\left[m_{t,t+1}(d_{t+1} + p_{t+1})\right] \tag{A.8}$$

Dividing through by p_t we obtain a pricing formula written in terms of returns (which are much more widely used in empirical asset pricing due to their superior statistical properties):

$$1 = E_t[m_{t,t+1}R_{t+1}] \tag{A.9}$$

Note that this formula applies to the returns of any tradeable financial asset, not just stock returns. In particular, writing the same equation for a risk free asset with (certain) return R^f_{t+s} yields $R^f_{t+1} = 1/E_t[m_{t,t+1}]$ (in fact this holds for any time horizon $t+s$).

Returning to equation 7 and expanding the expectation term on the right, we can re-write stock prices in terms of several important primitives:

$$p_t = \sum_{s=1}^{\infty}\left(E_t[m_{t,t+s}]E_t[d_{t+s}] + cov_t[m_{t,t+s}, d_{t+s}]\right) \tag{A.10}$$

$$p_t = \sum_{s=1}^{\infty}\frac{E_t[d_{t+s}]}{E_t[m_{t,t+s}]} + \sum_{s=1}^{\infty} cov_t[m_{t,t+s}, d_{t+s}] \tag{A.11}$$

$$p_t = \sum_{s=1}^{\infty}\frac{E_t[d_{t+s}]}{R^f_{t+s}} - \sum_{s=1}^{\infty} cov_t[-m_{t,t+s}, d_{t+s}] \tag{A.12}$$

In the last equation we use the already established fact that, for any particular horizon, the risk free rate equals the expectation of the stochastic discount factor with the same horizon. This equation shows that stock prices equal the risk-neutral valuation of the firm (i.e. the first term on the right, which discounts expected dividends using risk free rates), minus a penalty for risk (i.e. the second term on the right). Firms with dividend streams that covary negatively with marginal utility (and hence positively with consumption) will have lower prices because they result in a more volatile consumption stream for the investor. We can extend this intuition a bit further by rewriting the covariance terms in equation 12:

$$p_t = \sum_{s=1}^{\infty}\frac{E_t[d_{t+s}]}{R^f_{t+s}} - \sum_{s=1}^{\infty} corr_t[-m_{t,t+s}, d_{t+s}]\sigma_t[m_{t,+s}]\sigma_t[d_{t+s}] \tag{A.13}$$

This equation shows that stock price changes can be caused by changes in any of the following variables: expectations about future dividends ($E_t[d_{t+s}]$), interest rates (R^f_{t+s}), volatility of future dividends ($\sigma_t[d_{t+s}]$), volatility of future marginal utility of consumption ($\sigma_t[m_{t,+s}]$), and the correlation of the firm's dividends with the investor's marginal utility of consumption ($corr_t[m_{t,t+s}, d_{t+s}]$). Also note that the stock price p_t is in fact relative to the price of a unit of the consumption good (normalized to 1 above), so changes in the price level can also cause the nominal stock price to move. In this study, we do not attempt to identify which of these variables contribute significantly to the observed price reaction surrounding our events. We simply point out that a virtue of our method is the fact that stock price reactions capture the various effects that the event may have on the economy.

B 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.

C 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

$$AAR_j^e = \delta NTR\,Gap_j + \epsilon_{ji}. \tag{A.14}$$

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.[52]

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

$$AAR_j^{Belgrade} = \delta NTR\,Gap_j + X_j\gamma + \epsilon_i, \tag{A.15}$$

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 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}.

D 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.[53] As a consequence, his surprise victory offers another

[52] 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.

[53] 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

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[54] following the election, AAR_i^{Trump}, using an OLS specification of the form

$$AAR_i^{Trump} = \delta AAR_i^{PNTR} + \epsilon_i. \tag{A.16}$$

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.[55]

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

E Interpreting DID Point Estimates

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

$$r_t - E_{t-1}[r_t] = (E_t - E_{t-1})[\sum_{s=0}^{\infty} \rho^s (g_{t+s} - f_{t+s})] - (E_t - E_{t-1})[\sum_{s=0}^{\infty} \rho^s r_{t+s}] + k_t \tag{A.17}$$

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.[56] Equation (A.17) 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).

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.

[54]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 (7http://fortune.com/2016/11/09/donald-trump-president-gamble/).

[55]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.

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

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.17) 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.[57] 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 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.

F Distributional Effect Counterfactuals

As noted in Section 4.3 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 5. Two simple counterfactual predictions, plotted in Appendix Figure A.6, 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.

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

This section describes the technique for estimating *ex ante* event probabilities referred to in Section 5.2 of the main text. We follow Langer and Lemoine (2019) who show that the *ex ante* probability of an event, $\pi_{\tau-1}^{Y}$, 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

[57] 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.

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

$$C_{j,\tau-1,T}(P_{j,\tau-1}, K) = \pi^Y_{\tau-1} C_{j,\tau-1,T}(P^Y_{j,\tau-1}, K) + (1 - \pi^Y_{\tau-1}) C_{j,\tau-1,T}(P^N_{j,\tau-1}, K) \tag{A.18}$$

where $\pi^Y_{\tau-1}$, $P^Y_{j,\tau-1}$, and $P^N_{j,\tau-1}$ are defined in Section 5.2.

