Trade Policy Uncertainty and Stock Returns*

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Abstract

This paper documents new stylized facts on the effects of trade policy uncertainty on stock returns. We exploit quasi-exogenous variation in exposure to policy uncertainty arising from annual votes by US Congress to revoke China's MFN tariff rates between 1990 and 2000. Before the uncertainty was resolved by granting China permanent MFN rates, US manufacturing industries highly exposed to trade policy uncertainty had stock returns 10.4% higher per year than less exposed sectors. We argue that this difference in average returns is a risk premium for exposure to trade policy uncertainty. Indirect exposure to trade policy uncertainty through Input-Output linkages also commands a substantial risk premium.

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1 Introduction

The recent escalation in threats of a trade war between US and China has brought trade policy uncertainty to the forefront of the economic and policy debate. Figure 1 shows that average trade policy uncertainty in the US was more than six times higher in 2018 than in 2015.[1]

In this paper, we estimate the effect of trade policy uncertainty on US firms' stock returns. We focus on the uncertainty arising from annual votes by Congress to revoke China's ''Most Favored Nation'' (MFN) status between 1990 and 2000. Starting in 1980, US imports from China were subject to the relatively low Normal Trade Relations (NTR), or equivalently MFN tariff rates reserved for WTO members, even though China was not a member of the WTO. This required annual renewals by Congress, which were essentially automatic until the Tiananmen Square Crackdown in 1989. Starting in 1990, NTR renewal in Congress became more politically contentious, with the House passing resolutions against Chinese MFN renewal in 1991 and 1992.[2] Had NTR status been revoked, tariffs would have reverted to the higher non-NTR rates, established under the Smoot-Hawley Tariff Act of 1930.[3] Granting China Permanent Normal Trade Relations (PNTR), which eliminated the need for annual votes on NTR renewal, removed the threat of substantial U.S. import tariff increases on Chinese goods.

We argue that these Congressional annual votes generated uncertainty because (i) investors were uncertain about whether the NTR status would have been revoked or not, and (ii) they were uncertain about the future performance of US industries after (and if) NTR would have been revoked. We follow Pierce and Schott (2016), and quantify this uncertainty via the "NTR gap," defined as the difference between the non-NTR rates, to which tariffs would have risen if annual renewal had failed, and the NTR tariff rates. Our difference-in-differences identification strategy exploits the large cross-sectional variation in the NTR gaps before China was granted PNTR. The identification rests on the fact that 79% of the variation in the NTR gaps comes from variation in non-NTR rates, set by the Smoot-Hawley act in 1930, which are likely exogenous to the US industries' stock returns in the years around 2000.

Our baseline empirical analysis uses industry-year level stock returns between 1990 and 2007. We find that US manufacturing industries more exposed to tariff uncertainty, i.e. industries that before PNTR had a high gap between non-NTR and NTR rates, experienced significantly higher stock returns than less exposed industries before the policy change. We

[1] The figure is based on the Trade Policy Uncertainty index constructed by Baker et al. (2016).

[2] China's tariff status, however, did not change because the US Senate did not pass the House resolutions.

[3] In 2000, the average MFN tariff rate was 4 percent, but had China lost its MFN status, it would have faced an average tariff of 31 percent - see Handley and Limão (2017).

control for industry-time variation in firm fundamentals, as well as other US-China policy changes, such as the expiration of the global Multi- Fiber Arrangement (MFA), which governed Chinese textile and clothing export quotas, and the reduction in Chinese import tariffs associated with China's accession to WTO. For an industry at the average NTR gap, the baseline specification implies an 11.9% higher average return during the period of annual MFN votes, relative to hypothetical industry with a zero NTR gap. We also perform a portfolio analysis, along the lines of Fama and French (1993) and Barrot et al. (2018), which shows that, even after conditioning on the 5 factors in Fama and French (2015), the portfolio of stocks with the highest NTR gaps experienced a significantly lower average return after the policy change than the portfolio with the lowest NTR gaps.

We argue that the higher average returns that high gap industries experienced before China was granted PNTR is a risk premium for bearing tariff uncertainty. In fact, our results can be rationalized by the Pástor and Veronesi (2013) model, where the political costs of any policy action are uncertain, and thus investors must be compensated for risk associated with uncertainty about government policy choices. We examine stock returns in both the decades before 1990 and in the decade after 2000, and find that highly exposed industries had higher average returns only between 1990 and 2000, the decade characterized by tariff uncertainty. We also show that other potential explanations for the difference in average returns, which include i) expected poor performance of high-gap firms after PNTR, ii) a series of positive shocks, and iii) compensation for uncertainty associated with the timing of PNTR, cannot be consistent with the empirical evidence.

There is an extensive literature that attempts to empirically assess how policy uncertainty is priced into stocks and options (see e.g. Pastor and Veronesi (2012), Pástor and Veronesi (2013), Brogaard and Detzel (2015) and Kelly et al. (2016)). We have three major contributions to this literature. First, our paper exploits quasi-exogenous variation in the NTR gaps, which is an appealing identification strategy because it relies on non-NTR tariff rates that were set 70 years before the implementation of the policy. Aside from satisfying exogeneity, this has the additional advantage of being an *ex-ante* measure of uncertainty, rather than an ex-post measure, which may introduce a look-ahead bias. Ex-ante measures of uncertainty, such as the expected variance risk premium, are typically not directly observable, and thus their construction relies on strong assumptions on the underlying volatility processes, or on the agents' objective functions.[4] Furthermore, because the NTR gaps are directly observable,

[4]Suppose, for example, that one is interested in computing the expected variance risk premium. The widely-used method in Carr and Wu (2008) uses ex-post realized variance as a proxy for ex-ante expected variance, introducing a look-ahead bias. Other ways of avoiding a look ahead bias involve using past volatility data, see e.g. Bollerslev et al. (2009), which uses lagged volatility as a measure of expected future volatility. This relies on the strong assumption that volatility follows a martingale under the P measure.

there is no measurement error involved when constructing industries' exposure to uncertainty.

Second, we combine the long-run analysis with an event study methodology to decompose the differences in returns between high and low gap industries into a realized and an expected component. To this end, we run regressions of stock returns in a tight window around the dates of i) PNTR-related policy announcements, ii) Congressional votes to revoke China's MFN status, iii) firms' earnings announcements. We find that: i) On 10/10/2000, when President Clinton signed the law to grant China PNTR, conditional on joining the WTO, high-gap firms experienced substantially lower returns than low gap firms; ii) on other PNTR-related event dates, like China joining the WTO, or PNTR actually going into effect, there was no significant difference between the returns of high and low gap firms; iii) the response of high gap stocks to Congressional votes to revoke and not revoke MFN status was mixed; iv) high gap firms had lower returns around earnings announcement dates, relative to low gap firms, in the post-PNTR period, suggesting that investors initially under-estimated the impact of the policy on these industries. To evaluate whether our results are driven by the slow reaction of investors to PNTR or by stock prices responses to policy-related news, we re-run the main specification but exclude a 5-7 day window around each of these event days when computing annual stock returns. While this slightly attenuates our results, we still find a large risk premium of 10.4%.

