Using Equity Market Reactions to Infer Exposure to Trade Liberalization

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Abstract

We develop a method for identifying firm exposure to changes in policy using abnormal equity returns, and employ it to study US trade liberalization with China. Abnormal returns surrounding the liberalization's passage into law vary substantially even within industries, are correlated with but have explanatory power beyond traditional measures of import competition, and predict sharper relative changes in operating profit, employment and capital than abnormal returns during randomly chosen days. Predicted relative increases in operating profit among the very largest firms swamp the losses of smaller firms, providing further insight into this liberalization's distributional implications.

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1 Introduction

We propose a 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, e.g., 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 crowds" to obtain traders' assessment of the policy change's impact on firm value.

We demonstrate the usefulness of our approach by estimating US firms' exposure to a well-studied event in the trade literature, 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)). 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 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, the establishment of product standards or changes to intellectual property protections – that are not easily convertible into tariff equivalents.

Our approach addresses all of these limitations: it captures the expected *net* impact of all avenues of exposure, it yields estimates for firms in all sectors of the economy, and it can be used to study any liberalization. Furthermore, it relies upon stock price data that are readily available for a large number of countries, and can provide a direct assessment of how changes in trade policy affect the return to capital, an important but understudied dimension of the distributional implications of trade. [2]

PNTR was a non-traditional trade liberalization in that it substantially reduced *expected*, rather than applied US import tariffs on many Chinese goods, as well as uncertainty about US-China relations.[3] We compute US firms' AARs across five events critical to PNTR's

[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 positive shocks to import prices lead to increases in the return to capital, as measured by abnormally high stock returns. More recently, Tello-Trillo (2015) and Keller and Olney (2017) examine the relationship between globalization and executive compensation.

[3]Handley and Limão (2017) estimate that the reduction in trade policy uncertainty associated with PNTR is equivalent to a reduction in tariff rates of approximately 13 percent. Pierce and Schott (2016) show that

passage: the introduction of the bill in the US House of Representatives, the House vote, the Senate vote to invoke cloture to proceed to a vote, the Senate vote, and Clinton's signing of PNTR into law.

We find that US firms' PNTR AARs, hereafter AAR^{PNTR}, exhibit substantial heterogeneity, even across firms within narrolwly 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 more formal validation exercises. Within manufacturing, AAR^{PNTR} are negatively correlated with subsequent import growth from China in the business sectors in which firms operate, as well as the decline in those sectors' expected tariffs. In terms of external validation, AAR^{PNTR} exhibit a negative relationship with similarly constructed abnormal returns in the days following NATO's accidental bombing of the Chinese embassy in Belgrade in 1999. This reaction is in accord with expectations at the time that the bombing might derail US-China relations.[4]

We find that AAR^{PNTR} are positively correlated with firm survival after PNTR, and that they exhibit a positive relationship with firms' post-PNTR operating profit in generalized difference-in-differences (DID) regressions. This predictive power is consistent with the assumptions underlying our method, i.e., that PNTR is an important change in US policy and that market efficiency has AAR^{PNTR} encapsulating the effect of PNTR on firm value. This relationship is evident among both service firms and goods producers and, lending further support to idea that exposure transcends import competition, we demonstrate that it persists even after controlling for standard measures of such competition. Moreover, we find that the magnitudes of these relationships are large relative to those found in a placebo exercise using AARs computed during randomly chosen dates unrelated to PNTR. This placebo exercise mitigates concerns that our results are driven by the general forward-looking nature of financial market reactions.

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 manufacturing firms with positive AAR^{PNTR} are predicted to have substantial

US manufacturing industries and establishments facing greater reductions in expected tariffs exhibit relative declines in manufacturing employment, while Autor et al. (2013, 2014) find that regions more exposed to Chinese import competition during this period experience relative declines in employment and earnings.

[4]At the industry level, we find a negative and statistically significant relationship between the average AAR^{PNTR} across firms and the average of similarly constructed AARs in the seven days following the election of President Donald Trump. That is, industries whose profits were expected to rise with PNTR are those whose profits were expected to fall with the election of Trump, consistent with the anti-globalization rhetoric of his campaign.

relative gains, enough to offset the smaller firms' losses. Furthermore, because the predicted worldwide employment of these large firms does not grow in tandem with their operating profit, the cumulative predicted relative change in employment across all firms is negative, forecasting a relative increase in labor productivity. This trend indicates that at least part of the substantial rise in US manufacturing labor productivity 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 also highlights trade as a potential explanation for the rising share of economic activity attributed to "superstar" firms in Decker et al. (2014) and Autor et al. (2017). Finally, our findings 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 insight offered by our approach relates to our ability to examine exposure among service providers. While the pattern of results just described holds well for manufacturing, predicted relative growth in operating profit is more uniform across firms in other sectors. In mining, for example, almost all firms are predicted to experience relative growth after PNTR, while those in wholesale and retail are almost uniformly expected to relatively shrink. The latter is consistent with Wall Street analysts' expectations at the time (e.g., Kurtz and Morris (2000)) that greater availability of Chinese goods would lead to an increase in competition among retailers, and thereby an erosion of markups. It also resembles the relationship between the increasing "toughness" of competition and declining markups following trade liberalization developed in Melitz and Ottaviano (2008).

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.[5] 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. Thompson (1993) and Breinlich (2011) show that abnormal returns associated with the Canada-US Free Trade Agreement (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. Bianconi et al. (2018) show that industries with greater reductions in tariff rate uncertainty after PNTR exhibit relatively lower stock returns.

In contrast to this research, we use average abnormal stock returns *as* a measure of exposure to trade liberalization, and show that this measure can be used to predict sub-

[5] 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).

sequent changes in firm-level outcomes. In this respect, our aim is similar to that of prior researchers seeking 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.[6]

While useful, the method we propose has at least two limitations. First, because it is based on equity market reactions, it can be implemented only on firms whose shares are traded publicly. Second, AARs capture the impact of PNTR on firms relative to the market. Thus, as with difference-in-difference based approaches more generally, it only discerns relative exposure.

The paper proceeds as follows. In Section 2 we discuss the details of the event study and apply it to PNTR in Section 3. Section 4 relates our estimates to existing measures of Chinese import competition as well as the equity market response to the NATO bombing of the Chinese embassy in Belgrade. Section 5 examines the relationship between firms' average annual returns and firm outcomes, and compares the relative explanatory power of our proposed measure and the standard measure of import competition used to evaluate PNTR. Section 6 executes a placebo exercise and explores the robustness of our findings to alternative samples and specifications. Section 7 examines the distribution of outcomes across goods-producing and service firms. Section 8 concludes.

2 Estimating Abnormal Average Returns (AARs)

Assuming markets are efficient, a firm's stock price reflects all available information about its future profits. Thus, news that shifts expectations about profit streams causes a re-valuation of the firm, with positive news raising value and negative news lowering it.[7] We propose estimating firms' exposure to changes in policy in terms of their "abnormal" returns during

[6] Beyond the international trade literature, our approach is most similar to 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.

[7] As the stock price is the net present value of the cash flows of the firm, changes in prices (i.e. stock returns) may reflect either changes in the expected cash flows or the rate at which they are discounted. We emphasize the former in our discussion and application.

key events associated with the policy, such as legislative votes that codify the change into law.[8] A firm's return is simply the percent change in its market value from time $t-1$ to t. Abnormal returns are defined as the difference between the actual return of the firm during an event and an estimate of the "normal" return that would have prevailed absent any change in policy.[9]

The first step in estimating firms' AARs is identifying the key event or events to consider, and choosing the length of the windows around these events to measure returns. Windows that are too wide risk incorporating price changes driven by confounding events, while intervals that are too narrow can miss information that takes time to appear. The second step is to choose an asset pricing model that can be used to determine expected returns. By far the most common model used for this purpose is the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964), which relates firm j's expected return between trading days $t-1$ and t (R_{jt}) to the risk-free return (R_{ft}) across that interval and the firm's exposure to systematic risk. This model predicts that the market portfolio captures all sources of systematic risk. Hence, a firm's exposure to systematic risk (β_j) can be estimated via a regression of firm-level excess daily returns ($R_{jt}-R_{ft}$) on market excess returns ($R_{mt}-R_{ft}$),

$$R_{jt} - R_{ft} = \beta_j (R_{mt} - R_{ft}) + \epsilon_{jt}. \tag{1}$$

Equation 1 implicitly imposes an intercept of zero for all firms, i.e., $\alpha_j = 0$. Were this not the case, firms' expected returns would include a persistent component unrelated to market risk, in violation of market efficiency. That is, if markets are efficient, any such persistent firm-specific return is arbitraged away.

The daily average abnormal return for firm j over event e, AAR_j^e, with window length w centered on event day t_e, is calculated as the average of the daily abnormal returns over this period,

$$AAR_j^e = \frac{\sum_{t=t_e-w}^{t_e+w} (R_{jt} - R_{ft}) - \hat{\beta}_j (R_{mt} - R_{ft})}{w+1}. \tag{2}$$

If the number of events associated with this change in policy is n_e, then

$$AAR_j^{Policy} = \frac{\sum_{e \in E} \left(\sum_{t=t_e-2}^{t_e+2} (R_{jt} - R_{ft}) - \hat{\beta}_j (R_{mt} - R_{ft}) \right)}{n_e (w+1)}. \tag{3}$$

[8] Alternate applications might include gauging firms' sensitivity to monetary policy shocks, or changes in labor laws.

[9] For example, the Federal Open Market Committee (FOMC) released a statement regarding US monetary policy on May 16, 2000, one day after the May 15, 2000 introduction of the PNTR bill into the House of Representatives. Announcements by the FOMC are estimated to explain a substantial fraction of the movement of US equity markets (see e.g. Bernanke and Kuttner (2005) and Lucca and Moench (2015)). The abnormal returns we construct here capture firm deviations from these market movements.

Insofar as market returns incorporate some element of exposure to the change in policy, a given firm's AAR_j^{Policy} captures that firm's deviation from the market component. Thus, relating AAR_j^{Policy} to firm outcomes provides an estimate of the relative effects of exposure to the change in policy, compared to the market. Here, we prefer AAR to the more commonly used CAR (cumulative abnormal returns) in the finance literature because it maximizes the number of firms for which we can measure exposure across events. That is, if firm returns are missing for one or more days during an event, AAR can still be computed over the remaining days, while a comparable CAR cannot. We return to this point in Section 6.3.

The same fundamental attributes of the firm that help determine changes in its profitability in response to the change in policy may also influence firm profitability through other, unrelated channels. In that case, AAR_j^{Policy} will be correlated with these attributes, and regressions using AAR_j^{Policy} to predict subsequent firm outcomes will be biased unless these attributes are also included in the specification. In the next section, we show that AAR_j^{PNTR} is related to a series of firm observables, including firm size, which can be interpreted as proxies for the fundamental drivers of firm profitability. In Sections 5 and 6, we include these attributes as additional covariates in our difference-in-difference regressions.

3 Application: US Firms' Exposure to PNTR

In this section we apply the method outlined above to measure US firms' exposure to a specific change in US trade policy, the 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' incentives to invest in closer economic relations with China, and *vice versa.* Writing in 1999, a researcher from Goldman Sachs noted that

> "[T]he annual debate has been a highly politicized process, posing a substantial threat to Chinese exporters and US importers. Furthermore, as a non-WTO member, China is also vulnerable to a variety of unilateral trade sanctions, without the protection of a multilateral arbitration process. The United States and other countries may launch anti-dumping charges against China, treating it arbitrarily as a non-market economy."[10]

The uncertainty associated with China's renewable NTR status 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.

The US granting of PNTR to China was accompanied by several other substantial changes in policy in both the United States and China. First, as part of its accession, China agreed to reduce import tariffs and to eliminate export licensing, production subsidies, and barriers to foreign investment. Second, upon entry into the WTO, China immediately became eligible for the elimination of textile and clothing quotas. These reductions, agreed to during the 1994 Uruguay Round, took place in four phases, on January 1 of 1994, 1998, 2002 and 2005. When China joined the WTO, its quotas on phase 1 and phase 2 goods were relaxed. Its quotas on the remaining textile and clothing goods were then eliminated on schedule, in 2002 and 2005.

Investment banking reports at the time of PNTR's passage expected that China's entry into the WTO would benefit US firms in a variety of industries. Goldman Sachs (Hu (1999)), for example, 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. We assume that firms' AARs during the key legislative milestones associated with passage of PNTR incorporate the potential impact of all of these channels.

3.2 Computing AAR^{PNTR}

We assume that the key events during which the decline in expected tariffs associated with PNTR were incorporated into firms' stock prices are the five legislative hurdles required for its passage: (1) the May 15, 2000 introduction of the bill in the US House of Representatives; (2) the May 24, 2000 vote to approve China's PNTR status by the US House of Representatives; (3) the successful July 27, 2000 cloture motion to proceed with a vote on PNTR in the US

[10]The quote is from Hu (1999). Producers made a similar argument to Congress. As noted in Pierce and Schott (2016), a representative from Mattel testifying before the House Ways and Means Committee asserted that "[w]hile the risk that the United States would withdraw NTR status from China may be small, if it did occur the consequences would be catastrophic for US toy companies given the 70 percent non-MFN US rate of duty applicable to toys" (St. Maxens 2000, p. 185).

Senate; (4) the September 19, 2000 vote to approve China's PNTR status by the Senate; and (5) the October 10, 2000 signature of PNTR into law by President Clinton.[11] Figure 1, which plots the number of articles appearing in major news outlets containing the phrases "Permanent Normal Trade Relations," "China" and "United States" during calendar year 2000, indicates that these days are associated with major peaks in press coverage.[12]

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 surrounding each event, i.e., $w = 2$. Following the literature, we use the CAPM to compute expected returns, and estimate firms' exposure to systematic risk, $\hat{\beta}_j$, by running a separate regression for each firm over all trading days in 1999. We choose this period to ensure that our estimations of $\hat{\beta}_j$ do not occur during the period when relevant legislative information about PNTR became known.[13] Using data on firms' daily returns provided by the Center for Research in Security Prices (CRSP), we run these regressions for all publicly traded firms incorporated in the United States that trade on one of the three main stock exchanges (NYSE, AMEX and NASDAQ) and are present for at least 120 days of the 250-day estimation period.[14]

Our procedure yields daily PNTR average abnormal returns (AAR_j^{PNTR}) for 5,368 firms that are present during the pre-period used to estimate $\hat{\beta}_j$ and at least one of the five legislative events.[15] Across all five events the mean AAR_j^{PNTR} is -0.37 percent, with a standard deviation of 1.03 percent. By event (in chronological order), the means are 0.12, -0.65, -0.25, -0.40, and -0.67 percent, while standard deviations are 1.9, 2.1, 2.1, 1.8 and 2.2 percent. Figure 2 reports the distributions of these returns, by event.[16]

AAR_j^{PNTR} are lower and less dispersed than average abnormal returns generated randomly as a placebo. To illustrate this, we choose 1000 sets of 5 random trading days in 2000 and then compute average abnormal returns in the two days before, the day of, and the two days after these "events", as above, excluding any days that would give rise to intervals

[11] For the full list of actions related to PNTR passage, see https://www.congress.gov/bill/106th-congress/house-bill/4444/actions. The substantial gap between the cloture motion and the vote in the Senate is due to that body's August recess.

[12] The news outlets are: Associated Press, BBC Monitoring International Reports, The Boston Globe, The Chicago Tribune, CNN Transcripts, The Financial Times, The Los Angeles Times, The New York Times, The Washington Post, PR Newswire, and The Wall Street Journal.

[13] Results are qualitatively and quantitatively similar utilizing $\hat{\beta}$s that are estimated separately using the 250 days that end 30 days before each event.

[14] Data on the daily market return and risk-free rate are taken from Kenneth French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html). Following convention, we use the daily return of the one-month Treasury bill rate for R_{ft}, and the daily value-weighted return on the portfolio of all firms on the NYSE, AMEX and NASDAQ for R_{mt}.

[15] If a firm is missing from one or more events, its abnormal returns represent the average over the remaining events.