$\pi^Y_{\tau-1}$ 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.18) is reasonably approximated by

$$C_{j,\tau-1,T}(P_{j,\tau-1}, K) \approx \pi^Y_{\tau-1} C_{j,\tau-1,T}(P^Y_{j,\tau-1}, K), \tag{A.19}$$

which implies

$$\pi^Y_{\tau-1} \approx \frac{C_{j,\tau-1,T}(P_{j,\tau-1}, K)}{C_{j,\tau-1,T}(P^Y_{j,\tau-1}, K)}. \tag{A.20}$$

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.20) as

$$\pi^Y_{\tau-1} \approx \frac{C_{j,\tau-1,T}(P_{j,\tau-1}, K)}{C_{j,\tau,T}(P_{j,\tau}, K)} - E\left[\frac{C_{j,\tau-1,T}(P_{j,\tau-1}, K)}{C_{j,\tau,T}(P_{j,\tau}, K)} | X_\tau\right] \tag{A.21}$$

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:

$$CR_i = \frac{\pi^Y_{\tau_i-2}}{\pi^Y_{\tau_i+2}} \approx \widehat{\frac{C_{j,\tau_i-2,T}(P_{\tau_i-2}, K)}{C_{j,\tau_i+2,T}(P_{\tau_i+2}, K)}} \tag{A.22}$$

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:

$$log\left(\frac{C_{j,t-2,T}(P_{t-2},K)}{C_{j,t+2,T}(P_{t+2},K)}\right) = \alpha_j + \beta_i I_{\tau_i-2,\tau_i+2} + X_{j,t} + \epsilon_{j,t} \tag{A.23}$$

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.23). We use the β_i coefficient from this regression to obtain an estimate of CR_i in equation (A.22):

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

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.23), 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.8. 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.8 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.[58] The second interesting message in Table A.8 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.

H Additional Robustness Exercises

In this section we examine the robustness of the results presented in our study in several ways. First, we explore the robustness of our primary findings to alternative weighting strategies and a more restrictive set of fixed effects. Second, we address issues specific to financial market analysis, including alternative asset pricing models, potentially confounding events, and event window size. Finally, we re-estimate our results using a bootstrap to account for sampling error associated with estimation of firms' $\hat{\beta}_j$s.

H.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.7 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.7. As indicated in the figure, coefficient estimates are generally smaller in magnitude, but remain statistically significant, save for intangible capital among service firms.

[58] 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.

H.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.8 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.10, 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.[59] Exposures to these two new factors, as well as to the market portfolio can be estimated using the following statistical model:

$$(R_{j,t} - R_{ft}) = \alpha_j + \beta_j(R_{mkt,t} - R_{ft}) + \beta_j^{SMB} SMB_t + \beta_j^{HML} HML_t + \epsilon_{j,t}. \tag{A.24}$$

As before, the returns on these portfolios are taken from Kenneth French's website.[60] 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

[59] 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.

[60] To the extent that firm size is related to firms' ability to benefit from globalization, as is assumed in many models of international trade (e.g., 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.

(A.24).[61] As illustrated in the second panel of Figure A.8, 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 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.8. 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. [62]

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.11 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.

H.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

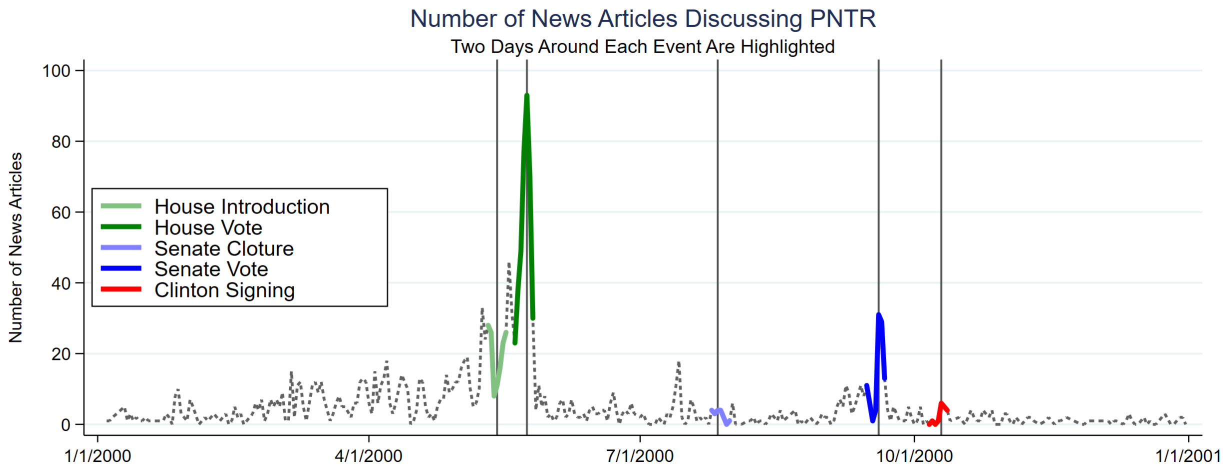
[61] The simple correlation between $\widetilde{AAR}_j^{PNTR}$ and AAR_j^{PNTR} is over 0.96.

[62] 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 $NTRGap_j$.

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 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.