Third, we show that also *indirect* exposure to trade policy uncertainty through domestic and international IO linkages is correlated with average returns during the tariff uncertainty period. We construct three measures of linkages in production that may affect each industry's exposure to trade policy uncertainty. The first, "China Upstream Exposure", is a weighted average of the NTR gaps of the sectors from which an industry is sourcing inputs from China. Uncertainty about future tariffs applied to intermediate products sourced from China may generate uncertainty on production costs. The second, "Downstream exposure" as in Acemoglu et al. (2016), is a weighted average of the NTR gaps of the downstream purchasers of an industry's output, while the third, "Upstream exposure", is a weighted average of the NTR gap of the upstream suppliers of each industry. We find that US industries which were more reliant on higher NTR-gap sectors in China, and from higher NTR-gap sectors in general, earned higher returns before PNTR. Therefore, sourcing a large fraction of inputs from industries highly exposed to tariff uncertainty affects the perceived uncertainty of an industry's production costs and thus uncertainty in general, affecting its expected return. On the other hand, downstream exposure to tariff uncertainty does not significantly affect average returns.

Our paper is complementary to the empirical literature that investigates the effect of trade policy uncertainty on *current* economic outcomes, such as Carballo et al. (2014), Handley and

Limao (2015), Handley and Limão (2017), Pierce and Schott (2016), Feng et al. (2017) and Crowley et al. (2018). Our contribution is to assess how tariff uncertainty affects investors' expectations of *future* risk and cash flows, which in turn affect firms' stock returns. Related to our paper, Huang et al. (2018) analyze the impact of the potential trade war between US and China in 2018 on stock returns. Griffin (2018) focuses on the effect of PNTR on stock returns of small vs large manufacturing firms. Greenland et al. (2019) use the reaction of stock returns to PNTR to create a firm-level measure of exposure to trade liberalization.

We also contribute to the recent literature on how China's accession to WTO, and specifically the granting of PNTR, has affected the US economy.[5] Pierce and Schott (2016) have shown that industries more exposed to PNTR experienced a relative decline in employment, while Pierce and Schott (2017) find that greater exposure to PNTR was associated with a relative decline in investment. Based on this empirical evidence, however, predicting the effect of the PNTR on stock returns is not obvious a priori. On one hand, lower employment and investment suggests that US firms suffered from competition with Chinese firms, implying lower future profits, higher riskiness, and thus lower returns. On the other hand, the decline in employment was partially the result of increased job off-shoring and use of capital-intensive technologies, which lowered production costs and could have increased expected profits and returns.

Our work also contributes to the trade literature that studies the impact of input-output linkages on economic outcomes, such as Caliendo and Parro (2014), Blaum et al. (2015), Acemoglu et al. (2016), and Antras et al. (2017). Our contribution is to measure the effect of these production linkages on stock returns in presence of trade policy uncertainty.

Finally, we also contribute to the body of literature that studies the effects of economic uncertainty on financial markets. Boguth and Kuehn (2013) find that sensitivity of firms' cash flow to economic uncertainty explains cross sectional variation in firms' expected returns. Bansal et al. (2014) show that time varying economic uncertainty explains the joint dynamics of returns on equity and human capital. Barrot et al. (2018) focus on risks associated with import competition and find that firms more exposed to import competition command a sizeable positive risk premium. Fillat and Garetto (2015) document that multinational firms exhibit higher excess returns than purely domestic firms. To our knowledge, we are the first to link trade policy uncertainty to firms' stock returns.

The paper proceeds as follows. Section 2 shows the key empirical evidence of the impact of removal of tariff uncertainty on expected and realized stock returns. Section 3 extends the

[5] Recent papers studying the impact of Chinese competition on the US include Autor et al. (2013), Caliendo et al. (2015) and Adao et al. (2018), among others. Coelli (2018) studies the impact of PNTR on innovation by Chinese firms.

analysis to examine the role on input-output linkages in affecting stock returns. Section 4 provides extensive discussion of the empirical results and Section 5 concludes.

2 Tariff Uncertainty and US Stock Returns

In this section, we use quasi-experimental variation in exposure to tariff uncertainty to identify the causal effect of trade policy uncertainty on stock returns.

2.1 Data and identification strategy

Starting in 1980, US imports from China were subject to the relatively low Normal Trade Relations (NTR) tariff rates reserved for members of the World Trade Organization (WTO). From 1980 to 1989, renewal of these NTR rates for China was essentially automatic. After the Tiananmen Square incident in 1989, however, the US House of Representatives introduced and voted on legislation to revoke China's temporary NTR status every year from 1990 to 2001. If Congress had failed to roll over the NTR rates, import tariffs on Chinese goods would have reset to the higher rates established in the Smoot-Hawley Tariff Act of 1930. Finally, in October 2000, the United States granted China Permanent Normal Trade Relations (PNTR) conditional on China joining the WTO. China joined the WTO at the end of 2001, and PNTR went into effect at the start of 2002. Granting China PNTR *permanently* removed tariff uncertainty by fixing US taxes on Chinese imports at NTR levels.

Following Pierce and Schott (2016), we quantify the transition from annual renewal to permanent normal trade relations via the "NTR gap", defined as the difference between the NTR and non-NTR rates to which tariffs would have risen if annual renewal had failed:

$$NTRGap_i = NonNTR_i - NTR_i \tag{1}$$

Our identification relies on the fact that, as argued in Pierce and Schott (2016), 79% of the variation in the NTR gap across industries arises from variation in non-NTR rates, set 70 years prior to passage of PNTR. This feature of non-NTR rates rules out reverse causality that would arise if non-NTR rates could be set to protect struggling industries.

Our difference-in-differences identification strategy exploits the large cross-sectional variation in the NTR gap before China was granted PNTR. We compare the relative performance of US manufacturing firms in high NTR gap industries to low NTR gap industries (first difference), before and after the policy change was implemented (second difference). [6] We

[6] Pierce and Schott (2016) compute NTR gaps using ad-valorem equivalent NTR and non-NTR tariff rates from 1989 to 2001 provided by Feenstra et al. (2002). Both types of tariffs are set at the eight-digit

use the NTR gaps in 1999 computed by Pierce and Schott (2016), because 1999 was the last year before China was granted PNTR. In 1999, the average NTR gap across industries was 0.29 with a standard deviation of 0.156. Its distribution is displayed in Figure 2.

In order to have time-consistent industry definitions for tracking stock returns and other controls over our sample period, we use the algorithm developed in Pierce and Schott (2012) to create "families" of four-digit SIC industries. Unless otherwise noted, all references to "industry" in this paper refer to these families.

To compute industry-level stock returns, we start with the universe of publicly listed US firms in CRSP that can be matched to Compustat. We then filter for ordinary common shares traded on major exchanges (NYSE, AMEX and NASDAQ). We match the SIC code in Compustat to the Pierce and Schott (2012) families of industries and only keep the matched firms.[7] Each month, we construct value-weighted portfolios at the industry level, where the weights are proportional to each firm's lagged market capitalization. We value-weight the portfolios to reduce the influence of small firms. We then compound these monthly returns to compute the annual returns. Table 1 reports some summary statistics about our sample in 1989 and 1999. We can see that low gap industries were, at the beginning of the sample, larger than high-gap industries, while they had the same market capitalization in 1999, when the PNTR was implemented.

2.2 PNTR and Expected Returns

To estimate the effect of trade policy uncertainty on expected returns, we run the following regression at the US industry/year level:

$$R_{it} = \theta PostPNTR_t \times NTRGap_i + \boldsymbol{X}'_{it}\lambda + \delta_i + \delta_t + \alpha + \epsilon_{it} \tag{2}$$

where the dependent variable is the return of each value-weighted industry portfolio i in year t, for the years 1990 to 2007. The first term on the right-hand side is the Difference-in-Differences (DID) term of interest, an interaction of the NTR gap and an indicator for the post- PNTR period, the years from 2001 forward. The second term on the right-hand side includes several time-varying industry characteristics. We also include industry and time fixed effects to account for unobserved differences across industries and years. Regression estimates are weighted by industry stock market capitalization in 1989. This minimizes the influence of outliers and it avoids biasing our results toward firms that eventually became

Harmonized System (HS) level. The gap for industry i is the average NTR gap across the eight-digit HS tariff lines belonging to that industry.