[16] By definition, average abnormal returns across all firms in the market are mean zero when weighted by market capitalization. The left skewness apparent in Figure 2 indicates that smaller firms in terms of market capitalization are more likely to have lower AAR_j^{PNTR}.

that overlap with the PNTR event windows. Figure 3 plots the distribution of AAR_j^{PNTR} against that of the 1000 iterations of $AAR_j^{Placebo}$. As indicated in the figure, AAR_j^{PNTR} are substantially more negative than $AAR_j^{Placebo}$. The standard deviations are relatively similar, but slightly smaller for AAR_j^{PNTR}.[17]

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.[18] We define firms to be goods producers if their business segments include Manufacturing (NAICS 31 to 33), Mining, Quarrying, and Oil and Gas Extraction (NAICS 21), or Agriculture, Forestry, Fishing and Hunting (NAICS 11), while non-goods (or "service") producers are defined as firms whose segments do not include these sectors. In 2000, our sample consists of 2381 goods producers and 2987 service firms. As illustrated in Figure 4, we find that the AAR_i^{PNTR} of goods-producing firms is more left-skewed than service firms. 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, 1.05 and 0.96 percent for service firms.

Consistent with Breinlich (2011) analysis of abnormal returns following the Canada-US Free Trade Agreement, we find that firms whose $AAR_j^{PNTR} > 0$ are larger along almost every dimension than firms with negative relative returns, even within narrow industries, and that these premia are approximately 50 percent higher for goods-producers than for service firms.[19] These relationships are illustrated in Table 1, which summarizes the results of a series of OLS regressions of various measures of firm size on a dummy variable indicating whether $AAR_j^{PNTR} > 0$ 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. Regressions are clustered at the 4-digit NAICS level. As indicated in the table, goods producers with $AAR_j^{PNTR} > 0$ 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 firms' efficiency, the relationships displayed in Table 1 are consistent with models of international trade that predict high-efficiency firms

[17] The mean, standard deviation, skewness and kurtosis of AAR_j^{PNTR} are -0.37, 1.03, -0.21 and 10.81 versus 0.008, 1.09, 0.72 and 23.21 for $AAR_j^{Placebo}$ across the 1000 iterations. Appendix Figure A.1 provides a more detailed comparison of the AAR_j^{PNTR} and $AAR_j^{Placebo}$ distributions, showing that the mean, standard deviation, skewness and kurtosis of the former lies at the 1st, 34th, 30th, and 49th percentiles of the latter distributions across their 1000 draws.

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

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

are better able to take advantage of reductions in trade costs by, for example, selling more in foreign markets or offshoring (Breinlich (2011); Antràs et al. (2017); Bernard et al. (2018)).

Finally, we show that firms' AAR_j^{PNTR} vary widely even within 6-digit NAICS industries. Figure 5 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 their market capitalization before 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.

A similar point is conveyed by Figure 6, which reports the distribution of AAR_j^{PNTR} across 2-digit NAICS sectors. In all sectors we observe substantial variation across firms' AAR_j^{PNTR}. Manufacturing, for example, includes a number of firms with NAICS code 334111, "Electronic Computer Manufacturing". Among these firms, Apple Computer Inc. and Dell Computer Corporation have positive AAR_j^{PNTR}, while Gateway Inc., also a supplier of PC's, has a negative AAR_j^{PNTR}. The former 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.[20]

4 Validity

In this section we establish the validity of our approach by demonstrating that AAR_i^{PNTR} is correlated with the standard measures of import competition as well as with firms' abnormal returns during an important, contemporaneous event in US-China relations: the accidental US bombing of China's embassy in Belgrade in 1999.

4.1 AAR_j^{PNTR} and Subsequent Import Growth

Table 2 examines the link between firms' AAR_j^{PNTR} and US import growth from China. For each firm, we calculate a weighted average of US import growth across its observed business

[20] For a history of Gateway, see http://www.fundinguniverse.com/company-histories/gateway-inc-history/.

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 firms operating in at least one goods-producing industry, 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. For ease of interpretation, all variables are de-meaned and divided by their standard deviation. Standard errors are clustered at the four-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 show that a similar relationship does not exist with respect to pre-PNTR import growth, from 1990 to 2000. Together, these results suggest that equity markets correctly anticipated an increase in import competition from China as a result of PNTR, 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 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 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.[21] 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. 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, -0.092, indicates that a 1 standard deviation increase in subsequent imports from China is associated 0.092 standard deviation decline in abnormal returns. This corresponds to a loss in market value of about 2.4 percent.[22]

4.2 AAR_j^{PNTR} and Changes in Expected US Import Tariffs

Existing research on PNTR measures industries' exposure to the change in trade policy in terms of the change in expected US import tariffs, or "NTR gap", 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 rate permitted under temporary NTR status,

[21] All firm attributes are for 2000 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. Our results still obtain when using the full sample.

[22] Multiplying the coefficient (-0.092) 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 the 2.4 percent indicated above.

$$NTR\,Gap_i = Non - NTR\,Rate_i - NTR\,Rate_i, \tag{4}$$

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).[23] Their mean and standard deviation are 0.29 and 0.15, and we summarize their distribution visually in appendix Figure A.2.

We investigate the relationship between firms' AAR_j^{PNTR} and the sales-weighted average NTR gap of their major segments ($NTR\,Gap_j$) using an OLS specification of the form

$$AAR_j^{PNTR} = \delta NTR\,Gap_j + \epsilon_{ji}. \tag{5}$$

As $NTRGap_j$ is not defined for service firms, we restrict estimation of this regression 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 account for supply chain linkages, we follow Pierce and Schott (2016) in also including up- and downstream NTR gaps in the specification, $NTR\,Gap_j^{Up3}$ and $NTR\,Gap_j^{Down3}$. For each industry i, we 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.[24] 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.

Results are reported in Table 3 where, as above, all variables are de-meaned and divided by their standard deviation, and standard errors are clustered at the four-digit NAICS level. Estimates in column 1 are consistent with expectations: the association between AAR_j^{PNTR} and own-industry exposure is negative, while the point estimate for $NTRGap_i^{Up3}$ is positive, and both are statistically significant. The point estimate for $NTRGap_j^{Down3}$ has the expected

[23]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).

[24]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 $NTR\,Gap_i^{Up3}$ and $NTR\,Gap_j^{Down3}$. 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 0.8. The analogous correlations for correlations with $NTRGap_i^{Up3}$ and $NTR\,Gap_j^{Down3}$ are 0.38 and -0.01.

sign but is not statistically significant at conventional levels.

The second and third columns of Table 3 consider two additional sets of covariates. The first account for three policy changes beyond PNTR associated with China's entry into the WTO: decreases in Chinese import tariffs, elimination of export licensing restrictions, and the expiration of the global Multi-Fiber Arrangement (MFA).[25] Including these additional variables does not change the sign and statistical significance of the NTR gap variables, but it does reduce the magnitude of the own-gap estimate from -0.24 to -0.14. Among the new policy variables, we find negative and statistically significant relationships with respect to changes in China's import tariffs and export licensing, and a positive relationship with respect to MFA exposure. The negative associations between AAR_j^{PNTR} and changes in Chinese import tariffs is consistent with higher expected profit in industries where it will be easier for US firms to export to China. The negative association between AAR_j^{PNTR} and the share of Chinese firms eligible export is also intuitive, as removal of these restrictions may increase competition for US producers in the exposed industries. The positive association between AAR_j^{PNTR} and exposure to elimination of MFA quotas may reflect the ability of some goods-producing firms to take advantage of greater production in China.

The second set of additional covariates included in Table 3 are the accounting variables described in the previous section. With these variables 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 Tables 2 and 3 suggest that firms' abnormal returns during the key votes associated with PNTR are related both to the typical measures of import competition used to evaluate this change in trade policy and variables capturing other important policy changes associated with China's entry into the WTO.[26] That is, abnormal returns surrounding PNTR legislative events reflect the anticipated effects of subsequent changes in US-China trade policy, including but not limited to changes in import competition. As a result, in Section 5, we use AAR_j^{PNTR} as the sole measure of firms' exposure to the change in US policy in predicting firm outcomes.

[25]Industry-level data on the change in Chinese import tariffs from 1996 to 2005 and the share of Chinese firms eligible to export are from Brandt et al. (2017) and Bai et al. (2015). As discussed in greater detail in the appendix, and as noted above, the elimination of quotas on US textile and clothing imports from China occurred in four phases between 1995 and 2005. Our control, from Pierce and Schott (2016), is the import-weighted average fill rate of the quotas removed in each 6-digit NAICS industry as of the PNTR votes. Fill rates are defined as actual divided by allowable imports and are a typically used measure of quota restrictiveness, with higher values indicating greater exposure to MFA quota reductions.

[26]In appendix Table A.1, we show that AAR_j^{PNTR} have a negative relationship with each individual legislative event, though these relationships are statistically insignificant at conventional levels for the introduction of the bill to the floor of the House and the Senate vote.

4.3 PNTR and the Belgrade Bombing

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] Given the proximity of the bombing to the passage of PNTR, we examine how firms' average abnormal returns in the seven trading days after it occurred, $AAR_j^{Belgrade}$, compare to AAR_j^{PNTR}.[28] A virtue of this external validity check, relative to the results reported in the previous table, is that we are able to investigate responses for both goods-producing and service firms.

We analyze the association between $AAR_j^{Belgrade}$ and AAR_j^{PNTR} via the following OLS regression,

$$AAR_j^{PNTR} = \delta AAR_j^{Belgrade} + \epsilon_i. \tag{6}$$

Results are presented for all firms, as well as for goods-producing and service firms separately in Table 4. We find that δ is *negative* and statistically significant 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 δ is substantially larger for service firms.[29]

5 Using AAR_j^{PNTR} to Predict Firm Outcomes

In this section we examine the predictive power of AAR_j^{PNTR}. We begin with the outcomes most directly related to firms' expected stream of cash flows – survival, sales, costs, and operating profit. We then examine changes to employment and capital.

[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." See https://www.wsj.com/articles/SB926284661489396187.

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

[29] In Appendix Table A.2 we document a positive relationship between the $NTRGap_j$ and $AAR_j^{Belgrade}$, further supporting the idea that firms expected to be harmed by PNTR respond favorably to the deterioration of US-China relations that followed the bombing. As an additional validity test, in Appendix Table A.3 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 (AAR_i^{Trump}), consistent with the idea that industries whose expected profits are expected to rise with PNTR are those whose profits are expected to fall with Trump's election despite the long intervening time interval.

5.1 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.[30]

We investigate the relationship between PNTR and exit in Table 5, which presents results from the estimation of a multinomial logit regression,

$$Pr(Y_j = d) = \delta AAR_j^{PNTR} + \mathbf{X_j^{2000}}\gamma + \epsilon_j, \tag{7}$$

where $Pr(Y_j = d)$ is the probability that firm j exits between 2000 and 2006 due to de-listing category d.[31]

As noted at the end of Section 2, 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_PNTR to predict subseqent changes in firm outcomes. As a result, the regression in this and subsequent sections of the paper we continue to include as covariates the accounting variables described above, $\mathbf{X}_j^{2000}$.[32]

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 probabilities of exit for these causes of 2.5 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.

In panels B and C, we estimate the multinomial logit separately for goods and service firms. For goods producers, we find that higher AAR_j^{PNTR} are negatively associated with

[30] See Appendix Table A.5 for a more detailed breakdown of these flags. We observe 1805 firms de-list between 2000 and 2006. The distribution of these de-listings across the three categories is 735, 894, and 176, respectively.

[31] 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.

[32] Balance sheet information is missing for 771 firms in 2-digit NAICS sector 52. 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.

the likelihood of exit via bankruptcy and contraction, and positively associated with exit due to being acquired. 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. In both cases, these relationships are larger in magnitude for service firms than for goods producers. In contrast to goods producers, however, we find no relationship between AAR_j^{PNTR} and exit due to merger among service firms.

The robust negative relationship between AAR_j^{PNTR} and exit due to bankruptcy or contraction provides additional support for our approach, as it suggests investors correctly 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.[33] 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.

5.2 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,

$$\begin{aligned} ln(Outcome_{jt}) &= \delta Post \times AAR_j^{PNTR} + \gamma Post \times \mathbf{X_j^{2000}} \\ &\quad + \alpha_j + \alpha_t + \epsilon_{jt}. \end{aligned} \tag{8}$$

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 described above.[34] 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.

[33] This difference is displayed in Appendix Figure A.4, which plots the distribution of both types of firms' profitability, as measured by the log of the firm's operating profit divided by the book value of its assets.

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

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 12.7, 10.4 and 12.9 log points, respectively.

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

Employment and 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 0.097, implying that a one standard deviation increase in AAR_j^{PNTR} is associated with a relative increase in employment of 9.7 log points in the post period. Perhaps surprisingly, the magnitude of this point estimate is larger for service-producing firms – 10.1 log points – than goods firms – 8.5 log points. We return to the implications of this result in Section 7 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 physical 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).[35]

[35] Autor et al. (2016) find that increases in Chinese import penetration negatively affects US manufacturers' innovative activities. Examining US manufacturing establishments, Pierce and Schott (2017) find that investment among continuing firms with greater exposure to PNTR via the NTR gap exhibits relative declines

5.3 The Relative Explanatory Power of AAR_j^{PNTR} vs $NTR\,Gap_j$

An important contribution of our approach is the ability of AAR_j^{PNTR} to capture the effects of PNTR through all channels, including, but not limited to direct import competition. To illustrate the potential importance of these additional channels, we assess the relative explanatory power of AAR_j^{PNTR} versus the NTR gap using a modified version of our baseline DID specification,

$$\begin{aligned} ln(Outcome_{jt}) \;=\; & \delta Post \times AAR_j^{PNTR} \\ & +\gamma_1 Post \times NTR\,Gap_j + \gamma_2 Post \times NTR\,Gap_j^{Up3} \\ & +\gamma_3 Post \times NTR\,Gap_j^{Down3} \\ & +\gamma_4 Post \times \mathbf{X_j^{2000}} \\ & +\alpha_j + \alpha_t + \epsilon_{jt}, \end{aligned} \tag{9}$$

where $NTRGap_j$, $NTR\,Gap_j^{Up3}$ and $NTR\,Gap_j^{Down3}$ are defined as above. All other aspects of the estimation remain the same.

Results for goods producers are reported in Table 8, while those for service producers are reported in Table 9. The latter excludes coefficient estimates for $NTR\,Gap_j$, which is by definition zero for service firms. The top panel of each table omits $Post \times AAR_j^{PNTR}$ from the specification. The bottom panel includes this term. To conserve space, estimates for all other controls are suppressed.

The coefficient estimates in these tables convey two messages. First, consistent with prior research, their top panels reveal that when included on their own, the NTR gap variables are useful predictors of outcomes among both goods-producing and service firms.[36] Second, the bottom panels of each table show that coefficient estimates for $Post \times AAR_j^{PNTR}$ are very similar to those reported in our baseline specifications (Tables 6 and 7), even when the NTR gaps are included. Here, too, this trend is evident among goods producers as well as service firms.

after the change in policy, and that these declines are relatively moderate for establishments with relatively high levels of initial labor productivity, skill intensity and capital intensity. Gutierrez and Philippon (2017) document relative increases in investment and innovation among industry leaders in response to PNTR. Similarly, Bombardini and Li (2016) document a heterogeneous patenting response to import competition.

[36] Pierce and Schott (2016), whose analysis of US manufacturing establishments' US employment is closest to the employment regression in Table 8, find that a one-standard deviation increase in an establishment's NTR gap (computed as the value weighted average gap across the set of 5-digit SIC goods they produce) is associated with a relative decline in employment of approximately 5.3 log points. That estimate is larger than the 3 log point effect observed for the own gap in Panel A. The difference in these estimates may be driven by a number of factors, including the larger size of firms in our sample as compared to the universe of establishments analyzed in Pierce and Schott (2016), and our examination of *worldwide* versus US employment.

6 Robustness

In this section we examine the robustness of the results presented above in several ways. First, we consider a placebo exercise that examines the predictive power of average abnormal returns generated using random dates. Second, we explore the robustness of our primary findings to alternative weighting strategies and a more restrictive set of fixed effects. Third, we address issues specific to financial market analysis, including alternative asset pricing models, potentially confounding events, and event window size. Fourth, we re-estimate our results using a more flexible difference-in-differences strategy to search for pre-trends. Finally, we re-estimate our results using a bootstrap to account for sampling error associated with estimation of firms' $\hat{\beta}_j$s.

6.1 Placebo Exercise

Given the forward-looking nature of financial markets, one concern in evaluating the explanatory power of AARs is that they may be predictive of firm outcomes even if they are not driven by PNTR. To address this concern we use the placebo average abnormal returns described in Section 3.2 in place of AAR_j^{PNTR} in our baseline DID specification for operating profit and employment. This exercise yields 1000 DID coefficients for each outcome, whose distributions are plotted in Figure 7. Here, in contrast to the baseline results reported in Tables 6 and 7, however, we estimate these specifications using non-standardized covariates, as comparisons between the placebo exercise and our baseline results in terms of standardized coefficients would be sensitive to the relative standard deviations of AAR_j^{PNTR} versus the $AAR_j^{Placebo}$ draws. Non-standardized coefficients, by contrast, compare the relationships between firm outcomes and a 1 percent increase in either $AAR_j^{Placebo}$ or AAR_j^{PNTR}.