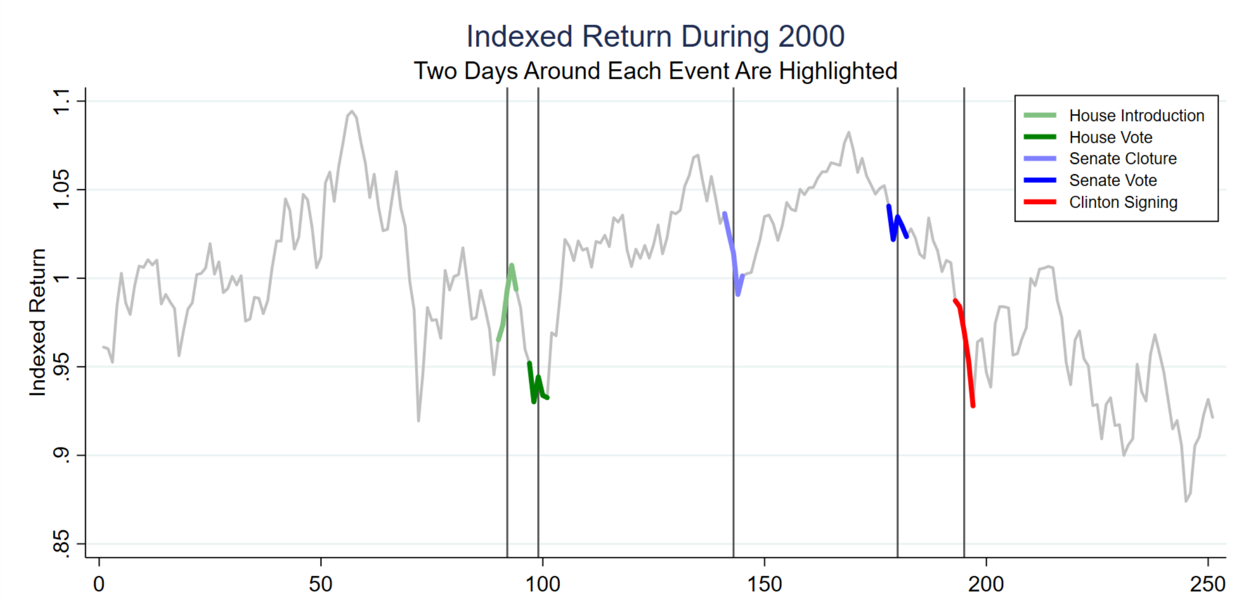
Appendix Tables A.9 and A.10 report a re-estimation of the results in Tables 6 and 7 using this procedure. For each covariate, the first line reports the baseline coefficient, the second line reports the bootstrap standard error, and the third line reports the average bootstrap coefficient, e.g., $\overline{Post * AAR_j^{PNTR}}$ 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.

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



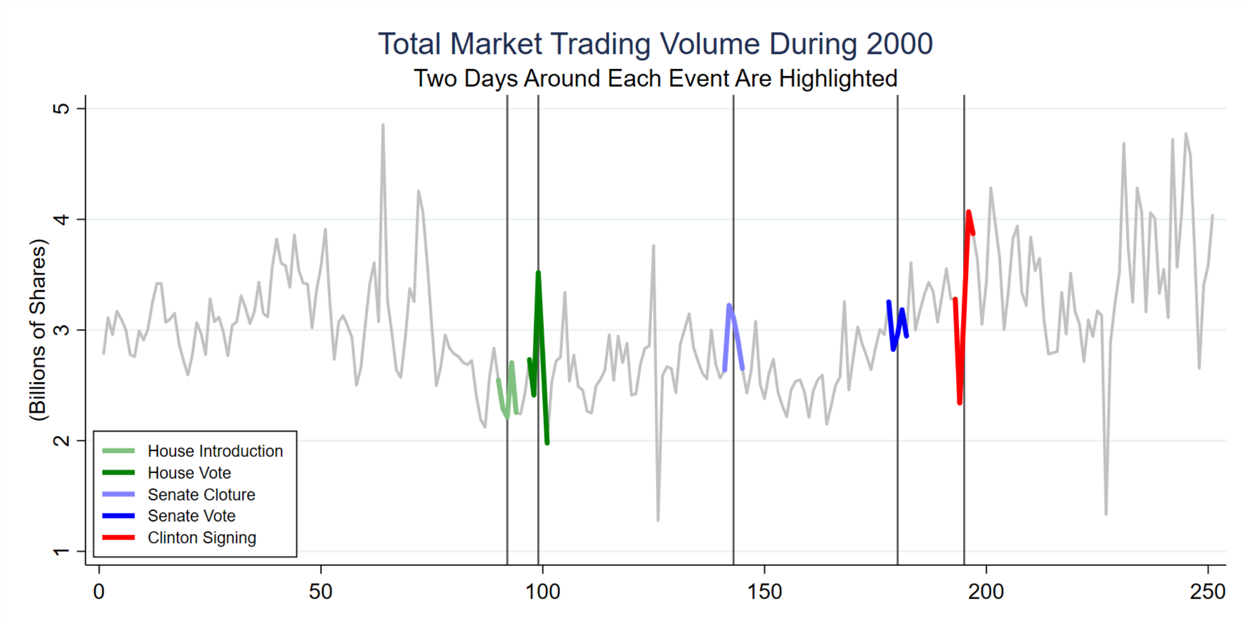
Source: Noted media outlets and authors' calculations. Figure reports the number of unique articles which mention PNTR during calendar year 2000 from the following sources: the Associated Press, BBC Monitoring International Reports, the Boston Globe, the Chicago Tribune, CNN Transcripts, the Financial Times, the Los Angeles Times, the New York Times, the Washington Post, PR Newswire and the 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: Market Return During PNTR Windows