[7] If the SIC code is not available in Compustat, we use the SIC code in CRSP. Our procedure of deferring to the SIC code in Compustat has also been adopted in Barrot et al. (2018).

large, specifically firms that benefited from granting China PNTR. Finally, standard errors are clustered at the industry level to allow for arbitrary error correlations within industries over time. The final sample consists of 344 different industries, over 18 years, for a total of 4,090 observations.

The baseline results are shown in Table 2. Column 1 shows the result of the regression with only the DID term and fixed effects. One concern is that contemporaneous policy changes related to China's accession to the WTO could have influenced the performance of US industries over our sample period. We control for these policy changes by including NTR rates and Chinese import tariffs from Brandt et al. (2012) in column 2. Column 3 adds several industry-level financial valuation and health metrics, such as the price/earnings ratio, the price/book ratio, the return on investment, the return on equity, the EV/EBITDA ratio, the debt/equity ratio and the current ratio.[8] As shown in Table 1, high gap firms experienced a higher growth in market capitalization from 1989 to 1999 than low-gap industries. To eliminate the possibility that a size effect (see e.g. Banz (1981) or Fama and French (1993)) is driving our results, we also control for one-year lagged industry market capitalization.[9] Column 3 represents the "baseline" specification to which we refer throughout the remainder of the paper.

The coefficient on the DID term of interest is negative and statistically significant throughout all the specifications: this implies that industries with higher uncertainty on the level of tariffs imposed on Chinese imports experienced a *relatively worse* stock performance when this uncertainty was removed. The difference-in-differences coefficient in the baseline specification in column 3 is significant at 1% level, and indicates that moving an industry from an NTR gap at the twenty-fifth (low uncertainty, 0.17) to the seventy-fifth percentile (high uncertainty, 0.38) of the observed distribution decreases the relative average stock return in the post-PNTR period by 11.2% per year.

We also calculate the average implied impact of PNTR. For each industry i, we multiply the estimated coefficient θ by the industry's NTR gap, and then we take an average of the implied relative effects for all manufacturing industries, using initial stock market capitalization as weights. The baseline specification implies an average decline in the stock returns of 11.9% per year, relative to a hypothetical industry with a zero NTR gap.

2.3 Robustness

We perform several exercises to gauge the robustness of our baseline results.

[8] In the Appendix, we describe the methodology used to compute the variables and their data sources.

[9] Even without controlling for firm size, it is unlikely that a size effect is driving our result, as size effects have been shown to be weak after 1990, see e.g. Asness et al. (2018).

2.3.1 Controls and alternative specifications

Column 1 in Table 3 reports the results using log-returns, rather than monthly-compounded returns as in the baseline. Log-returns reduce the effect of convexity and the importance of outliers in the construction of yearly returns. Not surprisingly, this reduces the point estimate by about 25%. Column 2 in Table 3, instead, weighs observations by the industry's previous year market capitalization.[10] Column 3 restricts the sample to industries that were classified as ''manufacturing'' throughout the whole sample period.[11] We can see that, in both cases, results are very close to the baseline.[12]

We also control for additional variables that could have affected the relationship between stock returns and exposure to the tariff uncertainty. First, we include measures of industry capital and skill intensity, interacted with the Post-PNTR dummy, because differences in these measures could affect the response of stock returns to granting China PNTR. Moreover, between 2002 and 2005, the Multi Fiber Arrangement implied the removal of import quotas on textile and apparel imports from less-developed countries. This contemporaneous policy change could have differentially affected the performance and thus the perceived riskiness of some industries. We control for this using data on US textile and clothing quotas from Khandelwal et al. (2013). Column 4 in Table 3 shows that such specification does not change the coefficient on the DID term.

As documented by previous empirical literature (see e.g. Fama and French (1988) and Lewellen (2002)), stock returns over long horizons are typically serially auto-correlated, which could bias the OLS coefficients. To control for the auto-correlation of the stock market returns, we implement an Arellano and Bond (1991) GMM estimator. Column 5 in Table 3 reports, that our annual industry portfolios' returns are negatively auto-correlated, and that using the GMM estimator, the DID coefficient is even larger in magnitude than in the baseline specification.

A concern with our baseline result is that high gap industries could be exposed different to systematic risks than low gap industries, and these risks changed after granting China PNTR. To account for time-variation in exposure to systematic risk, we re-run our baseline specification, and add industry-time varying estimated CAPM betas to the right-hand-side.[13]

[10]We do not use this weighting scheme as baseline because it may over-state the effects of PNTR on stock returns, as it may over-weigh firms with the highest NTR gap that had the highest returns between 1990 and 1999.

[11]Some industries are re-classified out of "manufacturing" over the years, thus we follow Pierce and Schott (2016) and focus on a "constant manufacturing sample" that excludes any families that contain SIC industries that are ever classified outside manufacturing.

[12]In unreported results, were-run the baseline specification using the Shumway (1997) adjustment for the delisting bias in CRSP, and results are almost unchanged.

[13]We compute betas using the previous 5 years of daily returns, as in Frazzini and Pedersen (2014). Results

Column 6 shows that the main coefficient is very close to the baseline estimates.

2.3.2 Dot-com crash

Around the same time that China was granted PNTR, the US stock market experienced a huge drop due to the dot-com crash. One concern is that the larger decline in average returns for high-gap industries after 2000 could be the result of differential exposure to the technology sector over these years. To mitigate this concern, we first re-estimate the baseline regression but exclude the years where the the dot-com boom/bust were strongest, 2000 and 2001. Column 1 in Table 4 reports that the coefficient is close the baseline in Table 2.[14] Column 2 uses data from 1990-2007, but controls for the industry-level stock turnover, calculated as a value-weighted average of (trading volume/shares outstanding), which could be interpreted as a measure of the intensity of exposure to the dot-com boom (see e.g. Cochrane (2009), which discusses the high trading volume for high-tech stocks during the boom). Column 3 excludes all industries associated with high-tech products. We can see that in all these alternative specifications, the DID coefficient is very similar to the baseline, suggesting that the estimated effect is not driven by the tech boom/bust.

2.3.3 Exogeneity

One concern with our identification strategy is that the US government could have set high tariff rates on WTO members (NTR rates) to protect industries that they expected to be especially exposed to Chinese competition after PNTR. This would imply lower NTR gaps for these industries, which could create a downward bias on the OLS coefficient. In order to evaluate the exogeneity of the NTR gaps, we examine three alternate specifications. First, we follow Pierce and Schott (2016) and estimate a two-stage least squares specification in which we instrument the baseline DID term, $PostPNTR_t \times NTRGap_i$, with an interaction of the post-PNTR indicator and the Smoot-Hawley non-NTR tariff rates, $PostPNTR_t \times NNTR_i$. As indicated in Column 4 of Table 4, the DID coefficient remains negative and statistically significant and is similar to the baseline. Second, we re-estimate our baseline specification using the NTR gap in 1990, rather than NTR gap observed in 1999, ten years prior to PNTR. As shown in Column 5 of Table 4, the DID coefficient estimate remains close to the baseline and is statistically significant. Third, we perform a placebo test, in which we draw a random NTR gap from the cross-sectional distribution of gaps each year and randomly assign it to an

are similar if we introduce a small look-ahead bias and use in-sample betas for each industry-year observation.