The vertical lines in Figure 7 indicate the location of our baseline DID estimates in the placebo DID coefficients' distributions. Two results stand out. First, the mean of the placebo DID coefficients for both outcomes is positive, indicating that higher AARs are, on average, associated with subsequent relative expansion. Second, the estimates for the PNTR DID coefficients lie in the far right tails of the placebo distributions, at the 97^{th} and 99^{th} percentiles, respectively. This placement suggests that higher AAR_j^{PNTR} are associated with substantially stronger relative profit and employment growth than one might expect during randomly selected periods of equal length. This outcome suggests that PNTR is a more persistent shock, in the sense that subsequent shocks of the opposite sign were less likely to reduce their predictive power, alleviating any concern that our baseline DID results are due solely to the forward-looking nature of financial market returns.

6.2 Sector-Year Fixed Effects and Weighting

In this section we consider two extensions of our baseline DID specifications. First, we re-estimate Equation 8 for each outcome, weighting each regression by the 1990 level of the dependent variable. Results are displayed in the upper three panels of Figure 8 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 8. As indicated in the figure, coefficient estimates are generally smaller in magnitude, but remain statistically significant, save for intangible capital among service firms.

6.3 Financial Market Concerns

In this section we re-estimate our baseline specification employing alternative event windows, using a different asset pricing model, and omitting firms with potentially confounding announcements during the relevant event windows.

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 here using a $[-1, 1]$ window around each event. As above, we report only the DID coefficients of interest and their 95 percent confidence intervals to conserve space. The top panel of Figure 9 reveals that the sign and statistical significance patterns of the coefficient estimates are broadly similar to those in our baseline specification.

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

$$(R_{jt} - R_{ft}) = \beta_j(R_{mkt,t} - R_{ft}) + \beta_j^{SMB} SMB_t + \beta_j^{HML} HML_t + \epsilon_{jt}. \quad (10)$$

As before, the returns on these portfolios are taken from Kenneth French's website.[38] 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 10.[39] As illustrated in the second panel of Figure 9, results are similar to those in our baseline specifications.

Potentially Confounding Announcements: Finally, 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 9. 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. [40]

[37] 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.

[38] 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.

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

[40] We also re-estimate column 1 of Table 3 in Table A.4 where we observe each of these alternate calculations of AAR_j^{PNTR} are similarly correlated with $NTRGap_j$.

6.4 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 8 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:

$$\begin{aligned} ln(Outcome_{jt}) \;=\; & \sum_{y=1990}^{2006} \delta_y \times 1\{t=y\} \times AAR_j^{PNTR} + \sum_{y=1990}^{2006} 1\{t=y\} \times \mathbf{X_j}\gamma_\mathbf{y} \\ & +\alpha_j + \alpha_t + \epsilon_{jt}. \end{aligned} \tag{11}$$

In all other respects, the estimation of Equation 11 resembles that of Equation 8.[41]

Results are reported in Figure 10, 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 statistically significant afterwards.

6.5 Generated Regressors

Thus far we have ignored the sampling error associated with a key input to the calculation of AAR_j^{PNTR}, the firms' $\hat{\beta}_j$s. Failing to account for this error can give rise to a classic generated-regressor problem where standard errors are biased downwards by an amount which is an increasing function of the sampling error in $\hat{\beta}_j$. In this section, we address this issue using a bootstrap. To allow standard errors to be clustered by 4-digit NAICS industry, we employ a clustered bootstrap as follows. First, we construct 1000 sets of $\hat{\beta}_j$ by drawing the requisite number of trading days, with replacement, in the pre-period for each firm. Second, we 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 8 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.6 and A.7 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

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

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.

7 Distributional Implications

Having established the robustness of our baseline results to alternative samples and specifications, we now use our estimates to explore the distributional implications of PNTR across firms. As with all difference-in-differences specifications, this exercise provides an estimate of the *relative* gains and losses among firms *vis a vis* the market, before versus after PNTR.

As noted above, firms vary substantially in terms of size, and larger firms are more likely to have positive $AARj^{PNTR}$. Figure 11 emphasizes the impact of this heterogeneity by plotting firms' cumulative predicted relative operating profit in the post period (2001 to 2006). Each point in this figure plots a particular firm's predicted operating profit in the post period relative to its operating profit in the pre-period,

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

$\hat{\delta}_s$ is the estimated coefficient from a DID specification analogous to equation 8 but using non-standardized covariates. It is indexed by $s \in \{goods,\ services\}$ to note that different estimates are used for goods-producing versus service firms. The product of $\hat{\delta}_s$ 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 firm j's operating profit in 2000 to convert it into levels. All firms are included in this analysis, including those that may subsequently have been de-listed.

In the figure, firms are sorted according to their pre-PNTR market capitalization along the horizontal axis from smallest to largest. Cumulative predicted relative operating profit generally declines with 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 100 billion dollars, at which point firms' predicted relative increases rise substantially. This growth among firms at the right tale of the size distribution suggests trade may play a role 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).[42]

[42]Exploiting COMPUSTAT data versus the administrative US Census data used by the papers cited in

Goods producers dominate the relative increase in operating profit in the right tail of Figure 11, as can be seen by comparing the relative locations of goods-producers and service firms (large black dots versus smaller red x's) at different levels of market capitalization in Figure 12. Both goods-producers and service firms appear frequently at lower levels of market capitalization, but this balance shifts toward goods-producing firms as firm size rises. Above 20 billion dollars, 55 percent of firms are goods producers. Above 50 billion dollars, they account for two-thirds of all firms. This imbalance holds true above 100 billion dollars as well.

Large firms' size as well as their AAR_j^{PNTR} contribute to their predicted relative growth *vis a vis* small firms. Two simple counterfactual predictions, plotted in Figure 13, 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 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.

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 14, this growth is zero or moderately negative among large 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 14, 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 profit, but more common for intangible capital.

Figure 15 reports the cumulative relative change in each outcome for two-digit NAICS sectors for which we observe a large number of firms: Mining, Utilities, Construction, Manufacturing, Wholesale/Retail, Transportation, Business Services and Healthcare. 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. As indicated in the figure, 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. This figure also suggests that the differential behavior of very large firms' operating profit in Figure 11 is driven primarily by the manufacturing sector.

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the main text, Gutierrez and Philippon (2019) argue that superstars do not account for a substantially larger fraction of employment or sales in 2017 versus 1960, though they do report a local increase according to both measures during our sample period.

We report the cumulative predicted relative changes for all outcomes across all two-digit NAICS sectors in Table 10. This table also reports the number of firms in our sample across sectors. Several results stand out. First, the predicted relative increase in operating profit in the manufacturing sector over the post period is 10.9 billion dollars per year compared to a (worldwide) employment loss of 149 thousand. Second, the predicted relative decline in operating profit in the retail sector is -3.8 billion dollars. This prediction is consistent with analysts expectations at the time that China's WTO entry would reduce markups in the United States that would not, at least initially, be offset by greater profit in China. For example, while a report for Goldman Sachs, Kurtz and Morris (2000), predicted a near tripling of Chinese sales for Wal-Mart in the first five years after the liberalization, it predicted that this growth would not make a meaningful contribution to Wal-Mart's bottom line. Finally, the information sector experienced large relative declines across all outcomes. This sector includes publishing, motion pictures, broadcasting, telecommunications, and data processing. While China agreed to substantial liberalization of its telecommunications sector as part of its WTO accession, this liberalization was phased in gradually and included a number of other limitations, for example, temporary restrictions on foreign ownership shares[43]. Additionally, the collapse of the tech bubble in the early 2000s may contribute to the losses observed for the information sector.

8 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 liberalization with 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 two-digit NAICS sectors.

Application of our method to other changes in policy is warranted. For example, assessing firm exposure to non-tariff barriers is notoriously difficult, as changes in these barriers can be hard to express in terms of equivalent increases or decreases in tariff rates (Goldberg and Pavcnik (2016)). Our approach may also prove useful for evaluating firm sensitivity to other shocks, such as changes in domestic labor laws, monetary policy surprises, or introduction

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

of new technology. We are currently exploring applications along these lines.

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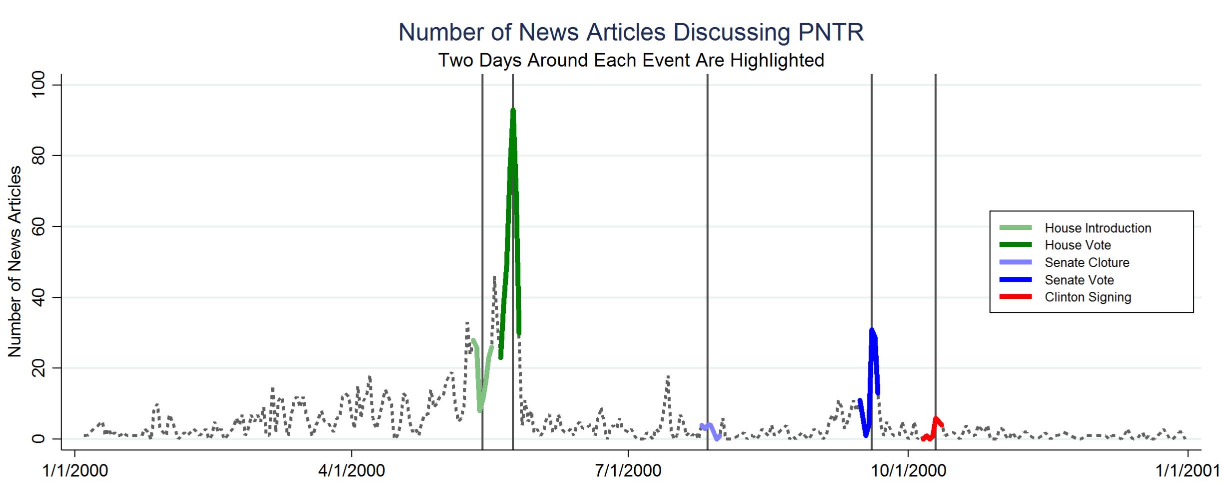
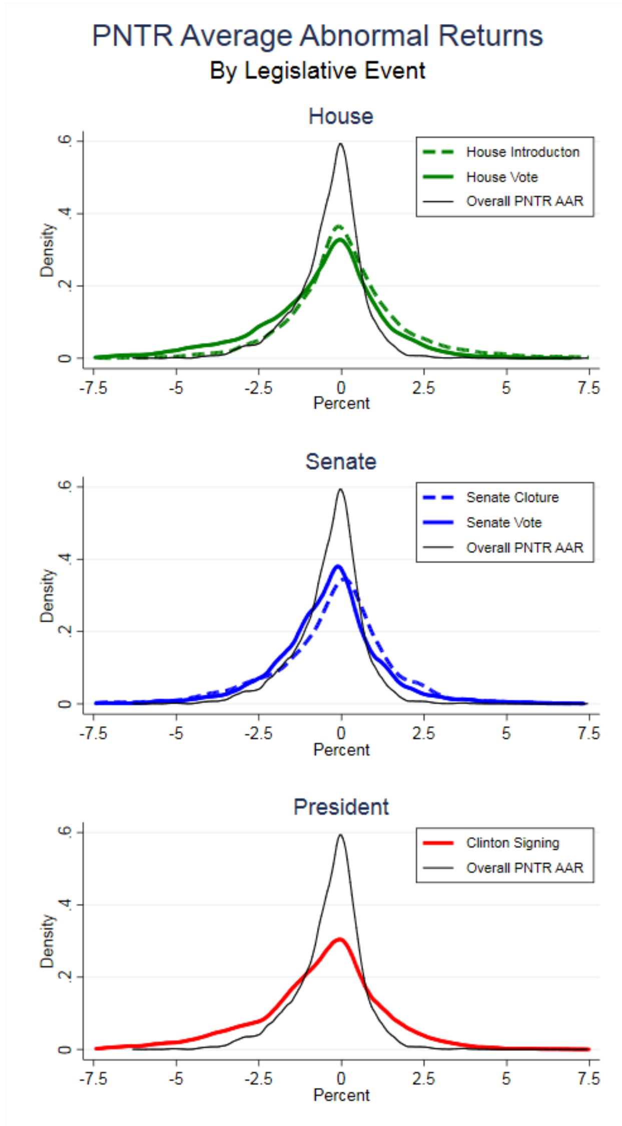
Figure 1: Count of Articles Mentioning "Permanent Normal Trade Relations"



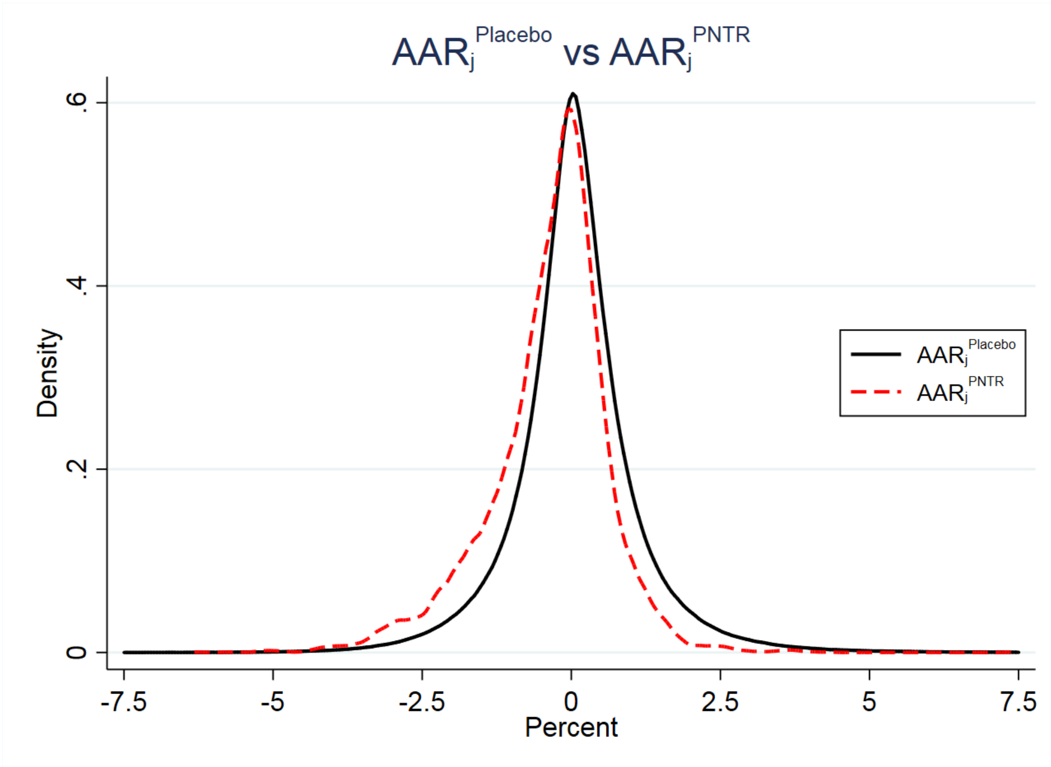
Source: Noted media outlets and authors' calculations. Figure reports the number of unique articles which mention PNTR during calendar year 2000 from the following sources: the Associated Press, BBC Monitoring Inernational Reports, the Boston Globe, the Chicago Tribune, CNN Transcripts, the Financial 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 2: PNTR Average Abnormal Returns, By Event



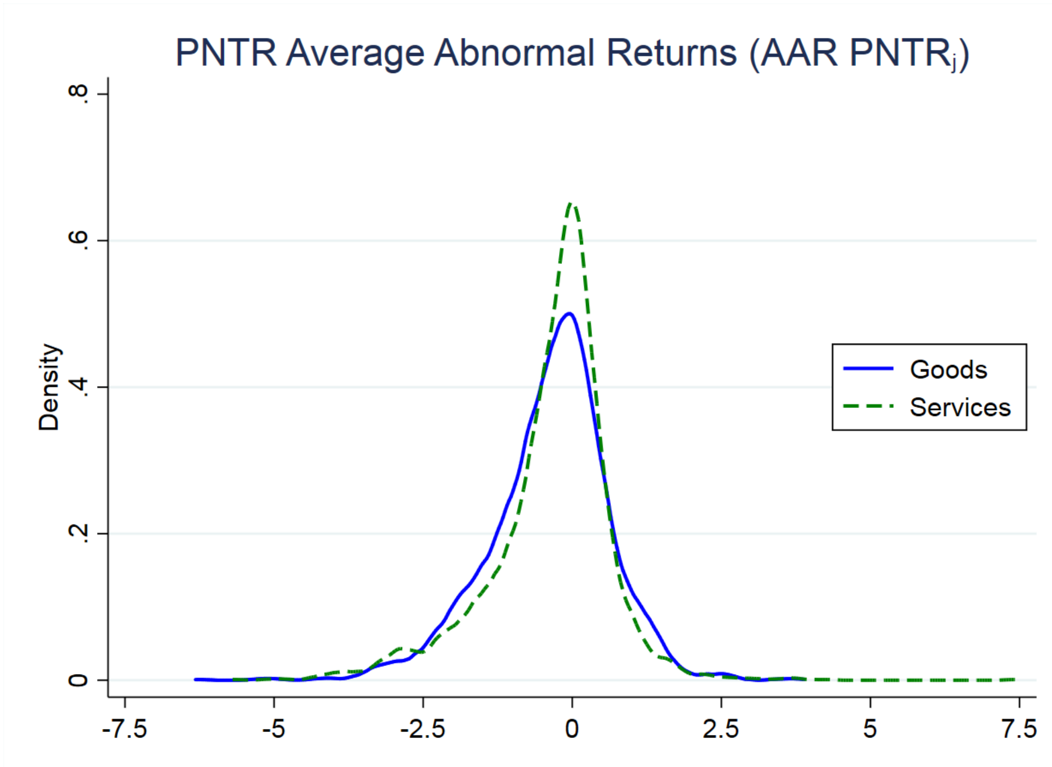
Source: CRSP and authors' calculations. Figure displays distributions of AAR_j^e across 5 PNTR legislative events, and overall. Values below -7.5 and above 7.5 percent are dropped to improve readability.