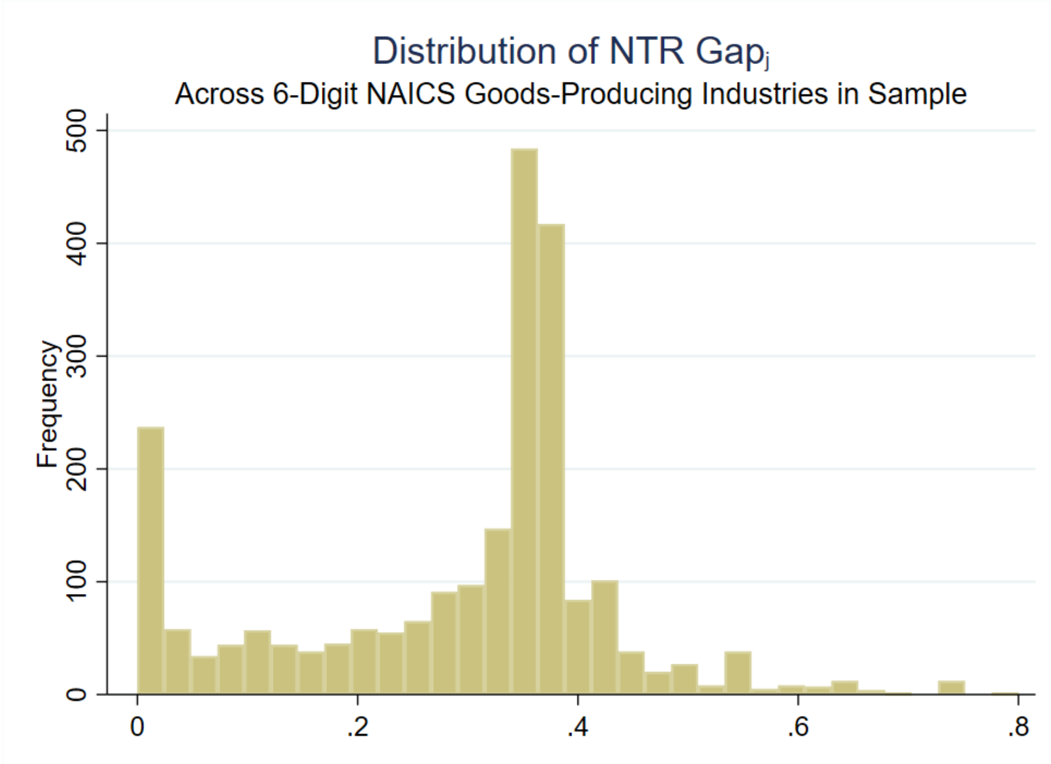
Source: CRSP and authors' calculations. Figure reports the daily market return during 2000. Segments in bold indicate the five legislative event windows considered in our analysis: the introduction of the bill in the House, the House vote, the Senate vote to bring the bill to the floor, the Senate vote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

Figure A.3: Market Volume During PNTR Windows



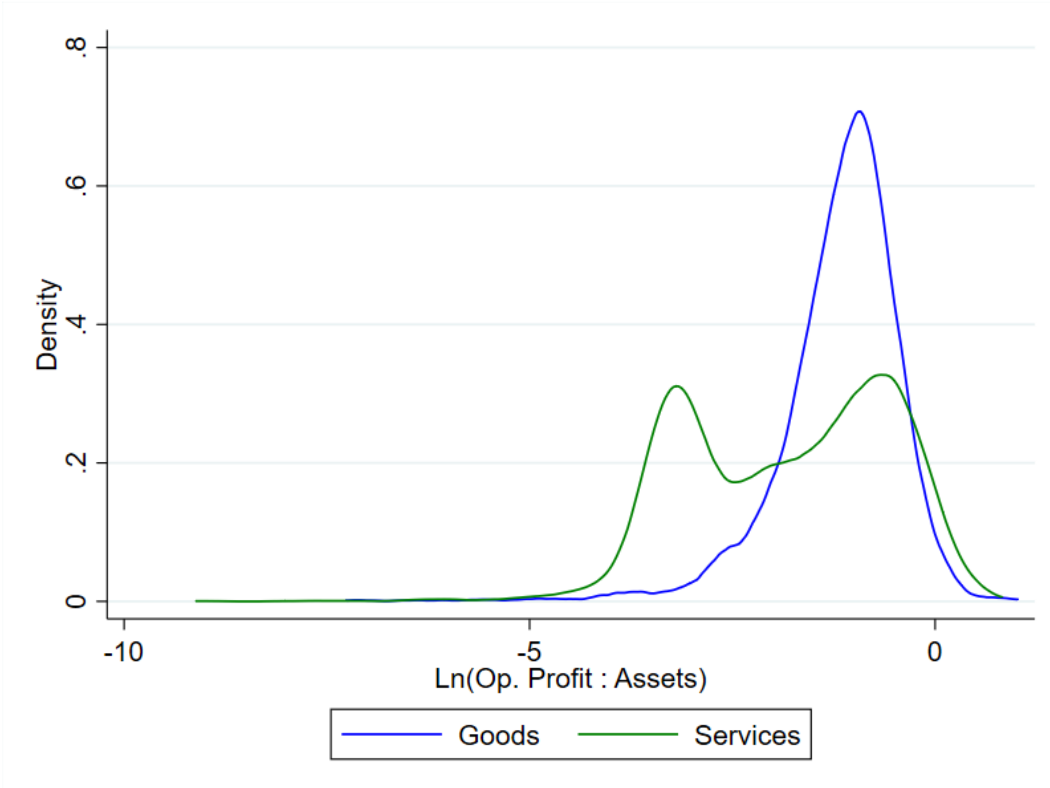
Source: CRSP and authors' calculations. Figure reports the daily market volume during 2000. Segments in bold indicate the five legislative event windows considered in our analysis: the introduction of the bill in the House, the House vote, the Senate vote to bring the bill to the floor, the Senate vote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

Figure A.4: Distribution of the NTR Gap



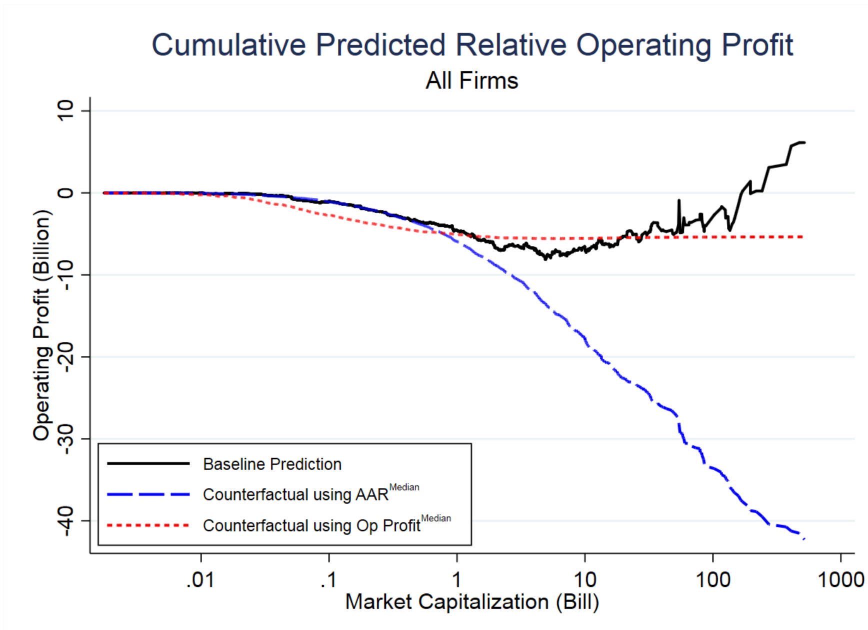
Source: Feenstra et al. (2002) and Pierce and Schott (2016). Figure displays the distribution of $NTR\,Gap_i^{Own}$ across goods-producing 6-digit manufacturing industries populated by firms in our sample. Goods-producing sectors are defined as: Manufacturing (NAICS 31-33), Mining (NAICS 21), and Agriculture,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