[14] The fact that the results are robust to excluding the year 2001 also suggests that our findings are not driven by a differential response of US industries' stock returns to the 2001 recession.

industry. If the gap, rather than some unobserved industry-by-time component, is responsible for the observed differences in returns, we would expect the coefficient on the placebo gap to be insignificant. Reassuringly, this is indeed what column 6 in Table 4 shows.

2.3.4 Firm-level analysis

In our baseline regression we aggregate firm-level returns to the industry level, as there is no variation in NTR gap across firms within the same industries. This, however, creates an issue in the aggregation of the controls to the industry level. For example, at the firm level, price-to-book may be a good predictor of future returns, but the value effect is driven by differences within industries, rather than across industries. This would imply that the price-to-book ratio is less useful at the industry level for predicting future returns. To account for this, we re-run the baseline regression at the firm-monthly level. We use monthly returns, as opposed to yearly returns to reduce the influence of missing returns in CRSP.[15] We weigh observations by previous-year market capitalization, in order to include all firms in the sample and not only the firms that were in the sample for all years between 1989 and 2007.[16] Results are shown in column 7 in Table 4. We can see that the coefficient is negative and statistically significant at 1% level. Interestingly, once we multiply the point estimate of -0.0375 by 12 to annualize it, we obtain a coefficient of -0.45, very close to the baseline reported in column 3 of Table 2.[17]

2.4 Portfolio analysis

In Section 2.3.1, we control for time-variation in exposure to market risk, but there are many other factors known to predict returns. In order to rule out the possibility that differences in factor loadings across high and low gap industries are driving our results, we run a portfolio analysis along the lines of Barrot et al. (2018). In particular, we first rank all the industries in our sample in 5 sub-groups, based on the NTR gap in 1999, such that there is an equal amount of market capitalization in each group.[18] We construct value-weighted portfolios within each group, and calculate returns for each month between 1990 and 2007. We then construct a "Trade Policy Uncertainty" (TPU) portfolio, which is the difference in returns

[15] At the firm level, missing returns are more common than at the industry level. This could create issues when aggregating the monthly returns to annual returns.

[16] In unreported results, we find that results are robust to weighing observations by initial market capitalization, and if using annual instead of monthly returns.

[17] Our results are robust also if we only include firms that were initially publicly listed after 1990.

[18] This approach reduces the influence of very small firms that appear in industries with the highest NTR gaps. In unreported analysis, we form quintiles, each with an equal number of firms, and results are similar.

between the highest gap and lowest gap firms. Our results in Table 5 show that, even after conditioning on the Fama and French (2015) 5-factor model, the TPU portfolio experienced a lower average risk-adjusted return after the policy change than in the pre-period. Further, the drop in average returns after PNTR is almost monotonically increasing from the low gap to high gap portfolios. One concern with this portfolio test is that granting China PNTR changed the systematic risk exposure of high and low gap firms. To account for this, we run the same regression, but allow the loadings on the 5 systematic risk factors to vary between the pre and post-PNTR period. While this does attenuate our results, the decline in returns for the TPU portfolio is still significant at the 5% level.

3 Discussion

Our empirical results show that high gap industries had higher average returns, relative to low gap industries, before China was granted PNTR. In this section, we argue that this difference in returns can be interpreted as a risk premium for exposure to tariff uncertainty. We also describe alternate potential explanations for this empirical evidence, and examine their plausibility. Throughout this section, we assume that investors have full home bias (see French and Poterba (1991)), so the U.S./China tariff uncertainty cannot be fully diversified away.

3.1 Risk Premium for Tariff Uncertainty

Recall that, although China was granted temporary WTO-member tariff rates in 1980, annual renewal was almost automatic until the Tiananmen Square incident in 1989. Then, from 1990 until China joined the WTO in 2001, NTR status required annual renewal by Congress. Our risk premium hypothesis rests on the premises that: i) investors were uncertain about whether the NTR status would have been revoked or not; ii) investors were uncertain about future performance of US industries after (and if) NTR would have been revoked; iii) such uncertainty was present only in the period from 1990 to 2000, and was resolved after.

For the first premise, we note that uncertainty about the tariff status of Chinese imports was a large concern for US companies and investors, throughout the whole temporary NTR period. Anecdotal evidence from media reports and congressional testimony suggests that threats to withdraw China's NTR status were taken seriously. For instance, testifying before the Senate in June 1996, Harry Pearce, Chief Financial Officer of Tyco Toys Inc., declared: "We cannot plan and run our business if we are wondering whether our most important source of supply is about to disappear. Without continuity and certainty of supply, American toy companies also cannot plan to take advantage of the growing Chinese market.'' Testifying before the House on June 1997, Eugene Milosh, President of the American Association of Exporters and Importers, stated: ``Any annual review process introduces uncertainty, weakening the ability of U.S. traders and investors to make long-run plans, and saddles US/China trade and investment with a risk factor cost not faced by our international competitors''.[19]

To assess the second premise, we investigate the market's expectations on the effects of revoking MFN status. In particular, we look at the returns of high and low gap stocks around Congressional voting dates. If the outcomes from Congressional votes regarding China's MFN status updated investors' beliefs about the likelihood of PNTR and its effects on US firms, we should observe instantaneous responses in stock returns.

Table 6 shows, for instance, that on 10/18/1990, the first time the House passed a resolution to revoke MFN status, high gap firms outperformed low gap firms, consistent with high tariffs being good news for them. On 6/8/1993, the first time House failed a vote to revoke China's MFN status, high gap firms under-performed low gap firms, also consistent with high tariffs being perceived as good news for high gap firms. The market, however, did not always respond in a way consistent with this view. For example, on 8/9/1994, when Congress failed to revoke China's MFN status, high gap firms outperformed low gap firms. We believe that this pattern of voting-day returns not always being consistent with a common view on the effects of revoking China's MFN status is evidence for uncertainty about the effects of MFN, as the market reacted differently to similar events over time. Therefore, investors were uncertain about the future performance of US industries, before the PNTR.

To evaluate the third premise, we run a modified version of our baseline regression, with data back to 1981. Specifically, we regress the yearly-industry stock returns on a dummy equal 1 for the years 1981-1980 (pre period) interacted with the NTR gap in 1999, as well as a dummy for the years 1990-2000 (uncertainty period) interacted with the NTR gap in 1999, leaving 2001-2007 (post period) as the omitted category.[20] If the third premise is true, we expect to find an insignificant coefficient on the interaction between the NTR gap and the pre period dummy, as well as a positive and significant coefficient on the interaction between the NTR gap and the 1990-2000 period dummy. Table 7 confirms this is the case: high gap firms only earned a higher average return than low gap firms between 1990 and 2000, when

[19]See Online Appendix of Pierce and Schott (2016) for additional pieces of anecdotal evidence.

[20]This regression weighs observations by each industry's market capitalization in 1989, to make the results comparable with the baseline regression, even though it introduces a look-ahead bias for the observations before 1989. We omit 1980, even though this was the start of China's temporary NTR status, because there was a large negative return for high-gap industries associated with granting China temporary NTR on 1/24/1980, which we interpret as a realized return, rather than part of an expected return.

there was uncertainty about tariffs on Chinese products. As an additional check, we repeat the portfolio analysis, but expand the sample to 1980. As above, we add dummy variables for the pre period and uncertainty period, leaving the post period as the omitted category. Table 8 shows that for the trade policy uncertainty portfolio (the returns of the high gap firms minus the returns of the low gap firms), only the uncertainty period dummy is significant, confirming that returns were higher for high-gap industries only in the period 1990-2000.