Figure 3: Distribution of $AAR_j^{Placebo}$ versus AAR_j^{PNTR}



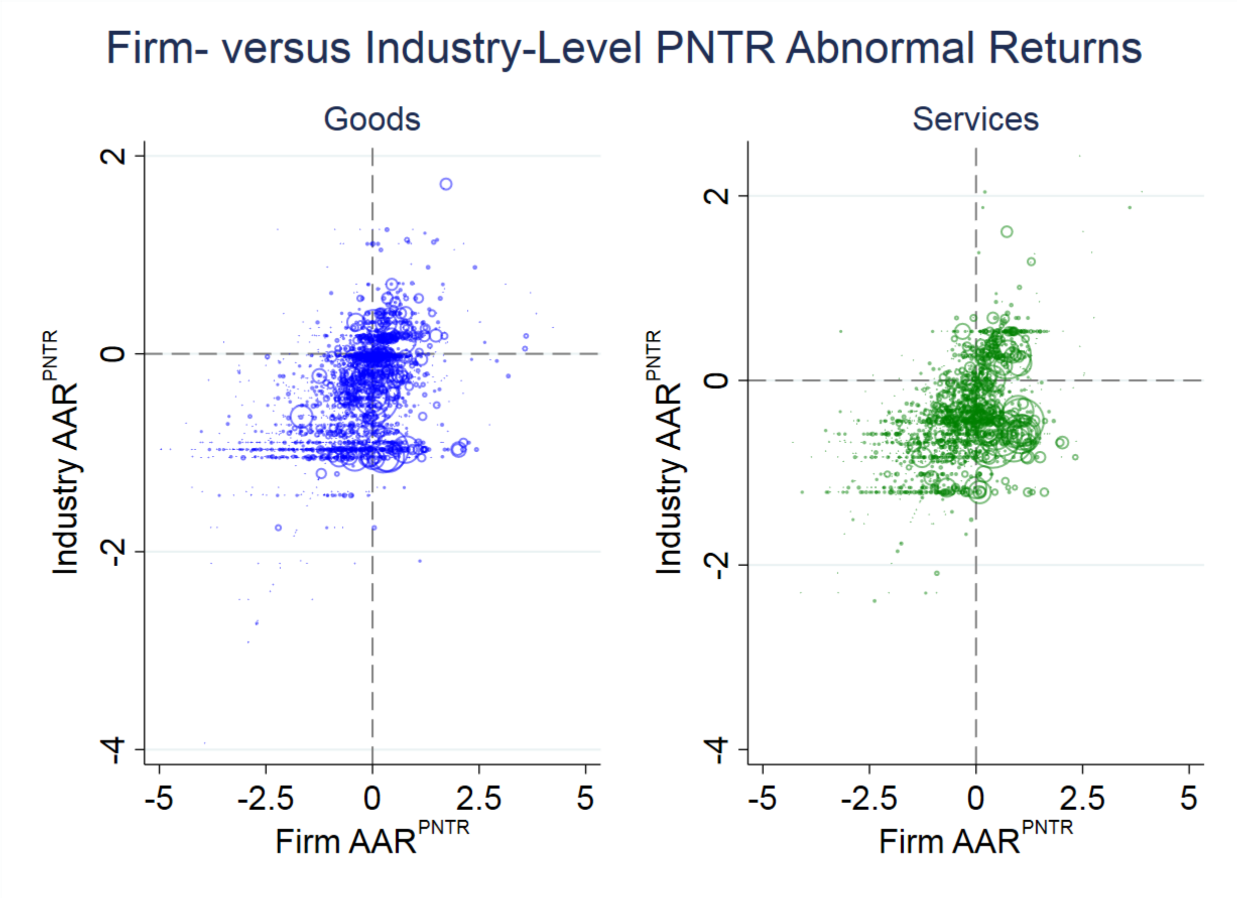
Source: CRSP and authors' calculations. Figure compares the distributions of AAR_j^{PNTR} against those of $AAR_j^{Placebo}$, where the latter are the average abnormal returns across 1000 draws of five randomly chosen events in 2000 (4.2 million observations).

Figure 4: PNTR Average Abnormal Returns, By Type of Firm



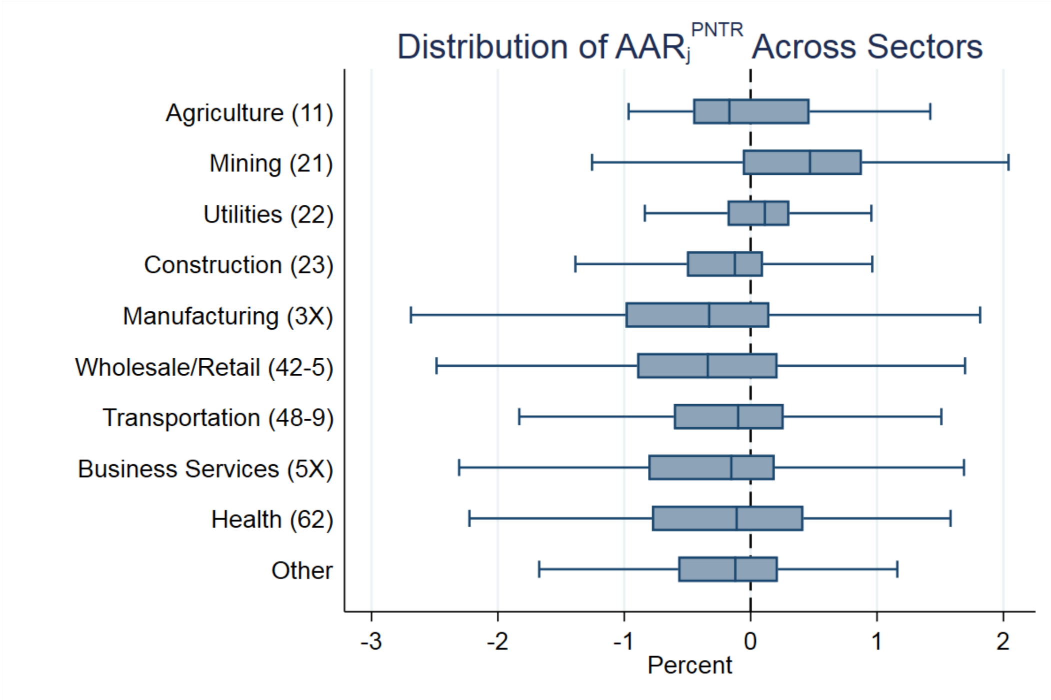
Source: CRSP and authors' calculations. Figure plots distribution of AAR_j^{PNTR} for two mutually exclusive firm types: Goods producers, which have business segments in NAICS 11, 21, 3X, and service firms, which do not. Values below -7.5 and above 7.5 percent are dropped to improve readability. The means and standard deviations for the two groups of firms are -0.38 and 1.00 percent and -0.35 and 1.05 percent respectively.

Figure 5: Firm- versus Industry-Level Average Abnormal Returns



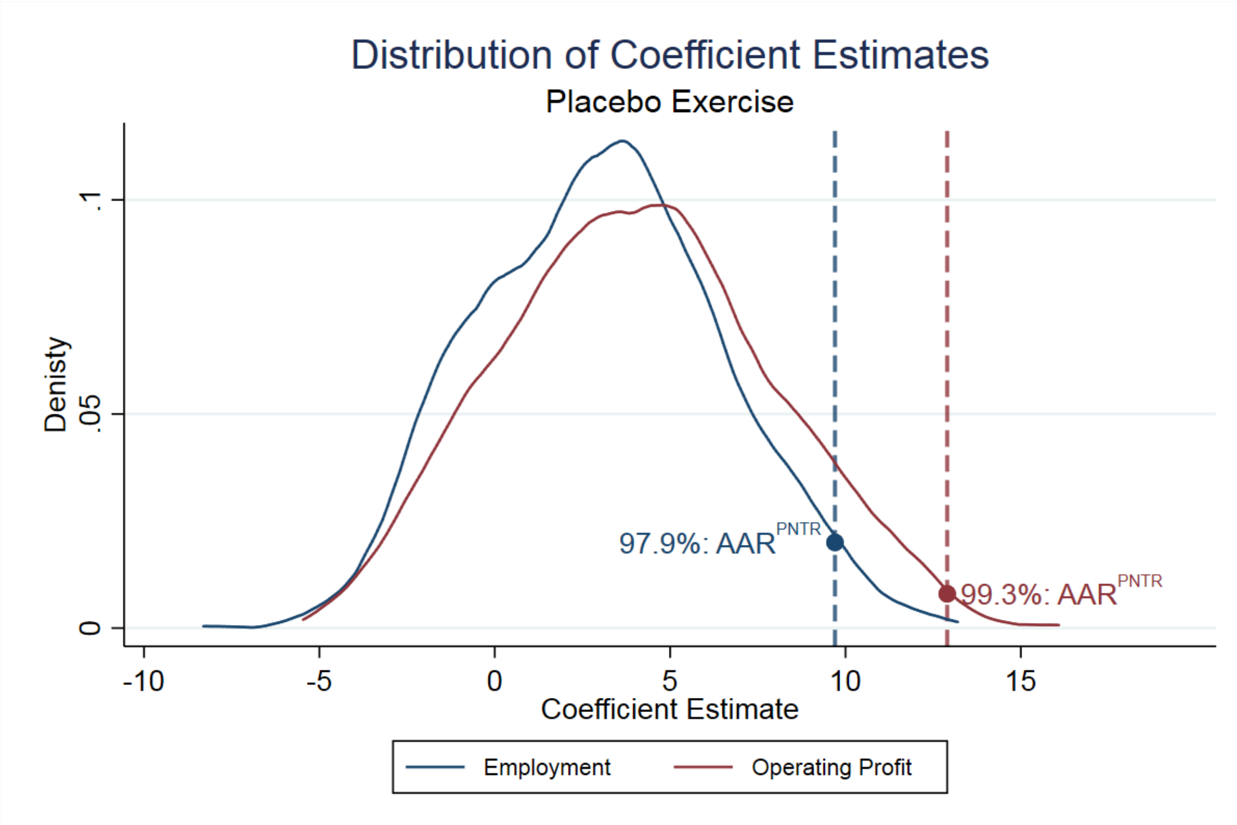
Source: CRSP, COMPUSTAT and authors' calculations. Figure compares firms' AAR_j^{PNTR} to the unweighted average industry AAR_i^{PNTR} of their primary 6-digit NAICS segment. Values below -5 and above 5 percent are dropped to improve readability. Firms' marker sizes in the figure are scaled to their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

Figure 6: Variation in AAR_j^{PNTR} Across Sectors



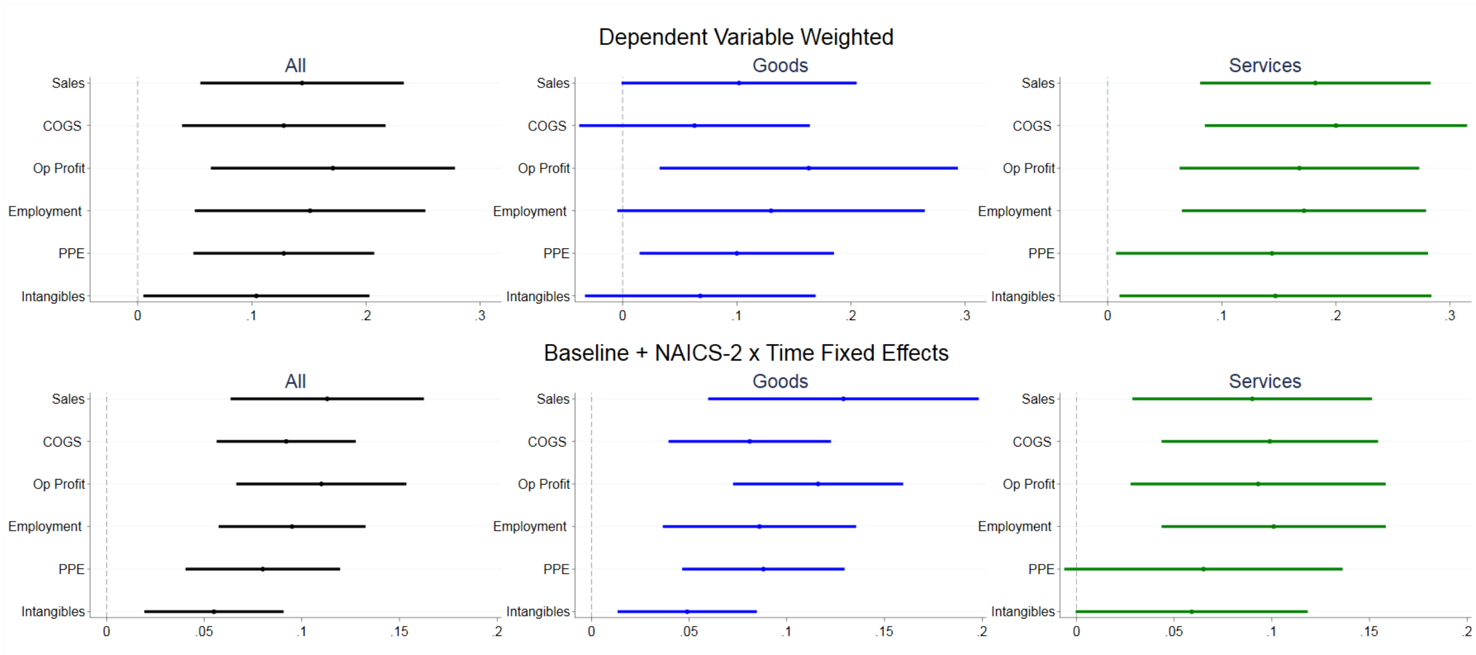
Source: CRSP, COMPUSTAT and authors' calculations. Figure displays the distribution of firm-level AAR_j^{PNTR} across 2-digit NAICS sectors. Firms appear in only one distribution, based on their largest business segment. Codes in parentheses refer to NAICS sectors. Codes with an "X" indicate that all sub-sectors within the 2-digit root are included. The numbers of firms in each sector are: 15, 141, 112, 66, 2055, 495, 103, 2078, 97 and 205.