Figure A.5: Distribution of $\mathrm{Ln}(\frac{OperatingProfit}{Assets})$ by Firm Type in 2000



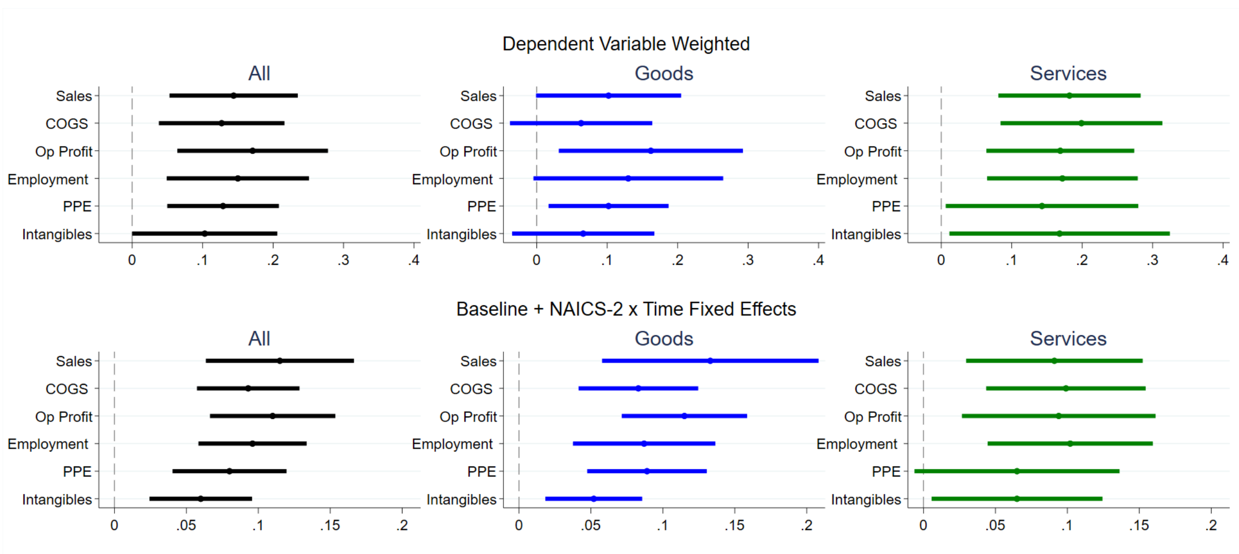
Source: CRSP, COMPUSTAT and authors' calculations. Figure displays the distribution of firm-level $\mathrm{Ln}(\frac{OperatingProfit}{Assets})$ among all goods and service producing firms in our sample in the year 2000. Goods firms have a business segment active in NAICS sectors 11, 21 and 3X. Service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

Figure A.6: Counterfactual Cumulative Relative Change in Operating Profit



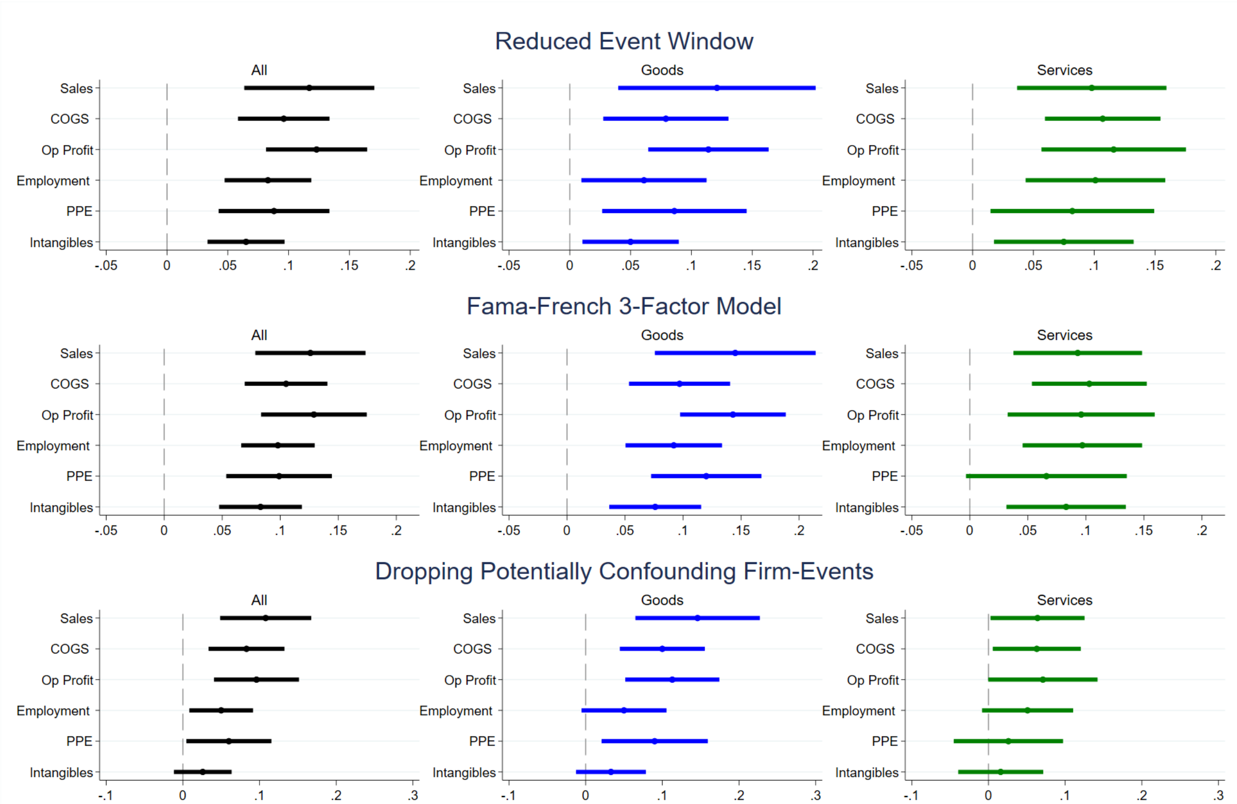
Source: CRSP, COMPUSTAT, and authors' calculations. Figure displays the predicted cumulative relative change in firms' operating profit implied by the baseline difference-in-differences estimates in Table 6 along with two coarse counterfactuals. The first plots the cumulative predicted relative change 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.7: AAR_j^{PNTR} and Firm Outcomes: Robustness Specifications