Having shown that there was trade policy uncertainty between 1990 and 2000, which had a greater effect on the returns of high-gap firms, we now argue that this was a risk premium commanded by investors for exposure to trade policy uncertainty. In standard asset pricing theory (see, e.g.Cochrane (2009)), in the long-run expected returns reflect the covariance between the Stochastic Discount Factor and the asset's return. Therefore, if such higher average returns were indeed risk premium, it must be that learning about China's MFN status, either through Congressional votes, Presidential policies, etc. enters into the SDF. Although China's NTR status did not actually change during 1990-2000, information regarding the future of China's NTR status was revealed.

The theoretical framework proposed in Pástor and Veronesi (2013) can help to rationalize this hypothesis. In their model, investors do not know the full implications of new government policies, but they learn about their effects over time. When policy news comes out, like voting to revoke China's MFN status, agents update their beliefs about the path for future government policies. There is, however, uncertainty about future changes in the government policies, because there exists a fundamental uncertainty about the future costs of such actions. In a framework with risk-averse agents, this implies that investors must be compensated for exposure to this uncertainty.

In the context of the US-China trade relationship, there were obvious political costs associated with granting China PNTR, given the different exposure to Chinese competition of different economic and political groups in the US. As time went on, because the Congressional voting outcomes were mixed, as shown in Table 6, agents did not learn much about the true cost of switching policies, and thus continued to demand a premium for exposure to this risk. Lastly, we note that trade policy uncertainty was, between 1990 and 2000, a systematic factor that could not be diversified away across stocks with different NTR gaps. In fact, as we have showed in Table 5, when we form diversified portfolios of high-gap firms, they all respond similarly in the post PNTR period.[21]

One concern about the risk premium interpretation of our empirical results is the length

[21] To be precise, if US firms belonging to the highest quintile by NTR gap responded differently to the PNTR, this effect would cancel out and we would not see the significant coefficient shown in column 5 in Table 5.

of the sample. There is evidence that, in order to estimate the risk premium, one needs a much longer sample period than the one we use (see e.g. Fama and French (2018)). In this respect, our analysis is constrained by the nature of the trade policy itself. We cannot extend the 'exposed to uncertainty' sample to the years before 1990, because the uncertainty about future tariff rates started after the Tiananmen Square crackdown. In addition, extending the sample after the year 2007 would include the troubling years of the global financial crisis, which may have differently affected high and low gap firms. This concern is, however, mitigated by the lack of a systematic relationship between NTR gaps and average returns in the years before 1990, as shown above.

Ambiguity aversion. Even if learning about PNTR does not directly enter the SDF, tariff uncertainty may still explain our results. Suppose investors are ambiguity averse: one way to model these preferences is that when there are multiple possible distributions of outcomes, agents assume the worst (see e.g. Gilboa and Schmeidler (1989)). In the context of our scenario, suppose investors did not know (1) whether MFN status would be revoked (2) what effect revoking MFN would have (3) whether China would eventually be granted NTR (4) what the full extent of granting China NTR would be. In a model with this type of ambiguity aversion, investors assume the worst case scenario, so increases in uncertainty are bad news, and would need to be compensated with higher returns.

3.2 Alternative Explanations

In this subsection we discuss a number of alternative explanations that could potentially rationalize our results, and we show that they are not fully consistent with the empirical evidence.

3.2.1 Alternative Explanation I: Compensation for Poor Performance

An alternative explanation for our results is that investors expected that once China entered the WTO, high-gap industries would be hurt by new Chinese import competition more than low-gap industries, and therefore commanded a higher expected return as compensation for this risk. In this scenario, our estimated risk premium would not be related to tariff uncertainty per se, but would be instead a premium for Chinese competition risk.

Suppose that all the effects of PNTR on high and low gap firms were known perfectly in 1989. Then, between 1990 and 2000, investors would have foreseen the real effects documented in Pierce and Schott (2016) and Pierce and Schott (2017): high gap firms would have a relatively worse *real* performance after China was granted PNTR. Suppose that investors didn't know exactly *when* PNTR would be granted. Then, they may have required a high return on high-NTR-gap firms to compensate them for the crash risk associated with granting China PNTR. This cannot fully explain our main results, however, as we provide evidence that agents did not fully foresee the effects of PNTR on high gap firms' performance. In fact, we find that high gap firms had significantly lower returns than low gap firms around earnings dates in the post period, relative to the pre period. This implies that, as firms released fundamental information, investors learned that these firms were more affected by PNTR than originally predicted, and pushed prices downward.

In a similar vein, suppose that agents did not fully anticipate the effects of PNTR, but they believed it would be bad for high gap firms, as evidenced by the low returns for high gap firms on the initial PNTR announcement date. Then, our results could be explained by investors requiring high returns in the pre-PNTR period to compensate them for the *possibility* that high gap firms would do poorly in the post period. This, however, would imply that the high gap firms would still carry additional risk relative to low-gap firms in the post PNTR period, and after the initial shock on the PNTR announcement date, would earn higher average returns. Our estimates, however, document that, even excluding earnings dates, average returns were relatively lower for high gap firms in the post period.

We also directly test this alternative hypothesis. We first create a dummy equal 1 for industries that had a high import share from China in 1999. Then we estimate a triple difference regression, in which we interact our DID term in equation (2) with the China dummy.

We adopt three alternative methods to compute the industry-level import shares from China. In the first approach, we compute this share from WIOD data as industry-level imports from China divided by total US expenditures in that industry. The shortcoming is that we have data only for 16 WIOD manufacturing sectors, and thus we assign the same import share to all industries in our classification that belong to the same WIOD sector. In the first approach we consider only trade flows in final goods, while in the second one we include trade flows in both intermediate and final goods. Given the lack of substantial variation across industries in the import shares, we also use a third method, in which we use trade flows data at the HS-6 level from UN Comtrade and aggregate them at the industry level. The advantage of using product-level flows is the resulting rich cross-industry variation in the import shares, but the shortcoming is the lack of data on domestic sales. Therefore, we compute the share of imports from China as a share of US industry imports, rather than US industry expenditures.

Table 9 shows that, in all the three approaches, despite the baseline DID term remaining significant, the triple interaction term is not significant. This suggests that differences in average returns were not concentrated among industries that were more exposed to Chinese competition.

3.2.2 Alternative Explanation II: Series of Positive Shocks

Another interpretation of our results is that the high returns in the pre-period were the result of a series of positive news: investors to some degree anticipated that PNTR would be bad for high gap firms, and each year that went by without China getting PNTR was a positive shock. This would be consistent with the evidence that realized returns around the PNTR announcement dates were statistically significantly lower for high-gap firms than low-gap firms.

This explanation, however, is not fully consistent with our results. If investors believed initially that granting China PNTR would have been bad for high-gap industries, then the same series of positive shocks that occurred between 1990 and 2000 also occurred between 1980 and 1989, as China was also not granted PNTR in these years. Our results show that high gap firms did not earn higher returns than low gap firms between 1980 and 1989, which suggests that our results are specific to the tariff *uncertainty* that arose after the Tiananmen square incident in 1989 with the start of annual votes on China's MFN status.