Figure 7: Placebo Estimates vs AAR_j^{PNTR}



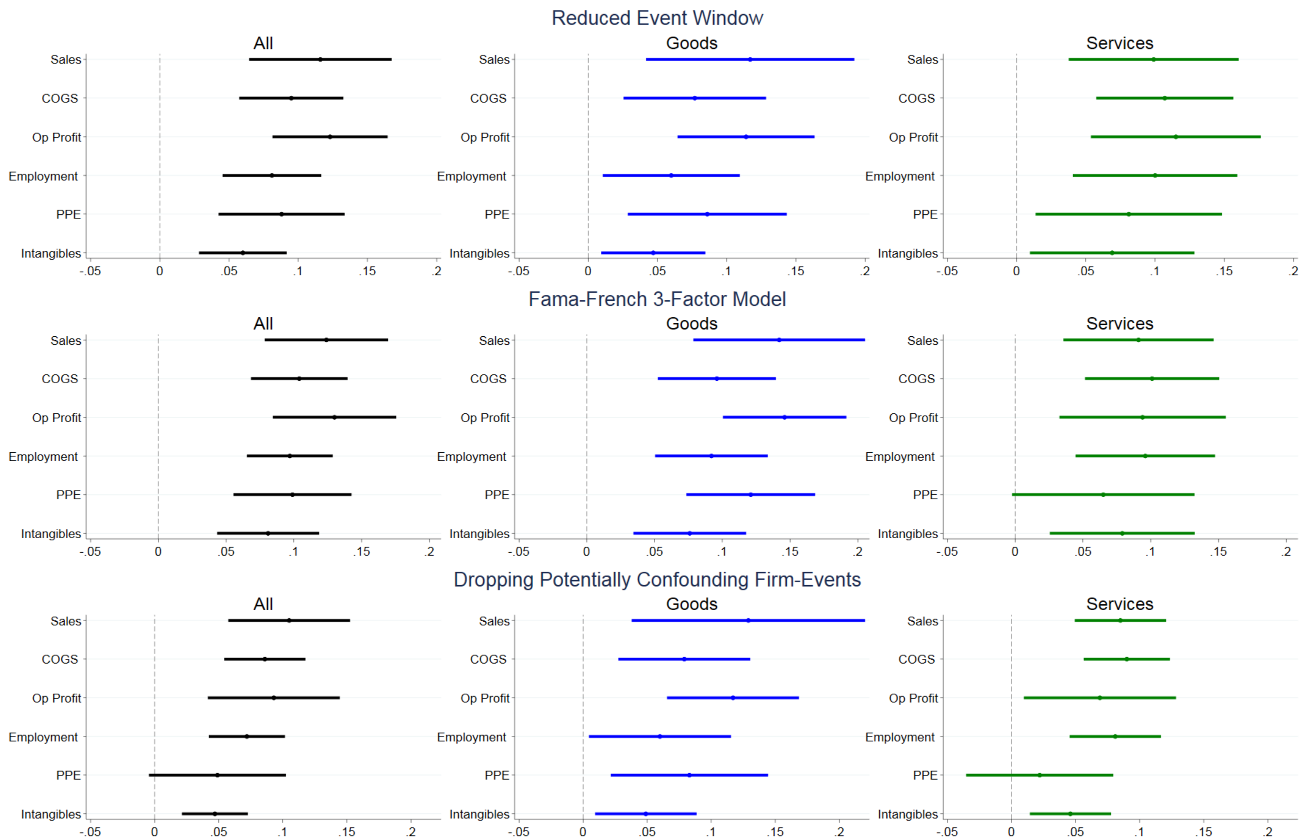
Source: CRSP, COMPUSTAT and authors' calculations. Figure presents the distribution of (non-standardized) DID coefficient estimate from equation 8 using $AAR_j^{Placebo}$ in place of AAR_j^{PNTR}. The vertical lines indicate the non-standardized version of the coefficient estimates obtained in our baseline results (Tables 6 and 7), and the percentiles at which they would fall in the placebo coefficient distribution.

Figure 8: AAR_j^{PNTR} and Firm Outcomes: Robustness Specifications



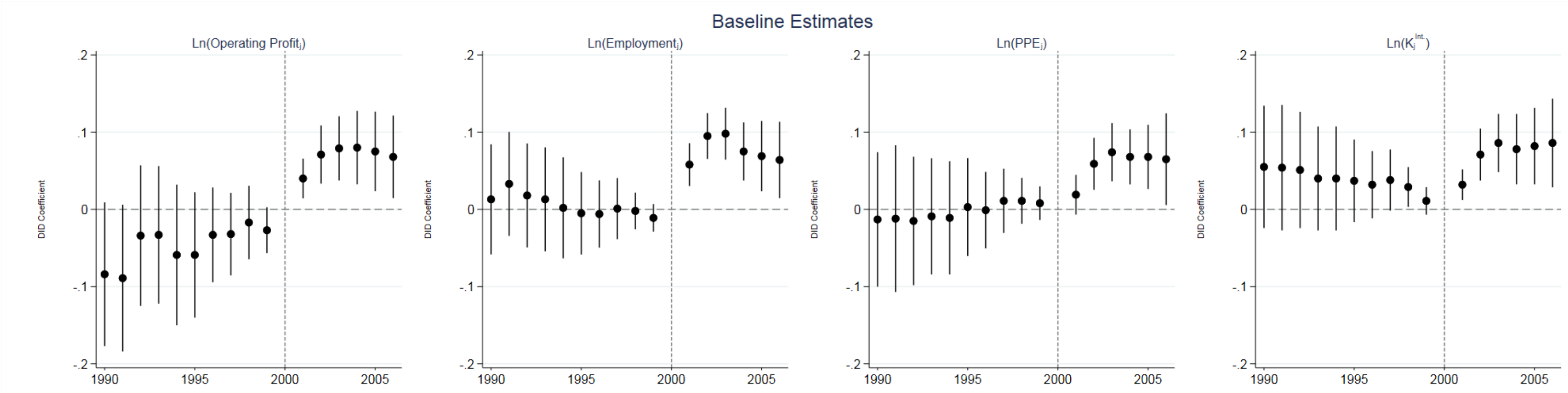
Source: CRSP, COMPUSTAT and authors' calculations. Figure displays a series of 95 percent confidence intervals for the difference-in-difference term of interest from Equation 8. In contrast to the baseline estimates reported in Tables 6 and 7, estimations here are weighted by the firms' initial value of the dependent variable (top panel) or include 2-digit NAICS by year fixed effects reflecting firms' primary activity (bottom panel). Each interval represents the DID coefficient of interest, an interaction of AAR_j^{PNTR} with an indicator variable for years after 2000 ($Post$), from a seperate, firm-level OLS panel regression. All covariates are standardized by subtracting their means and dividing by their standard deviations. As a result, coefficient estimates report the impact on the dependent variable of a one standard deviation increase in firms' AAR_j^{PNTR}. Sample period is 1990 to 2006. Sample includes up to 4517 firms, depending on year. Covariates also include a set of initial firm accounting attributes interacted with $Post$. These covariatse are winsorized at the 1 percent level. 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 used to construct confidence intervals are clustered at the 4-digit NAICS level.

Figure 9: AAR_j^{PNTR} and Firm Outcomes: Finance Robustness Specification



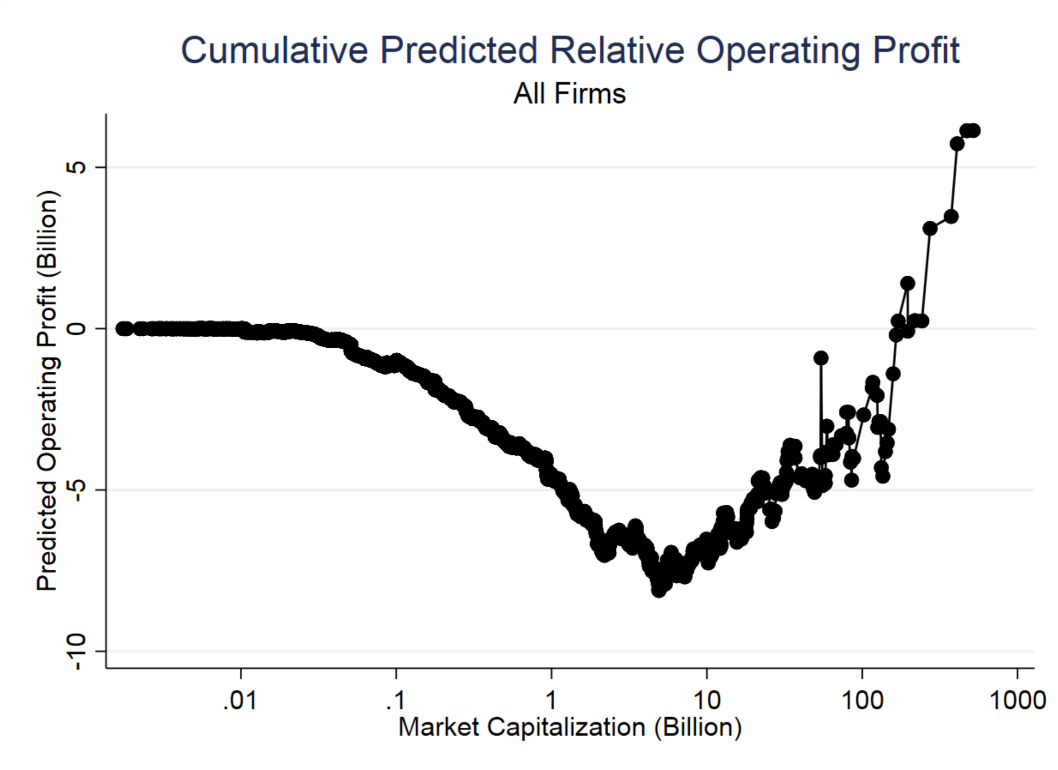
Source: CRSP, COMPUSTAT and authors' calculations. Figure displays a series of 95 percent confidence intervals for the difference-in-difference term of interest in Equation 8. In contrast to the baseline estimates reported in Tables 6 and 7, estimations here are based on AAR_j^{PNTR}: (i) from narrower windows (top panel); (ii) the Fama-French 3-Factor asset pricing model in place of CAPM (middle panel); or (iii) stripped of counfounding events (bottom panel). Each interval represents the DID coefficient of interest, an interaction of AAR_j^{PNTR} with an indicator variable for years after 2000 ($Post$), from a seperate, firm-level OLS panel regression. All covariates are standardized by subtracting their means and dividing by their standard deviations. As a result, coefficient estimates report the impact on the dependent variable of a one standard deviation increase in firms' AAR_j^{PNTR}. Sample period is 1990 to 2006. Sample includes up to 4517 firms, depending on year. Covariates also include a set of initial firm accounting attributes interacted with $Post$. These covariatse are winsorized at the 1 percent level. 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 used to construct confidence intervals are clustered at the 4-digit NAICS level.

Figure 10: AAR_j^{PNTR} and Firm Profit: Annual Specification



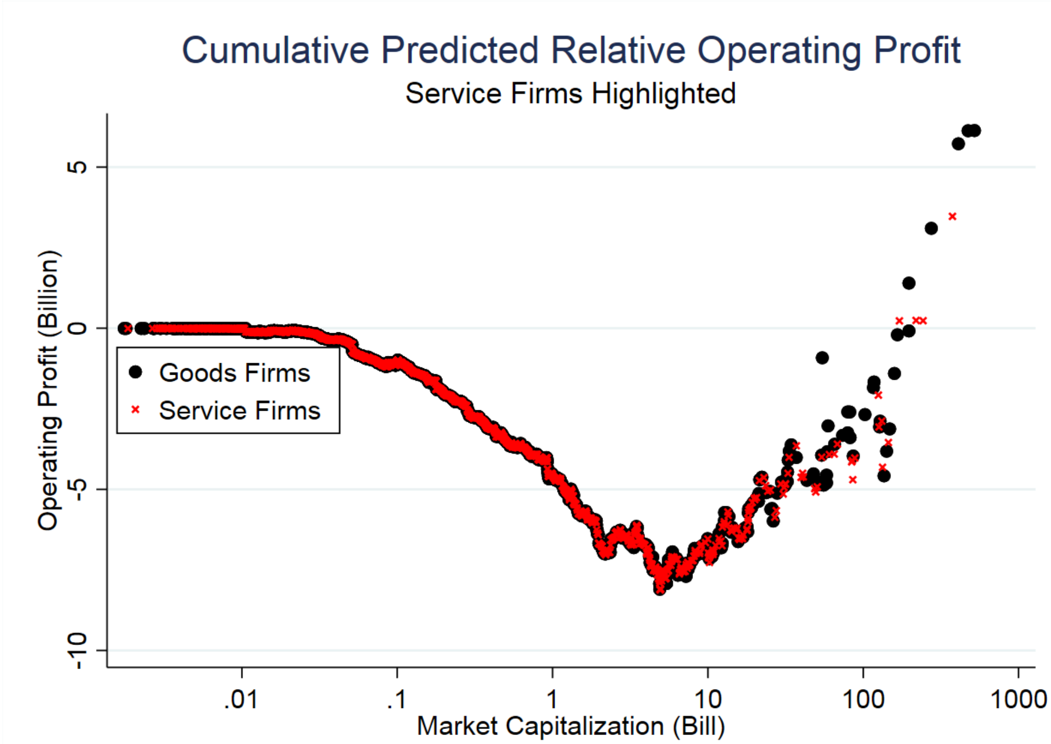
Source: CRSP, COMPUSTAT and authors' calculations. Figure displays a series of 95 percent confidence intervals for the difference-in-difference term of interest in Equation 11. Each panel is from a separate, firm-level OLS regression of noted firm outcome on PNTR average abnormal returns (AAR_j^{PNTR}) interacted with a full set of year dummy variables as well as a series of initial (1990) firm accounting attributes, also interacted with year dummy variables and winsorized at the 1 percent level. Sample period is 1990 to 2006. Sample includes 4505 firms. All covariates are de-meaned and divided by their standard deviations. Standard errors used to construct confidence intervals are clustered at the 4-digit NAICS level.

Figure 11: Cumulative Relative Change in Operating Profit



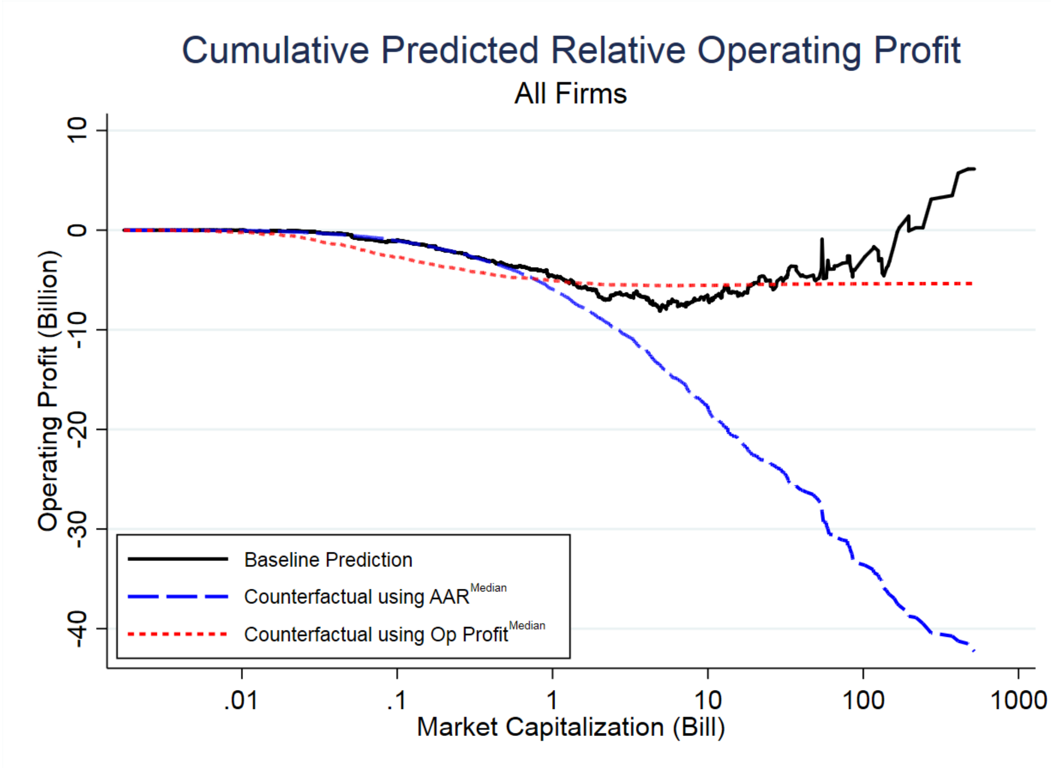
Source: CRSP, COMPUSTAT, and authors' calculations. Figure displays the predicted cumulative relative change in firms' operating profit implied by the baseline difference-in-differences estimates in Table 6. Firms' market capitalization is from 2000, prior to PNTR.