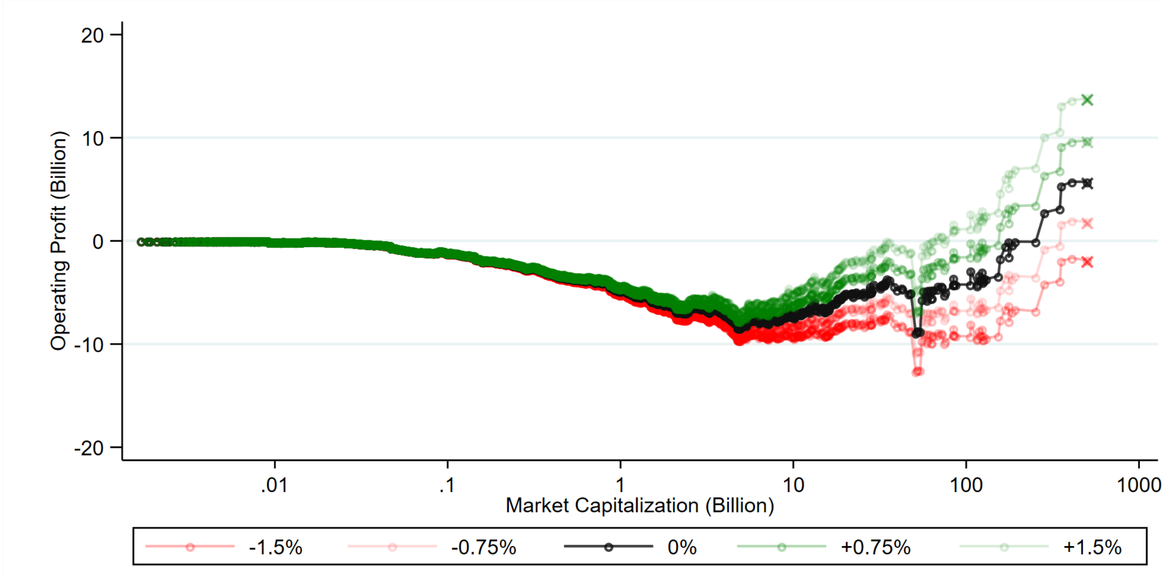
Source: CRSP, COMPUSTAT and authors' calculations. Figure displays a series of 95 percent confidence intervals for the difference-in-difference term of interest from equation (12). Each interval is from a separate regress. Top panel weights observations by firms' initial value of the dependent variable. 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.8: AAR_j^{PNTR} and Firm Outcomes: Finance Robustness Specification



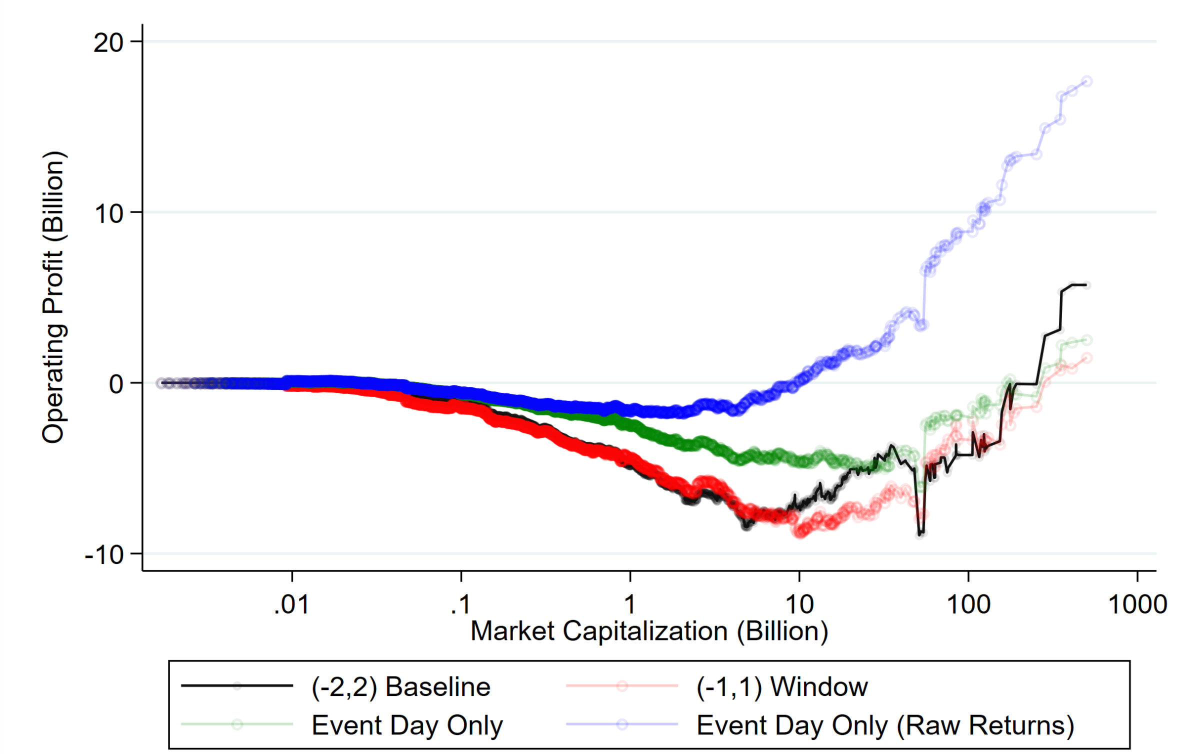
Source: CRSP, COMPUSTAT and authors' calculations. Figure displays a series of 95 percent confidence intervals for the difference-in-difference term of interest from equation (12). Each interval is from a separate regress. Top panel uses narrower event windows, middle panel uses Fama-French 3-Factor 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.9: Cumulative Relative Changes Using Different Aggregate Assumptions