3.2.3 Alternative Explanation III: Resolution of Timing Uncertainty

For some parameterizations of Epstein and Zin (1991) preferences, agents prefer early resolution of uncertainty.[22] This implies that risk-averse agents need to be compensated for exposure to timing uncertainty. To be conservative, suppose that the effects of PNTR on firm performance was known in 1989. Then, the only source of uncertainty at that time was *when* China would be granted PNTR. In this case, we would expect high-gap firms to command higher returns in the pre-period for exposure to this timing risk, including the years 1980-1990. However, Table 7 shows that there was no difference in average returns between high and low gap firms in the pre period 1980-1990. In addition, on the event day we might expect to see an increase in high-gap firms' stock prices from the resolution of uncertainty, since the risk was removed. Our results in Table 10 in Section 4, however, point toward largely negative and significant realized returns for high-gap firms, partially contradicting this explanation.

[22] In particular, this happens if and only if the risk aversion is larger than the inverse of the elasticity of intertemporal substitution.

4 PNTR and Realized Returns

In this section we investigate the extent to which the results from the yearly regressions could have been driven by differences in *realized* returns. If capital markets are efficient, stock prices adjust quickly after a news announcement, incorporating any changes in expected future cash-flows and discount rates (see MacKinlay (1997), Andrade et al. (2001) and Alfaro et al. (2018)). Therefore, if financial markets expected high-gap industries to perform relatively worse after granting China PNTR status, this should be reflected into lower realized returns around the dates of the policy announcement. Similarly, if investors did not immediately internalize the differential long-run effects of PNTR on US industries, then we might also expect a significant response of returns around high-gap firms' earnings announcements, as investors update their beliefs.

We empirically examine whether each of these event days had an effect on stock returns, and then investigate whether our yearly regressions are being driven by such possible differences in realized returns.

4.1 Policy announcement

We first perform an event study on days with PNTR-related news announcements to estimate the market's perceived effect of the policy change on firm performance. We focus on three news announcements: i) 10/10/2000, when China was granted NTR, conditional on joining the WTO; ii) 12/11/2001, when China joined the WTO; iii) 1/2/2002, the day the PNTR actually went into effect.

We regress the industry-level daily stock returns in a 5-day window around these dates on the NTR gap in 1999, from t-1 to t+3, where t is the event date of interest.[23] In this specification, we do not control for differences in industry/firm fundamentals as given the short length of the window around the announcement, we expect the announcement to be the major factor driving returns.[24]

Columns 1-3 of Table 10 report the results. We can see that, around 10/10/2000, when China was granted NTR conditional on joining the WTO, industries with higher gaps experienced lower stock returns than industries with lower gaps. This effect is significant at 5% level, and is also economically large: it implies an average decline in realized stock returns of 5%, relative to a hypothetical industry with a zero NTR gap. In contrast, for the

[23] Results are robust to the choice of the time window.

[24] In unreported results, we re-run the regression using CAPM residuals, both computed with in-sample betas and out-of-sample betas on the market factor. We find that results are similar, but less statistically significant. One explanation for this is that estimating the betas introduces an additional degree of noise, which over such short horizons could drown out the effects of the news event.

other two dates, we do not find significant difference between high and low gap industries. This is consistent with the effect of NTR being already priced into stocks after China joined the WTO.

We interpret this finding as financial markets expecting high-gap industries becoming riskier, or having lower future dividends/cash flows than low-gap industries, as a result of the PNTR. One explanation for this result is that, once the policy was announced, investors believed that future lower expected tariffs on Chinese products would have increased competition in a given sector from Chinese firms, lowering US firms' market shares of and thus their expected profits. There was no effect on the second two event days because, at that point, the effects of PNTR were already incorporated into stock prices.

4.2 Earnings announcements

A concern may be that the differences in stock returns we pick up across high and low gap industries are driven by returns around earnings announcements. This could be a concern for our research design if investors did not fully anticipate the effects of PNTR on firm performance, so they were consistently negatively surprised when firms released earnings information. In that case, we would expect lower returns around earnings days for high-gap firms in the PNTR period. We identify earnings days using the Institutional Brokers Estimates System (I/B/E/S) database.[25] To avoid issues with missing time of earnings releases early in the sample, and possible discrepancies in earnings days between I/B/E/S and Compustat, we look at the cumulative return from t-5 to t+1, where t is an earnings announcement date, as in Barrot et al. (2018).

Column 4 of Table 10 reports a negative and 5% statistically significant coefficient for the interaction between the NTR gap and the post-PNTR period. Therefore, high-gap industries, around the days of earnings announcements, experienced significantly lower stock returns than low-gap industries, after PNTR. The implied average (relative) effect, however, is small, being only -0.2% per earnings day. This is consistent with investors initially under-estimating the effect on PNTR on high-gap firms' performance. We address how this affected our baseline specification in the next section.

4.3 Expected returns revisited

In light of this evidence about an impact of PNTR on realized returns, we repeat the main yearly specification of Section 2.2, but exclude PNTR-related announcement dates and a

[25]If earnings are announced after the market is closed, or on a trading holiday, we set the effective earnings day to the first trading-day after earnings are announced.

7-day window around earnings announcements. We also exclude Congressional voting dates on China's MFN status.[26] Table 11 reports the corresponding results and shows that our baseline results are not driven by the effect of PNTR on realized returns, although the coefficients are smaller than the baseline. The table implies that a conservative estimate of the effect of tariff uncertainty on expected returns is 10.4%, slightly smaller than our baseline estimate of 11.9%.

5 IO linkages and Stock Returns

A recent literature has emphasized the importance of input-output linkages in the propagation of a shock to the economy, e.g. Caliendo and Parro (2014), Boehm et al. (2015) and Acemoglu et al. (2016). We analyze the role of such linkages in the effect of tariffs uncertainty on expected returns.

We identify three sources of linkages in production that may affect an industry's exposure to trade policy uncertainty. The first is related to the fact that US firms, besides competing with Chinese firms on goods markets, may use Chinese products as intermediate inputs in production. Uncertainty about US tariffs applied to Chinese inputs, then, translates into uncertainty about the cost of production. To capture the exposure of a US industry to tariff uncertainty through inputs sourced from China, we construct the "China upstream exposure" as follows:

$$\eta_j^c = \sum_s \omega_s^j Gap_s \tag{3}$$

where ω_s^j is the share of intermediate inputs expenditures of US industry j on Chinese industry s, and Gap_s is the NTR gap of industry s, both in 1999, before the PNTR was implemented. Intuitively, industries that, before 2001, were sourcing inputs from Chinese industries that were threatened by potentially high tariffs, could be perceived as riskier by financial markets, affecting the expected returns.

The second and third sources of IO linkages refer to production linkages within the US economy. In particular, we follow Acemoglu et al. (2016) and construct the "downstream exposure" measure as:

$$\eta_j^d = \sum_s \alpha_j^s Gap_s \tag{4}$$

where α_s^j is the share of industry j's total sales that are used as inputs by industry s in 1999. Thus, (4) is a weighted average of the tariff uncertainty, proxied by the NTR gap, faced by the downstream purchasers' of j's output. Selling a large fraction of the sales to industries

[26] In section 3 we undertake a detailed analysis of the response of realized returns to Congressional votes.

highly exposed to tariff uncertainty, could potentially increase the uncertainty on industry's sales and thus profits, affecting an industry's expected returns.