Figure 12: Cumulative Relative Change in Operating Profit: Service Firms Highlighted



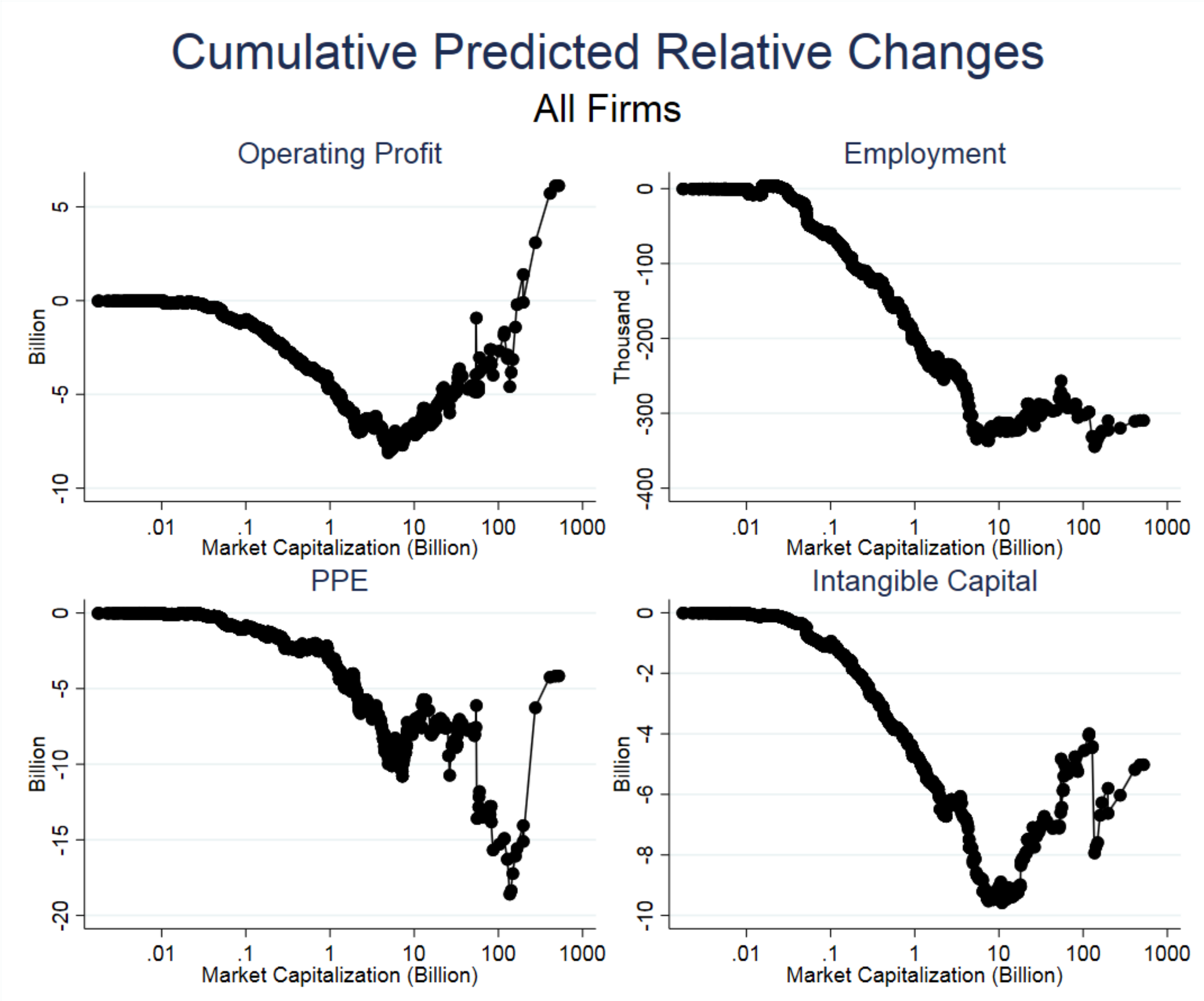
Source: CRSP, COMPUSTAT, and authors' calculations. Figure displays the predicted cumulative relative change in goods versus service firms' operating profit implied by the baseline difference-in-differences estimates in Table 6. Firms' market capitalization is from 2000, prior to PNTR.

Figure 13: Counterfactual Cumulative Relative Change in Operating Profit



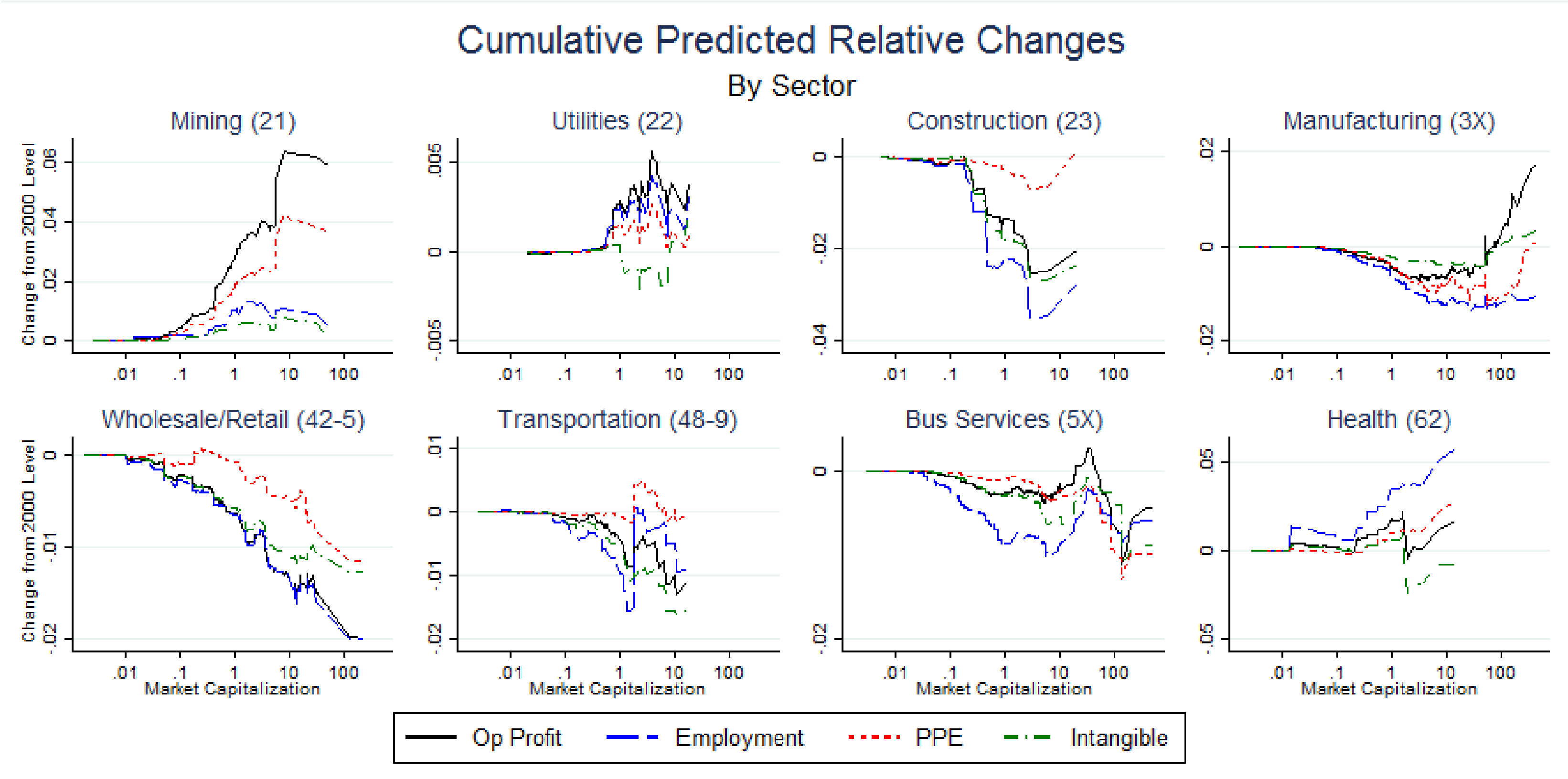
Source: CRSP, COMPUSTAT, and authors' calculations. Figure displays the predicted cumulative relative change in firms' operating profit implied by the baseline difference-in-differences estimates in Table 6 along with two coarse counterfactuals. The first plots the cumulative predicted relative change 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 14: 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 15: 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.

Table 1: $AAR_j^{PNTR} > 0$ Size Premia: NAICS-6 FE

	(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.

Table 2: AAR_j^{PNTR} versus Chinese Import Growth

	(1) AAR_j^{PNTR}	(2) AAR_j^{PNTR}	(3) AAR_j^{PNTR}
Δ Ln(Imports)$_j^{2000-6}$	-0.122***	-0.122***	-0.092***
	(0.045)	(0.044)	(0.030)
Δ Ln(Imports)$_j^{1990-00}$		0.002	-0.008
		(0.034)	(0.040)
Ln(PPE per Worker)$_j$			0.000
			(0.037)
Ln(Mkt Cap)$_j$			0.111***
			(0.021)
$\frac{CashFlows}{Assets}_j$			0.230***
			(0.034)
Book Leverage$_j$			0.077**
			(0.034)
Tobins Q$_j$			0.030
			(0.032)
Constant	-0.079	-0.079	-0.066
	(0.051)	(0.051)	(0.041)
Observations	1894	1894	1894
R^2	0.015	0.015	0.120

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.

Table 3: AAR_j^{PNTR} versus the NTR Gap and Firm Attributes

	(1) AAR_j^{PNTR}	(2) AAR_j^{PNTR}	(3) AAR_j^{PNTR}
NTR Gap_j	-0.243***	-0.139***	-0.075**
	(0.056)	(0.047)	(0.034)
NTR Gap_j^{Up3}	0.113**	0.082*	0.096***
	(0.051)	(0.046)	(0.034)
NTR Gap_j^{Down3}	-0.037	-0.032	-0.089***
	(0.040)	(0.041)	(0.029)
MFA $Exposure_j$		0.008**	0.006*
		(0.004)	(0.003)
Δ China $Licensing_j$		-0.227***	-0.168***
		(0.063)	(0.039)
Δ China Import $Tariffs_j$		-0.069**	-0.033*
		(0.027)	(0.017)
Ln(PPE per $Worker)_j$			0.074**
			(0.035)
Ln(Mkt $Cap)_j$			0.094***
			(0.022)
$\frac{CashFlows}{Assets}_j$			0.236***
			(0.028)
Book $Leverage_j$			0.034
			(0.033)
Tobins Q_j			0.016
			(0.042)
Constant	-0.089	0.094	0.040
	(0.073)	(0.093)	(0.053)
Observations	2264	2084	2084
R^2	0.056	0.080	0.176

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.

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

	(1) $\text{AAR}_{\text{j}}{}^{PNTR}$	(2) $\text{AAR}_{\text{j}}{}^{PNTR}$	(3) $\text{AAR}_{\text{j}}{}^{PNTR}$
$\text{AAR}_{\text{j}}{}^{Belgrade}$	-0.081***	-0.047**	-0.126***
	(0.020)	(0.022)	(0.036)
Constant	0.016	-0.015	0.041
	(0.061)	(0.072)	(0.086)
Observations	4917	2238	2679
R^2	0.007	0.003	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.

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

	Survival	Contraction/Bankruptcy	Merger	Other
	Panel A: All Firms			
$\text{AAR}_{\text{j}}{}^{PNTR}$		-0.259***	0.025	-0.080
		(0.072)	(0.050)	(0.089)
Marginal Effect	0.015	-0.025***	0.011	-0.001
	(0.012)	(0.007)	(0.008)	(0.002)
Unconditional Probability	0.586	0.169	0.205	0.04
Δ Prob.	0.026	-0.149	0.055	-0.036
Pseudo R^2	.122	.122	.122	.122
Observations	4360	4360	4360	4360
	Panel B: Goods Only			
$\text{AAR}_{\text{j}}{}^{PNTR}$		-0.199**	0.151**	-0.136
		(0.088)	(0.065)	(0.084)
Marginal Effect	-0.008	-0.017**	0.028***	-0.003*
	(0.013)	(0.007)	(0.010)	(0.002)
Unconditional Probability	0.634	0.146	0.182	0.039
Δ Prob.	-0.012	-0.117	0.155	-0.082
Pseudo R^2	.127	.127	.127	.127
Observations	2256	2256	2256	2256
	Panel C: Service Only			
$\text{AAR}_{\text{j}}{}^{PNTR}$		-0.295***	-0.049	-0.044
		(0.089)	(0.045)	(0.125)
Marginal Effect	0.031**	-0.033***	0.001	0.000
	(0.013)	(0.010)	(0.008)	(0.003)
Unconditional Probability	0.535	0.193	0.23	0.042
Δ Prob.	0.058	-0.17	0.006	0.008
Pseudo R^2	.123	.123	.123	.123
Observations	2104	2104	2104	2104

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 Appendix Table A.5. Firms exiting due to equity exchange are omitted from the analysis. 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. 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 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}	0.127***	0.145***	0.094***	0.104***	0.095***	0.102***	0.129***	0.144***	0.096***
	(0.026)	(0.034)	(0.032)	(0.020)	(0.023)	(0.028)	(0.026)	(0.026)	(0.036)
Post*PPE per $Worker_j$	0.054	0.150***	-0.015	0.046	0.130***	-0.005	0.036	0.151***	-0.041
	(0.040)	(0.054)	(0.028)	(0.034)	(0.049)	(0.022)	(0.044)	(0.054)	(0.030)
Post*Ln(Mkt $Cap)_j$	-0.067***	-0.092***	-0.058**	-0.075***	-0.099***	-0.067***	-0.072***	-0.106***	-0.054**
	(0.023)	(0.026)	(0.028)	(0.020)	(0.024)	(0.025)	(0.024)	(0.027)	(0.026)
Post*$\frac{CashFlows}{Assets}{}_j$	-0.138***	-0.199***	-0.046	-0.060***	-0.096***	-0.015	-0.138***	-0.212***	-0.046*
	(0.031)	(0.033)	(0.029)	(0.020)	(0.022)	(0.028)	(0.036)	(0.040)	(0.027)
Post*Book $Leverage_j$	-0.037*	-0.096***	0.027	-0.026	-0.077***	0.024	-0.033	-0.083***	0.018
	(0.019)	(0.021)	(0.023)	(0.020)	(0.025)	(0.025)	(0.023)	(0.025)	(0.025)
Post*Tobins Q_j	0.127***	0.163***	0.093***	0.125***	0.144***	0.103***	0.111***	0.157***	0.069**
	(0.022)	(0.042)	(0.023)	(0.020)	(0.036)	(0.024)	(0.025)	(0.040)	(0.027)
Firm Type	All	Goods	Services	All	Goods	Services	All	Goods	Services
R^2	.925	.927	.922	.927	.930	.923	.914	.92	.907
Observations	50960	28589	22371	51043	28672	22371	48420	26848	21572
Unique Firms	4505	2336	2169	4506	2337	2169	4350	2234	2116

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

	Ln($\text{Employment}_\text{j}$)			Ln(PPE_j)			Ln($\text{Intangibles}_\text{j}$)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post*$\text{AAR}_\text{j}{}^{PNTR}$	0.097***	0.085***	0.101***	0.091***	0.111***	0.060	0.060***	0.052***	0.061**
	(0.018)	(0.022)	(0.030)	(0.024)	(0.025)	(0.037)	(0.019)	(0.019)	(0.030)
Post*PPE per Worker_j	0.036*	0.103***	-0.006	-0.061	0.013	-0.130***	0.010	0.072**	-0.012
	(0.020)	(0.022)	(0.027)	(0.045)	(0.065)	(0.025)	(0.025)	(0.028)	(0.034)
Post*Ln(Mkt $\text{Cap})_\text{j}$	-0.069***	-0.091***	-0.063***	-0.075***	-0.117***	-0.033	-0.021	-0.058***	0.011
	(0.015)	(0.017)	(0.024)	(0.025)	(0.030)	(0.025)	(0.019)	(0.016)	(0.038)
Post*$\frac{CashFlows}{Assets}{}_\text{j}$	-0.025	-0.056***	0.032	-0.031*	-0.043**	-0.005	-0.037*	-0.062***	0.005
	(0.020)	(0.018)	(0.027)	(0.016)	(0.019)	(0.027)	(0.021)	(0.018)	(0.031)
Post*Book Leverage_j	-0.052***	-0.091***	-0.011	-0.049**	-0.108***	0.023	-0.049***	-0.077***	-0.027
	(0.018)	(0.021)	(0.025)	(0.021)	(0.026)	(0.024)	(0.017)	(0.022)	(0.024)
Post*Tobins Q_j	0.117***	0.167***	0.080***	0.169***	0.230***	0.129***	0.189***	0.232***	0.146***
	(0.015)	(0.027)	(0.016)	(0.027)	(0.042)	(0.028)	(0.033)	(0.029)	(0.048)
Firm Type	All	Goods	Services	All	Goods	Services	All	Goods	Services
R^2	.936	.941	.927	.944	.949	.939	.919	.943	.891
Observations	50840	28669	22171	51052	28853	22199	48449	28195	20254
Unique Firms	4511	2343	2168	4511	2343	2168	4389	2309	2080