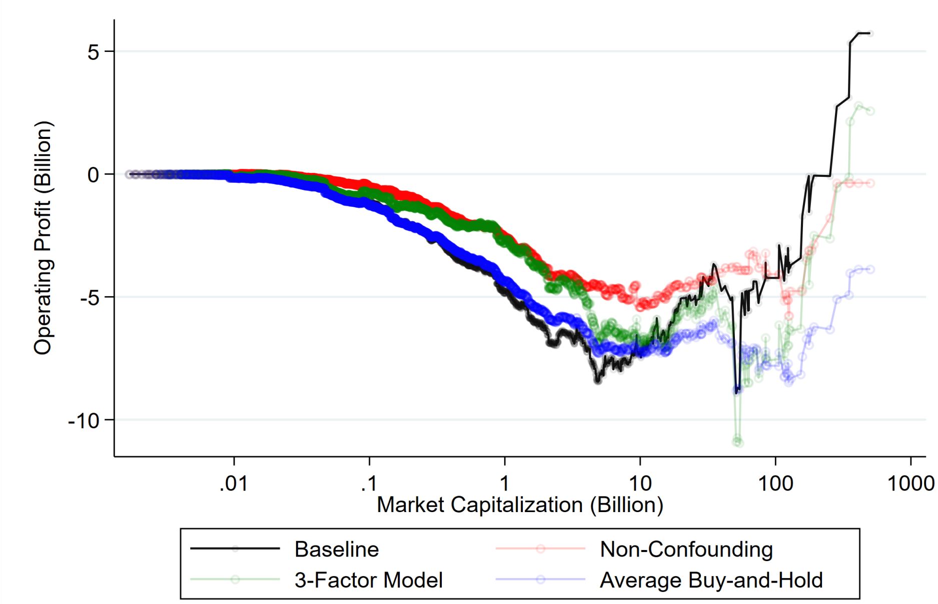
Source: CRSP, COMPUSTAT, and authors' calculations. Figure displays the predicted cumulative relative change in firm operating profit implied by the difference-in-differences estimates performed by adding $\widehat{\beta_j} * F^e_\tau$ to AAR^{PNTR}_j where F^e_τ is the effect of PNTR on returns over 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.

Figure A.10: 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.11: 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.

Table A.1: AAR_j^{PNTR} 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 $NTRGap_j$. 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. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

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

	(1)	(2)	(3)
	$\mathrm{AAR_j}^{Belgrade}$	$\mathrm{AAR_j}^{Belgrade}$	$\mathrm{AAR_j}^{Belgrade}$
NTR $\mathrm{Gap_j}$	0.076**	0.105***	0.073**
	(0.031)	(0.033)	(0.032)
NTR $\mathrm{Gap_j}^{Up3}$		-0.080***	-0.080***
		(0.029)	(0.028)
NTR $\mathrm{Gap_j}^{Down3}$		-0.073**	-0.063**
		(0.033)	(0.031)
Ln(PPE per $\mathrm{Worker})_\mathrm{j}$			-0.019
			(0.035)
Ln(Mkt $\mathrm{Cap})_\mathrm{j}$			-0.123***
			(0.035)
$\frac{CashFlows}{Assets}\mathrm{j}$			0.013
			(0.027)
Book $\mathrm{Leverage_j}$			-0.030
			(0.025)
Tobins $\mathrm{Q_j}$			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 $NTRGap_j$ 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. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

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. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

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 regessions reported in Table 5.

Table A.5: AAR_j^e and Operating Profit

	Ln(Operating Profit)					
	(1) House Intro	(2) House Vote	(3) Senate Cloture	(4) Senate Vote	(5) Clinton	(6) PNTR
	All Firms					
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)
R2	.913	.913	.913	.912	.913	.913
Observations	48486	48463	48465	48311	48259	48551
Unique Firms	4353	4351	4347	4325	4317	4360
	Service Producers					
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)
R2	.919	.919	.919	.919	.92	.92
Observations	26912	26901	26894	26804	26784	26928
Unique Firms	2235	2234	2232	2222	2219	2237
	Service Firms					
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)
R2	.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 G and reported in table A.8. 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. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

Table A.6: Goods Firms: Relative Explanatory Power of AAR_i^{PNTR} and the NTR Gap