Similarly, we construct the "upstream exposure" measure as:

$$\eta_j^u = \sum_s \pi_s^j Gap_s \tag{5}$$

where π_{st}^j is the share of intermediate inputs expenditures of US industry j on US industry s in 1999. Thus, (5) is a weighted average of the tariff uncertainty, proxied by the NTR gap, faced by the upstream suppliers of industry j. If an industry sources a large fraction of its inputs from industries highly exposed to tariff uncertainty, that can increase the uncertainty on industry j' s production costs and thus profits, affecting its expected return.[27]

To compute the shares ω_{st}^j needed to obtain equation (3), we use data on manufacturing trade flows in final goods and intermediate inputs from the World Input Output Database for the year 1999. We compute the shares α_j^s and π_s^j using the US Input-Output table from the BEA and following the cleaning procedure used in Acemoglu et al. (2016).

Results in Table 12 provide evidence that PNTR's effect on stock returns can be transmitted through supply chains. Column 1 shows that a higher upstream exposure from China, i.e. a higher weighted average of the NTR gaps of the Chinese industries used as inputs, lowers the average return after the uncertainty was removed. This effect is significant at 1% level. This means that industries that were sourcing more from riskier sectors in China were also commanding a higher expected return before PNTR. Similarly, Column 2 in Table 12 shows that industries whose suppliers were more exposed to PNTR, as measured by the upstream NTR gap, had lower returns after the PNTR than industries with less exposed suppliers. Column 2 reports that having customers more exposed to tariff uncertainty, as measured by the downstream NTR gap, does not significantly affect the average return of an industry.

Note that the upstream and downstream measures we have used so far only capture the exposure of an industry to its "direct" purchasers or suppliers. However, each supplier of an industry is itself exposed to the uncertainty faced by its suppliers, and they are in turn exposed to uncertainty of their suppliers, and so on. To account for the full chain of linkages in production, we follow Acemoglu et al. (2016) and compute for each industry the inverse of the Leontief matrix of downstream and upstream linkages. Column 3 reveals that, taking into account for the full chain of linkages in production has a negative effect on average returns for the upstream channel, significant at the 1% level. This suggests that indirect

[27]These three different measures of IO linkages can be easily derived by means of a first order approximation of a trade model with a production function with constant input expenditure shares, i.e. Cobb-Douglas, and CES demand, in which gross profits are a constant share of revenues. See Acemoglu et al. (2016) for details.

exposure to tariff uncertainty through upstream IO linkages also affected average returns in the pre-PNTR period..

6 Conclusions

We use quasi-experimental variation arising from China's temporary NTR status to show that US manufacturing industries more exposed to trade policy uncertainty experienced significantly higher stock returns than less exposed industries. Our measure of uncertainty, which relies on the difference between current NTR and non-NTR tariff rates, has the advantage of being directly observable, exogenous, and fully ex-ante. As such, it is not subject to the concerns associated with ex-post measures of uncertainty used by the literature.

Our estimated risk premium is substantial, even after accounting for the fact that investors may have under-estimated the effects of granting China PNTR, and for the response of stock prices to PNTR-related policy announcements. Industries highly exposed to policy uncertainty earned a risk premium of 10.4% per year relative to less exposed sectors, which can have substantive asset allocation effects under optimal portfolio risk management strategies.

Our approach, which exploits cross-sectional variation in industry exposure to uncertainty, allows us to decompose the differences in returns between high and low gap industries into a realized and expected part and we argue that this decomposition is important for the identification of risk premia. In addition, we show that even indirect exposure to trade policy uncertainty, through upstream IO linkages, is priced in the cross-section of stock returns.

While several papers examined the real implications of China's temporary NTR status on employment and investment of firms, we focus on the implications on the financial performance of firms and uncover the potential asset allocation impact of trade policy uncertainty.

Important avenues for future research emerge from our study. Further research into the implications of the mechanisms of trade policy uncertainty through upstream IO linkages on the cross-section of stock returns is worth pursuing as it is an innovative contribution of this paper. Our focus here was on the removal of uncertainty after China entered the WTO, but currently the U.S.-China trade relationships are also subject to political uncertainty and can generate a potential trade war. Our results of a large risk premium for this type of uncertainty may serve as a word of caution to policymakers.

References

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., Price, B., 2016. Import competition and the great us employment sag of the 2000s. Journal of Labor Economics 34 (S1), S141--S198.

Adao, R., Arkolakis, C., Esposito, F., 2018. Spatial linkages, global shocks, and local labor markets: Theory and evidence.

Alfaro, I., Bloom, N., Lin, X., 2018. The finance uncertainty multiplier. Tech. rep., National Bureau of Economic Research.

Andrade, G., Mitchell, M., Stafford, E., 2001. New evidence and perspectives on mergers. Journal of economic perspectives 15 (2), 103--120.

Antras, P., Fort, T. C., Tintelnot, F., 2017. The margins of global sourcing: Theory and evidence from us firms. American Economic Review 107 (9), 2514--64.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. Review of Economic Studies 58 (2), 277--297.

Asness, C., Frazzini, A., Israel, R., Moskowitz, T. J., Pedersen, L. H., 2018. Size matters, if you control your junk. Journal of Financial Economics.

Autor, D., Dorn, D., Hanson, G. H., 2013. The china syndrome: Local labor market effects of import competition in the united states. The American Economic Review 103 (6), 2121--2168.

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

Bansal, R., Kiku, D., Shaliastovich, I., Yaron, A., 2014. Volatility, the macroeconomy, and asset prices. The Journal of Finance 69 (6), 2471--2511.

Banz, R. W., 1981. The relationship between return and market value of common stocks. Journal of financial economics 9 (1), 3--18.

Barrot, J.-N., Loualiche, E., Sauvagnat, J., 2018. The globalization risk premium. Journal of Finance, Forthcoming.

Blaum, J., Lelarge, C., Peters, M., 2015. The gains from input trade in firm-based models of importing.

Boehm, C., Flaaen, A., Pandalai-Nayar, N., 2015. Input linkages and the transmission of shocks: Firm-level evidence from the 2011 tōhoku earthquake.

Boguth, O., Kuehn, L.-A., 2013. Consumption volatility risk. The Journal of Finance 68 (6), 2589--2615.

Bollerslev, T., Tauchen, G., Zhou, H., 2009. Expected stock returns and variance risk premia. The Review of Financial Studies 22 (11), 4463--4492.

Brandt, L., Van Biesebroeck, J., Wang, L., Zhang, Y., et al., 2012. WTO accession and performance of Chinese manufacturing firms. Centre for Economic Policy Research.

Brogaard, J., Detzel, A., 2015. The asset-pricing implications of government economic policy uncertainty. Management Science 61 (1), 3--18.

Caliendo, L., Dvorkin, M., Parro, F., 2015. The impact of trade on labor market dynamics. Tech. rep., National Bureau of Economic Research.

Caliendo, L., Parro, F., 2014. Estimates of the trade and welfare effects of nafta. The Review of Economic Studies, rdu035.

Carballo, J., Handley, K., Limão, N., 2014. Trade collapses: The role of economic and policy uncertainty in the great recession.

Carr, P., Wu, L., 2008. Variance risk premiums. The Review of Financial Studies 22 (3), 1311--1341.

Cochrane, J. H., 2009. Asset pricing: Revised edition. Princeton university press.

Crowley, M., Song, H., Meng, N., 2018. Tariff scares: Trade policy uncertainty and foreign market entry by chinese firms. Journal of International Economics.

Epstein, L. G., Zin, S. E., 1991. Substitution, risk aversion, and the temporal behavior of consumption and asset returns: An empirical analysis. Journal of political Economy 99 (2), 263--286.

Fama, E. F., French, K. R., 1988. Permanent and temporary components of stock prices. Journal of political Economy 96 (2), 246--273.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of financial economics 33 (1), 3--56.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1--22.