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

	Ln($\mathrm{Sales_j}$)	Ln($\mathrm{COGS_j}$)	Ln($\mathrm{Profit_j}^{OP.}$)	Ln($\mathrm{Employment}_j$)	Ln(PPE_j)	Ln($\mathrm{K}_j^{Int.}$)
			Panel A			
Post*NTR $\mathrm{Gap_j}$	-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 $\mathrm{Gap_j}^{Up3}$	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 $\mathrm{Gap_j}^{Down3}$	-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*$\mathrm{AAR_j}^{PNTR}$	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 $\mathrm{Gap_j}$	-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 $\mathrm{Gap_j}^{Up3}$	-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 $\mathrm{Gap_j}^{Down3}$	-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 9: Service 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$_j^{Up3}$	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 Gap$_j^{Down3}$	-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*AAR$_j^{PNTR}$	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 Gap$_j^{Up3}$	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 Gap$_j^{Down3}$	-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 10: Cumulative Relative Effects by Sector

Sector	Profit	Employment	PPE	Intangibles	Firms
(11) Agriculture	-32	-2	-38	-27	15
(21) Mining	1,108	1	4,423	6	138
(22) Utilities	112	1	53	41	91
(23) Construction	-163	-12	22	-186	69
(31-3) Manufacturing	10,953	-122	463	2,229	2,035
(42) Wholesale	-90	0	-52	-236	204
(44-5) Retail	-3,796	-151	-2,327	-2,165	290
(48-9) Transportation	-272	-11	-54	-168	116
(51) Information	-2,356	-40	-8,474	-5,315	511
(52-3) FIRE	-864	11	-1,800	-225	349
(54) Professional	1,331	13	1,115	360	283
(56) Administrative	143	-39	626	81	119
(61) Educational	-12	-1	-6	-8	22
(62) Health Care	171	48	761	-83	97
(71) Entertainment	27	-2	-19	11	33
(72) Accomodation	-7	-8	-43	-85	123
(81) Other	-105	-7	-65	-222	24
(92) Public	1	0	2	0	1

Source: CRSP, COMPUSTAT and authors' calculations. Each cell in the table reports the cumulative predicted relative change in each outcome across firms whose largest business segment is in the noted 2-digit NAICS sector. The prediction for each firm is, e.g., $\Delta^{2000-6}\widehat{Op\,Profit_j} = \hat{\delta} \times AAR_j^{PNTR} \times Op\,Profit_j^{2000}$, where the first term is the estimated DID coefficient for goods or service firms from Table 6 (in non-standardized form), the second term is the firm's average abnormal PNTR return and the final term is firm's operating profit in 2000, prior to PNTR. We similarly construct predicted values for employment, PPE, and intangible capital. We note that all firms are included in this cumulative total, including those that may subsequently have been de-listed. Employment is reported in thousands, Operating Profit, PPE, and Intangibles are in millions.

Online Appendix (Not for Publication)

This online appendix contains additional empirical results as well as more detailed explanations of data used in the main text.

A The NTR Gap

Figure A.2 reports the distribution of the 1999 $NTRGap_i$ across goods-producing industries. Figure A.3 compares firms' AAR_j^{PNTR} to their business segment weigthed average $NTRGap_j$.

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

$$AAR_j^{Belgrade} = \delta NTR\,Gap_j + X_j\gamma + \epsilon_i, \tag{A.1}$$

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}.

B AAR_j^e and the NTR Gap

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

$$AAR_j^e = \delta NTR\,Gap_j + \epsilon_{ji}. \tag{A.2}$$

Resuls 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.[44]

C 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 ten-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

[44] 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.

then used as the weights to calculate the time varying exposure discussed above.

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.[45] As a consequence, his surprise victory offers another opportunity to examine the external validity of AAR_j^{PNTR}. Here, however, we conduct the analysis at the industry level given the degree of firm attrition and industry-switching that occurs between 2000 and 2016. We compare the market capitalization weighted average AAR_j^{PNTR} across firms' major industries, AAR_i^{PNTR}, to similarly constructed returns in the seven days[46] following the election, AAR_i^{Trump}, using an OLS specification of the form

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

As above, i indexes 6-digit NAICS industries, all variables are de-meaned and divided by their standard deviations, and standard errors are clustered at the four-digit NAICS level.[47]

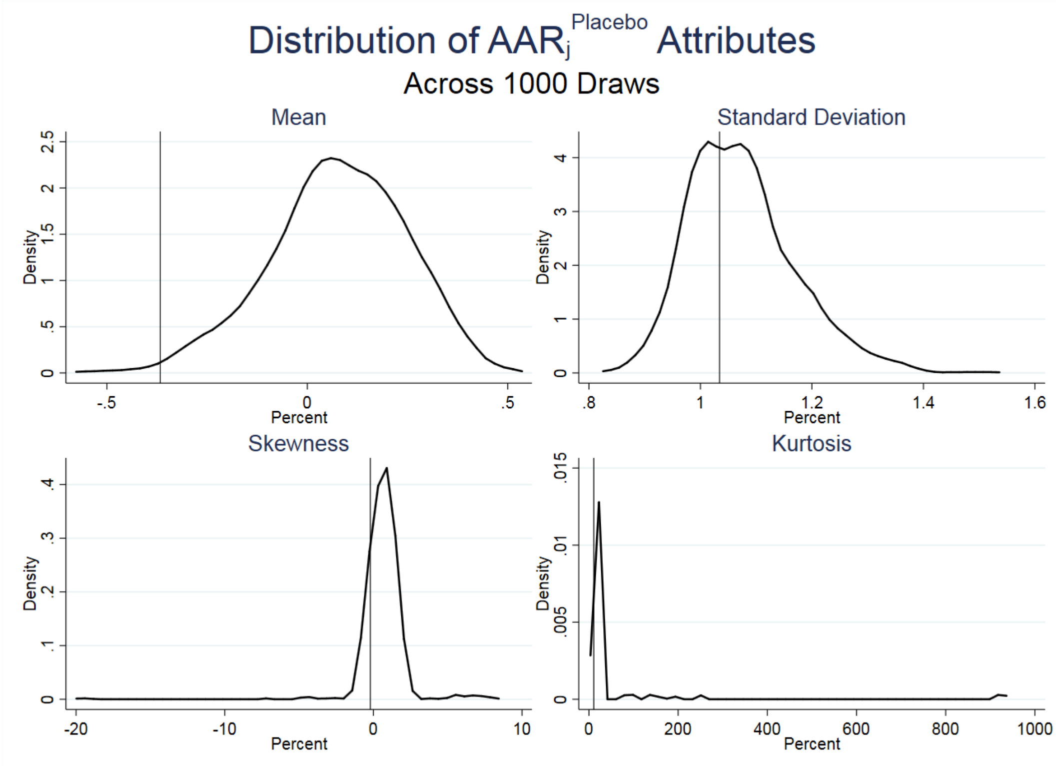
Results, reported in Table A.3, are consistent with the idea that industries whose expected profits might rise with PNTR are those whose profits might fall with Trump's election. That is, we find a negative and statistically significant relationship between AAR_i^{PNTR} and AAR_i^{Trump}, where the coefficient 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.

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

[46]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/).

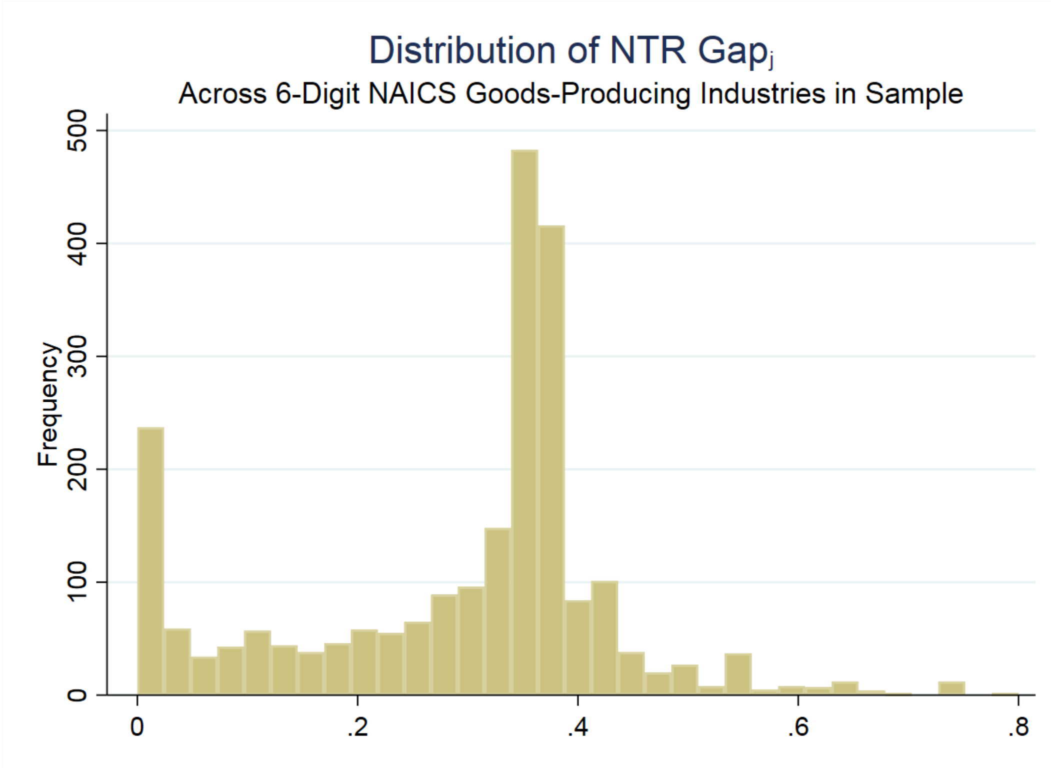
[47]These attributes are for 2000 and are drawn from COMPUSTAT. They represent market capitalization weighted averages of each attribute across firms within each six-digit NAICS industry. As before, all accounting ratios derived from COMPUSTAT are winsorized at the 1 percent level.

Figure A.1: $AAR_i^{Placebo}$ Attributes



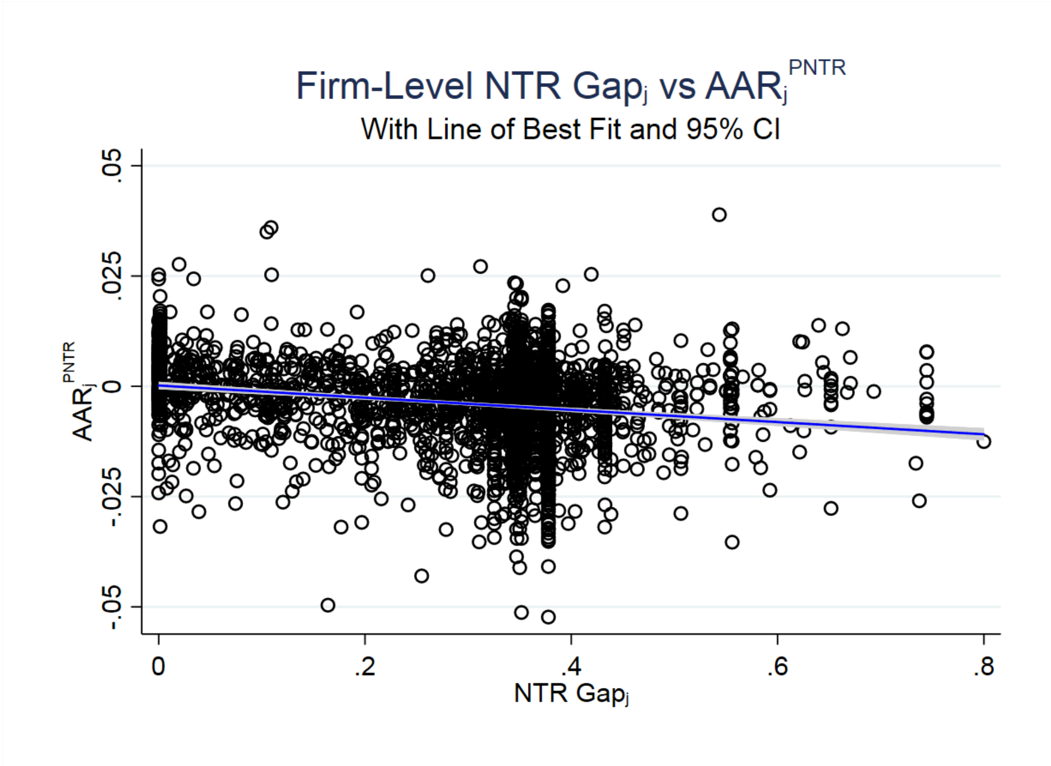
Source: Source: CRSP, COMPUSTAT and authors' calculations. Each panel plots the distribution of a different statistic summarizing each of the 1000 draws of $AAR_i^{Placebo}$. Skewness is computed as $m_3 m_2^{-3/2}$, where m_r is r_{th} moment about the mean, i.e., : $m_r = \frac{1}{n}\sum(x_i - \bar{x})^r$. Kurtosis, which captures the "peakedness" of a distribution, is defined as $m_4 m_2^{-2}$. Symmetric distributions have skewness 0, and flatter distributions have smaller kurtosis.

Figure A.2: Distribution of the NTR Gap



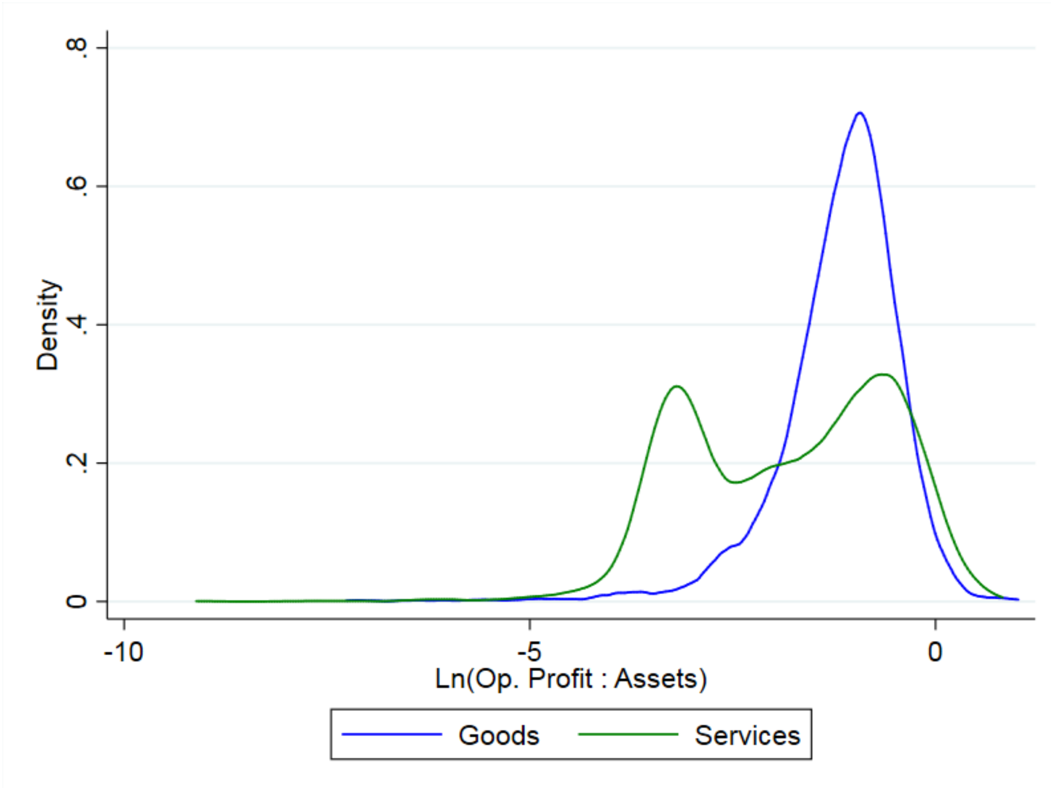
Source: Feenstra et al. (2002) and Pierce and Schott (2016). Figure displays the distribution of $NTRGap_i^{Own}$ across goods-producing 6-digit manufacturing industries populated by firms in our sample. Goods-producing sectors are defined as: Manufacturing (NAICS 31-33), Mining (NAICS 21), and Agriculture,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