	Ln(Sales$_j$)	Ln(COGS$_j$)	Ln(Profit$_j{}^{OP.}$)	Ln(Employment$_j$)	Ln(PPE$_j$)	Ln(K$_j^{Int.}$)
			Panel A			
Post*NTR Gap$_j$	-0.066***	-0.073***	-0.065**	-0.020	-0.075**	0.021
	(0.025)	(0.022)	(0.032)	(0.019)	(0.029)	(0.026)
Post*NTR Gap$_j{}^{Up3}$	0.011	0.020	-0.035	0.004	-0.043	-0.067**
	(0.019)	(0.020)	(0.036)	(0.019)	(0.026)	(0.031)
Post*NTR Gap$_j{}^{Down3}$	-0.087***	-0.059***	-0.143***	-0.063***	-0.068**	-0.052**
	(0.019)	(0.020)	(0.031)	(0.020)	(0.027)	(0.024)
R^2	.927	.930	.92	.942	.949	.943
P-value (Gaps)	0	0	0	.007	.001	.048
			Panel B			
Post*AAR$_j{}^{PNTR}$	0.130***	0.079***	0.112***	0.077***	0.096***	0.053***
	(0.037)	(0.023)	(0.025)	(0.025)	(0.025)	(0.019)
Post*NTR Gap$_j$	-0.045*	-0.060***	-0.051*	-0.008	-0.060**	0.030
	(0.023)	(0.021)	(0.030)	(0.020)	(0.028)	(0.026)
Post*NTR Gap$_j{}^{Up3}$	-0.002	0.012	-0.041	-0.004	-0.053*	-0.072**
	(0.019)	(0.020)	(0.035)	(0.020)	(0.028)	(0.032)
Post*NTR Gap$_j{}^{Down3}$	-0.075***	-0.051**	-0.129***	-0.056***	-0.059**	-0.047*
	(0.019)	(0.020)	(0.031)	(0.020)	(0.028)	(0.025)
R^2	.927	.931	.921	.942	.949	.943
P-value (Gaps)	0	.003	0	.033	.002	.062
Observations	28378	28457	26649	28456	28637	27995
Unique Firms	2313	2314	2212	2320	2320	2290

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. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

Table A.7: Service Firms: Relative Explanatory Power of AAR_i^{PNTR} and the NTR Gap

	$\text{Ln(Sales}_\text{j})$	$\text{Ln(COGS}_\text{j})$	$\text{Ln(Profit}_\text{j}{}^{OP.})$	$\text{Ln(Employment}_j)$	$\text{Ln(PPE}_j)$	$\text{Ln(K}_j^{Int.})$
			Panel A			
Post*NTR $\text{Gap}_\text{j}{}^{Up3}$	0.052	0.036	0.026	0.006	0.055	0.110
	(0.044)	(0.038)	(0.062)	(0.042)	(0.059)	(0.076)
Post*NTR $\text{Gap}_\text{j}{}^{Down3}$	-0.081***	-0.071***	-0.084***	-0.050**	-0.028	-0.012
	(0.020)	(0.023)	(0.027)	(0.020)	(0.023)	(0.024)
R^2	.922	.923	.908	.927	.940	.89
P-value (Gaps)	0	.008	.001	.018	.461	.35
			Panel B			
Post*$\text{AAR}_\text{j}{}^{PNTR}$	0.083***	0.092***	0.082**	0.092***	0.058	0.064**
	(0.031)	(0.029)	(0.035)	(0.030)	(0.036)	(0.031)
Post*NTR $\text{Gap}_\text{j}{}^{Up3}$	0.061	0.046	0.033	0.015	0.061	0.114
	(0.045)	(0.038)	(0.065)	(0.045)	(0.061)	(0.078)
Post*NTR $\text{Gap}_\text{j}{}^{Down3}$	-0.072***	-0.061***	-0.075***	-0.040*	-0.022	-0.005
	(0.021)	(0.023)	(0.029)	(0.021)	(0.023)	(0.024)
R^2	.922	.924	.908	.928	.940	.89
P-value (Gaps)	.003	.032	.009	.125	.560	.309
Observations	21903	21903	21132	21697	21738	19797
Unique Firms	2128	2128	2076	2127	2127	2041

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. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

Table A.8: Ex-ante Event Probabilities

	(1) HouseIntro	(2) HouseVote	(3) SenateCloture	(4) SenateVote	(5) Clinton
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. Standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

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 H.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. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

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 H.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. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

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

	Ln(Sales)	Ln(COGS)	Ln(Operating Profit)	Ln(Employment)	Ln(PPE)
			Panel A		
$\Delta\tau_{88,94}^{USA}$	0.007	0.024	-0.009	0.024	0.039*
	(0.017)	(0.017)	(0.017)	(0.018)	(0.021)
$\Delta\tau_{88,94}^{Can}$	-0.014	-0.010	-0.019	-0.041	-0.033
	(0.023)	(0.023)	(0.023)	(0.025)	(0.024)
R2	.949	.950	.936	.951	.961
Observations	21764	21775	21180	21682	21843
Unique Firms	1955	1955	1915	1958	1959
			Panel B		
$\Delta\tau_{88,94}^{USA}$	-0.001	0.018	-0.021	-0.000	0.020
	(0.013)	(0.014)	(0.014)	(0.014)	(0.017)
R2	.949	.950	.936	.951	.961
Observations	21764	21775	21180	21682	21843
Unique Firms	1955	1955	1915	1958	1959
			Panel C		
$\Delta\tau_{88,94}^{Can}$	-0.010	0.003	-0.024	-0.027	-0.011
	(0.018)	(0.018)	(0.019)	(0.019)	(0.020)
R2	.949	.950	.936	.951	.961
Observations	21764	21775	21180	21682	21843
Unique Firms	1955	1955	1915	1958	1959
Cluster	SIC-3	SIC-3	SIC-3	SIC-3	SIC-3
Years	1978-1993	1978-1993	1978-1993	1978-1993	1978-1993

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.