Figure A.3: AAR_i^{PNTR} versus $NTRGap_j^{Own}$



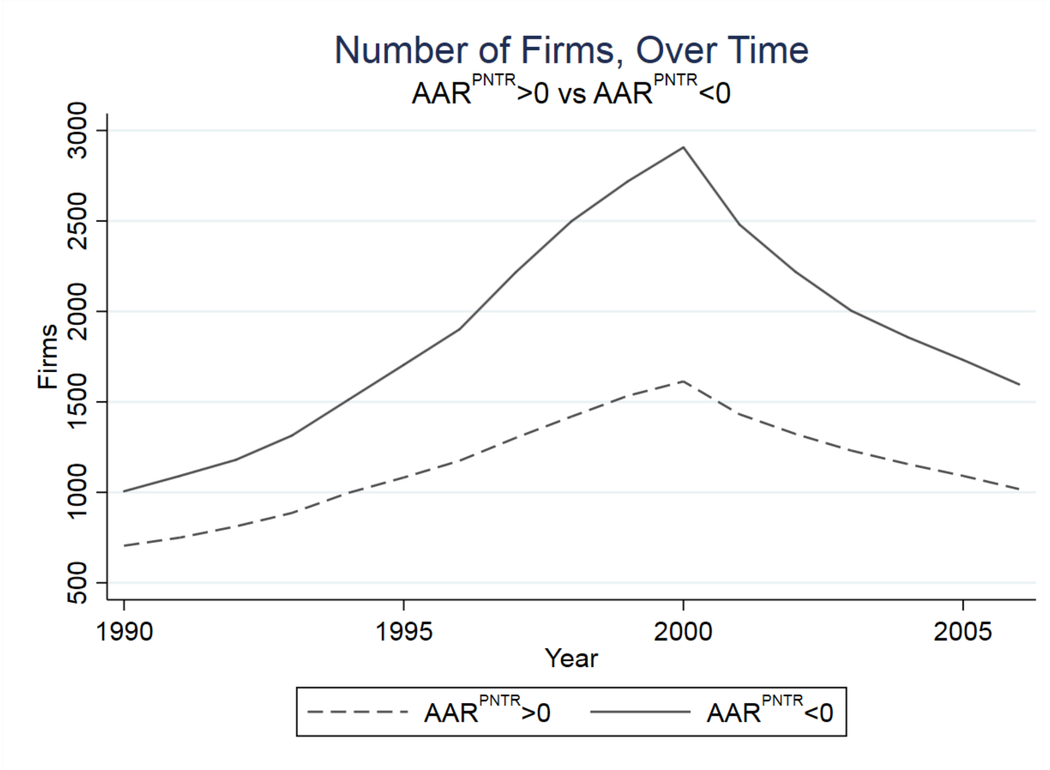
Source: Feenstra et al. (2002), Pierce and Schott (2016), CRSP and authors' calculations. Figure compares firms' AAR_i^{PNTR} to their business segment weighted average $NTRGap_j$.

Figure A.4: Distribution of Ln($\frac{OperatingProfit}{Assets}$) by Firm Type in 2000



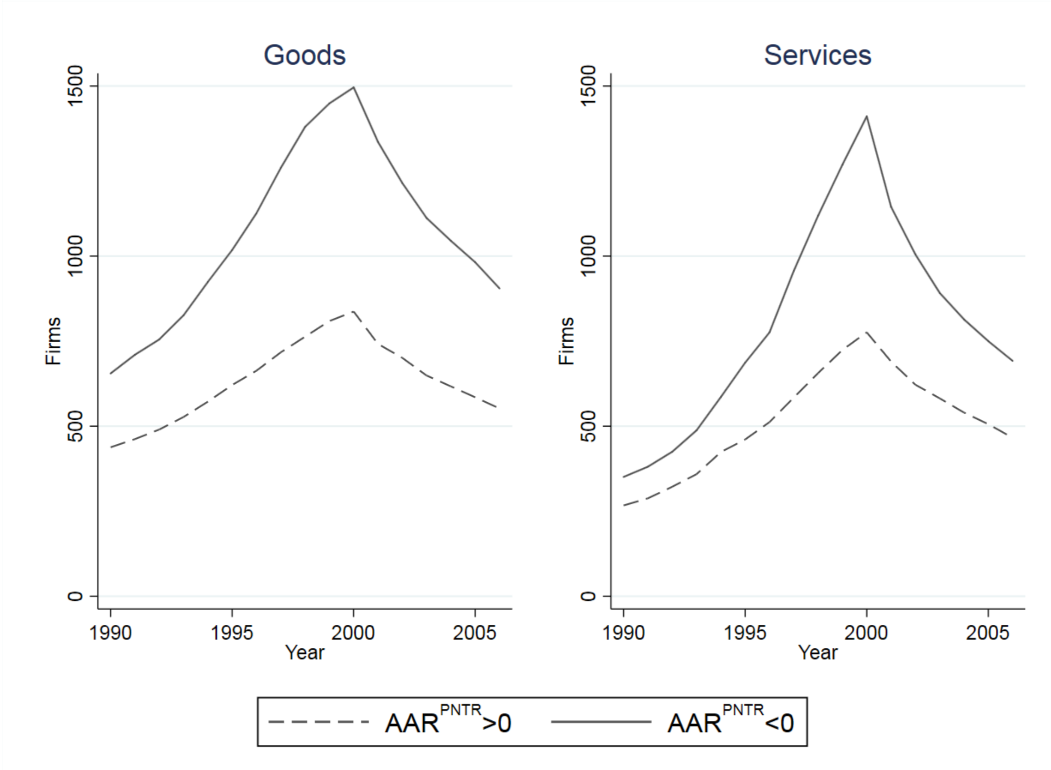
Source: CRSP, COMPUSTAT and authors' calculations. Figure displays the distribution of firm-level Ln($\frac{OperatingProfit}{Assets}$) among all goods and service producing firms in our sample in the year 2000. Goods firms have a business segment active in NAICS sectors 11, 21 and 3X. Service firms have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

Figure A.5: Number of Firms in Sample, by Year"



Source: CRSP, authors' calculations. Figure displays the number of firms included in our baseline sample, by year. The increase in firms up to 2000 is driven by entry, while the decline in firms after 2000 is driven by exit. There is no exit prior to 2000, and no entry after 2000 given that firms must be present in 2000 in order to estimate AAR_j^{PNTR}.

Figure A.6: Number of Goods vs Service Firms in Sample, by Year"



Source: CRSP, COMPUSTAT and authors' calculations. Figure displays the number of firms included in our baseline sample, by year. Goods firms have a business segment active in NAICS sectors 11, 21 and 3X. Service firms have no business segments in these sectors The increase in firms up to 2000 is driven by entry, while the decline in firms after 2000 is driven by exit. There is no exit prior to 2000, and no entry after 2000 given that firms must be present in 2000 in order to estimate AAR_j^{PNTR}.

Table A.1: AAR_j^{PNTR} versus the NTR Gap

	(1) $\mathrm{AAR_j}^{HouseIntro}$	(2) $\mathrm{AAR_j}^{HouseVote}$	(3) $\mathrm{AAR_j}^{SenateCloture}$	(4) $\mathrm{AAR_j}^{SenateVote}$	(5) $\mathrm{AAR_j}^{Clinton}$	(6) $\mathrm{AAR_j}^{PNTR}$
NTR $\mathrm{Gap_j}$	-0.017	-0.133***	-0.125***	-0.020	-0.193***	-0.200***
	(0.039)	(0.048)	(0.030)	(0.024)	(0.047)	(0.053)
Constant	0.113***	-0.081	-0.054	-0.010	-0.005	-0.021
	(0.034)	(0.062)	(0.044)	(0.025)	(0.042)	(0.057)
Observations	2311	2311	2311	2311	2311	2311
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 key PNTR legislative milestones on $NTR\,Gap_j$. The regression sample is restricted to firms in goods-producing industries,i.e., NAICS sectors 11, 21 and 3X.. All variables are de-meaned and divided by their standard deviation. Standard errors are reported below coefficient estimates and are clustered by 4-digit NAICS industries. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.

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

	(1) $\text{AAR}_\text{j}{}^{Belgrade}$	(2) $\text{AAR}_\text{j}{}^{Belgrade}$	(3) $\text{AAR}_\text{j}{}^{Belgrade}$
NTR Gap_j	0.073**	0.103***	0.072**
	(0.031)	(0.032)	(0.031)
$\text{NTR Gap}_\text{j}{}^{Up3}$		-0.083***	-0.083***
		(0.028)	(0.026)
$\text{NTR Gap}_\text{j}{}^{Down3}$		-0.077**	-0.067**
		(0.032)	(0.031)
$\text{Ln(PPE per Worker)}_\text{j}$			-0.016
			(0.036)
$\text{Ln(Mkt Cap)}_\text{j}$			-0.123***
			(0.036)
$\frac{CashFlows}{Assets}{}_\text{j}$			0.016
			(0.026)
$\text{Book Leverage}_\text{j}$			-0.034
			(0.026)
Tobins Q_j			0.147***
			(0.050)
Constant	0.001	0.056	0.079**
	(0.043)	(0.044)	(0.037)
Observations	2192	2192	2192
R^2	0.004	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 co-variates 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) $\text{AAR}_{\text{i}}{}^{Trump}$	(2) $\text{AAR}_{\text{i}}{}^{Trump}$	(3) $\text{AAR}_{\text{i}}{}^{Trump}$
$\text{AAR}_{\text{i}}{}^{PNTR}$	-0.135**	-0.225***	-0.040
	(0.054)	(0.077)	(0.069)
Constant	0.020	0.007	0.031
	(0.059)	(0.083)	(0.082)
Observations	375	202	173
R^2	0.017	0.043	0.002
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: AAR_j^{PNTR} versus the NTR Gap: Alternate Samples

	(1) $\text{AAR}_\text{j}{}^{PNTR:[-1,1]}$	(2) $\text{AAR}_\text{j}{}^{PNTR:Non-Confounding}$	(3) $\text{AAR}_\text{j}{}^{PNTR:3-Factor}$
NTR Gap_j	-0.159***	-0.138***	-0.183***
	(0.043)	(0.034)	(0.051)
Constant	-0.014	-0.006	-0.026
	(0.041)	(0.038)	(0.049)
Observations	2333	2317	2333
R^2	0.027	0.024	0.034

Source: CRSP and authors' calculations. This table presents firm-level OLS regressions of average abnormal returns during PNTR on the NTR Gap. Each column employs either a different sample or calculation of abnormal returns. The regression sample is restricted to firms in goods-producing industries. 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.5: 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	59
580	Delisted by current exchange - delinquent in filing, non-payment of fees.	Contraction/Bankruptcy	60
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	103
584	Delisted by current exchange - does not meet exchange's financial guidelines for continued listing.	Contraction/Bankruptcy	197
552	Delisted by current exchange - price fell below acceptable level.	Contraction/Bankruptcy	234
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	565
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	58
570	Delisted by current exchange - company request (no reason given).	Other	65
-	-	Survivor	2555

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.6: 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$_j^{PNTR}$	0.127***	0.145***	0.094***	0.104***	0.095***	0.102***	0.129***	0.144***	0.096***
	(0.026)	(0.037)	(0.031)	(0.020)	(0.024)	(0.028)	(0.025)	(0.026)	(0.035)
$\overline{Post * AAR_j^{PNTR}}$	0.119	0.138	0.085	0.097	0.089	0.093	0.117	0.134	0.086
Post*PPE per Worker$_j$	0.054	0.150***	-0.015	0.046	0.130**	-0.005	0.036	0.151**	-0.041
	(0.039)	(0.058)	(0.029)	(0.034)	(0.054)	(0.024)	(0.044)	(0.059)	(0.031)
$\overline{Post * PPEperWorker_j}$	0.049	0.127	-0.016	0.041	0.109	-0.007	0.029	0.127	-0.038
Post*Ln(Mkt Cap)$_j$	-0.067***	-0.092***	-0.058**	-0.075***	-0.099***	-0.067**	-0.072***	-0.106***	-0.054**
	(0.022)	(0.028)	(0.030)	(0.020)	(0.026)	(0.026)	(0.024)	(0.028)	(0.026)
$\overline{Post * Ln(MktCap)_j}$	-0.063	-0.082	-0.056	-0.071	-0.089	-0.065	-0.068	-0.095	-0.054
Post*$\frac{CashFlows}{Assets}_j$	-0.138***	-0.199***	-0.046	-0.060***	-0.096***	-0.015	-0.138***	-0.212***	-0.046*
	(0.034)	(0.038)	(0.031)	(0.022)	(0.026)	(0.030)	(0.035)	(0.042)	(0.027)
$\overline{Post * \frac{CashFlows}{Assets}}$	-0.134	-0.193	-0.045	-0.058	-0.093	-0.013	-0.134	-0.203	-0.045
Post*Book Leverage$_j$	-0.037*	-0.096***	0.027	-0.026	-0.077***	0.024	-0.033	-0.083***	0.018
	(0.020)	(0.022)	(0.024)	(0.021)	(0.025)	(0.026)	(0.023)	(0.026)	(0.024)
$\overline{Post * BookLeverage_j}$	-0.037	-0.097	0.025	-0.026	-0.077	0.023	-0.032	-0.081	0.016
Post*Tobins Q$_j$	0.127***	0.163***	0.093***	0.125***	0.144***	0.103***	0.111***	0.157***	0.069**
	(0.024)	(0.045)	(0.026)	(0.022)	(0.041)	(0.026)	(0.025)	(0.041)	(0.030)
$\overline{Post * TobinsQ_j}$	0.128	0.164	0.098	0.125	0.146	0.106	0.113	0.156	0.073
Observations	50960	28589	22371	51043	28672	22371	48420	26848	21572
Unique Firms	4505	2336	2169	4506	2337	2169	4350	2234	2116

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 6.5. 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 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.7: 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}	0.097***	0.085***	0.101***	0.091***	0.111***	0.060*	0.060***	0.052***	0.061**
	(0.019)	(0.023)	(0.029)	(0.023)	(0.025)	(0.034)	(0.018)	(0.018)	(0.028)
$\overline{Post * AAR_j{}^{PNTR}}$	0.091	0.083	0.090	0.084	0.103	0.054	0.054	0.049	0.053
Post*PPE per Worker$_j$	0.036*	0.103***	-0.006	-0.061	0.013	-0.130***	0.010	0.072**	-0.012
	(0.020)	(0.024)	(0.028)	(0.044)	(0.069)	(0.026)	(0.026)	(0.031)	(0.033)
$\overline{Post * PPEperWorker_j}$	0.035	0.097	-0.005	-0.068	-0.014	-0.131	0.005	0.061	-0.012
Post*Ln(Mkt Cap)$_j$	-0.069***	-0.091***	-0.063**	-0.075***	-0.117***	-0.033	-0.021	-0.058***	0.011
	(0.015)	(0.018)	(0.025)	(0.024)	(0.030)	(0.026)	(0.020)	(0.017)	(0.038)
$\overline{Post * Ln(MktCap)_j}$	-0.067	-0.087	-0.060	-0.071	-0.104	-0.032	-0.020	-0.054	0.010
Post*$\frac{CashFlows}{Assets}_j$	-0.025	-0.056**	0.032	-0.031*	-0.043**	-0.005	-0.037*	-0.062***	0.005
	(0.022)	(0.023)	(0.030)	(0.018)	(0.022)	(0.028)	(0.022)	(0.022)	(0.031)
$\overline{Post * \frac{CashFlows}{Assets}}$	-0.022	-0.052	0.033	-0.029	-0.041	-0.003	-0.031	-0.055	0.006
Post*Book Leverage$_j$	-0.052***	-0.091***	-0.011	-0.049**	-0.108***	0.023	-0.049***	-0.077***	-0.027
	(0.018)	(0.021)	(0.026)	(0.022)	(0.026)	(0.025)	(0.017)	(0.022)	(0.023)
$\overline{Post * BookLeverage_j}$	-0.052	-0.092	-0.013	-0.048	-0.107	0.020	-0.048	-0.075	-0.027
Post*Tobins Q$_j$	0.117***	0.167***	0.080***	0.169***	0.230***	0.129***	0.189***	0.232***	0.146***
	(0.016)	(0.032)	(0.019)	(0.028)	(0.047)	(0.030)	(0.035)	(0.034)	(0.049)
$\overline{Post * TobinsQ_j}$	0.118	0.172	0.082	0.172	0.233	0.136	0.193	0.234	0.150
Observations	50840	28669	22171	51052	28853	22199	48449	28195	20254
Unique Firms	4511	2343	2168	4511	2343	2168	4389	2309	2080

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 6.5. 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 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.