Fama, E. F., French, K. R., 2018. Long-horizon returns. The Review of Asset Pricing Studies 8 (2), 232--252.

Feenstra, R. C., Romalis, J., Schott, P. K., 2002. US imports, exports, and tariff data, 1989-2001. NBER Working Paper 9387.

Feng, L., Li, Z., Swenson, D. L., 2017. Trade policy uncertainty and exports: Evidence from china's wto accession. Journal of International Economics 106, 20--36.

Fillat, J., Garetto, S., 2015. Risk, return and multinational production. The Quarterly Journal Economics 130 (4), 2027--2073.

Frazzini, A., Pedersen, L. H., 2014. Betting against beta. Journal of Financial Economics 111 (1), 1--25.

French, K. R., Poterba, J. M., 1991. Investor diversification and international equity markets. Tech. rep., National Bureau of Economic Research.

Gilboa, I., Schmeidler, D., 1989. Maxmin expected utility with non-unique prior. Journal of Mathematial Economics 18 (2), 141--153.

Greenland, A., Iony, M., Lopresti, J., Schott, P., 2019. Using equity market reactions to infer exposure to trade liberalization.

Griffin, T. P., 2018. Globalization and us industry concentration. Available at SSRN 3287328.

Handley, K., Limao, N., 2015. Trade and investment under policy uncertainty: theory and firm evidence. American Economic Journal: Economic Policy 7 (4), 189--222.

Handley, K., Limão, N., 2017. Policy uncertainty, trade, and welfare: Theory and evidence for china and the united states. American Economic Review 107 (9), 2731--83.

Huang, Y., Lin, C., Liu, S., Tang, H., 2018. Trade linkages and firm value: Evidence from the 2018 us-china'trade war'.

Kelly, B., Pástor, L., Veronesi, P., 2016. The price of political uncertainty: Theory and evidence from the option market. The Journal of Finance 71 (5), 2417--2480.

Khandelwal, A. K., Schott, P. K., Wei, S.-J., 2013. Trade liberalization and embedded institutional reform: evidence from chinese exporters. American Economic Review 103 (6), 2169--95.

Lewellen, J., 2002. Momentum and autocorrelation in stock returns. The Review of Financial Studies 15 (2), 533--564.

MacKinlay, A. C., 1997. Event studies in economics and finance. Journal of economic literature 35 (1), 13--39.

Pastor, L., Veronesi, P., 2012. Uncertainty about government policy and stock prices. The journal of Finance 67 (4), 1219--1264.

Pástor, L., Veronesi, P., 2013. Political uncertainty and risk premia. Journal of Financial Economics 110 (3), 520--545.

Pierce, J. R., Schott, P. K., 2012. Concording us harmonized system codes over time. Journal of Official Statistics 28 (1), 53--68.

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

Pierce, J. R., Schott, P. K., 2017. Investment responses to trade liberalization: Evidence from us industries and plants. Tech. rep., National Bureau of Economic Research.

Shumway, T., 1997. The delisting bias in crsp data. The Journal of Finance 52 (1), 327--340.

7 Appendix

7.1 Construction of valuation variables

The price-to-earnings ratio (P/E ratio) is a valuation multiple, typically measured at the firm level as current share price relative to earnings per-share. To aggregate this to the industry level, we take the ratio between total market capitalization of all firms in the industry and total earnings. We construct this using annual Compustat data..

The Price-to-book ratio is also a valuation multiple, typically measured at the firm level as the ratio of price to book value per-share.. This is also constructed at the industry level using annual Compustat data, as the ratio of the total industry market capitalization, divided by total book value of equity. We exclude firms with negative book values from both the numerator and denominator..

The EV/EBITDA ratio is computed with annual Compustat data as the total enterprise value of an industry divided by the total EBITDA.

The Return on invested capital (ROI), is a measure of the profitability, or the return earned on capital invested in operating assets. We compute this with annual Compustat data as the ratio of net income - total industry cash dividends, divided by the industry's total capital, measured as the book value of equity plus the book value of debt, minus cash and cash equivalents.

The Return on equity (ROE) measures profitability. We compute this with annual Compustat data as the total net income of the industry, divided by the industry's total market capitalization.

The debt-to-equity ratio is a leverage metric which compares the company's debt to its stockholder equity. It is calculated as total liabilities over stockholders' equity and indicates what proportion of shareholders' equity and debt a company is using to finance its assets. We compute this with annual Compustat data as the ratio of total long-term debt to total market capitalization.

The Current ratio is a liquidity ratio that measures a company's ability to pay short-term and long-term obligations. We compute this with annual Compustat data as the the total current assets divided by total current liabilities.

Aggregating controls to the industry level. In our baseline specification, our unit of observation is industry-year. As mentioned above, we construct the controls by summing each part of each ratio within each industry/year, and then computing the ratio. Alternatively, we could have: (1) Computed the ratio for each firm/year, and then taken a value-weighted average (weights proportional to the previous year's market capitalization) at the industry level. This would lead to an under-weighting of leveraged firms, with small market equity relative to total assets (2) Run the regressions at the firm level, and avoid the issue of aggregating controls. As shown in section 2.3, we re-run our baseline regressions with firm-level data, and the results are essentially unchanged. If we aggregate the firm-level monthly returns to annual returns, and re-run the baseline regression, the point estimate is similar as well.

8 Tables and Figures

Figure 1: Trade Policy Uncertainty

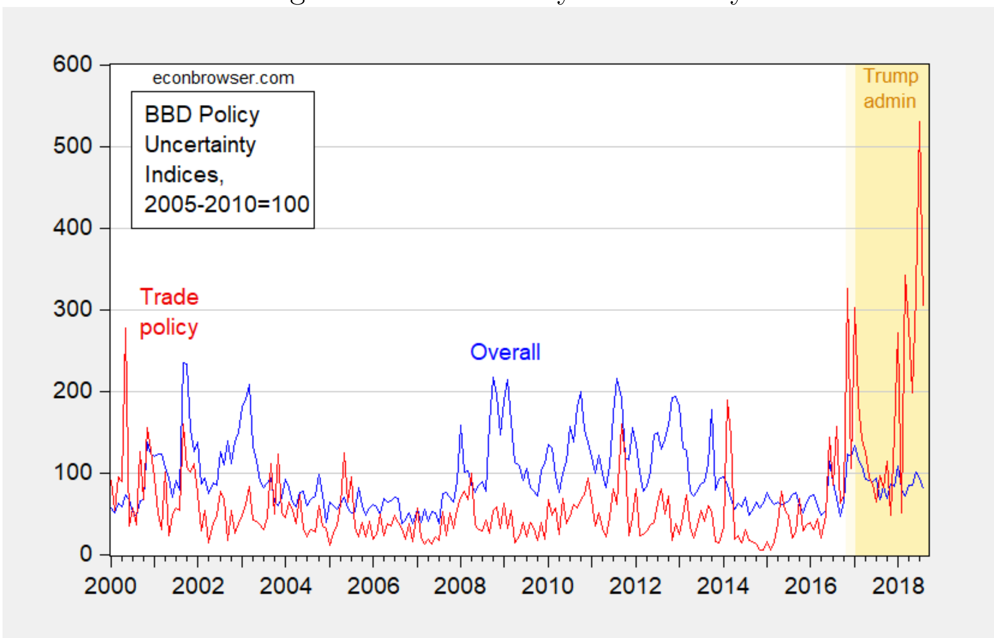

Figure 2: Distribution of NTR gaps

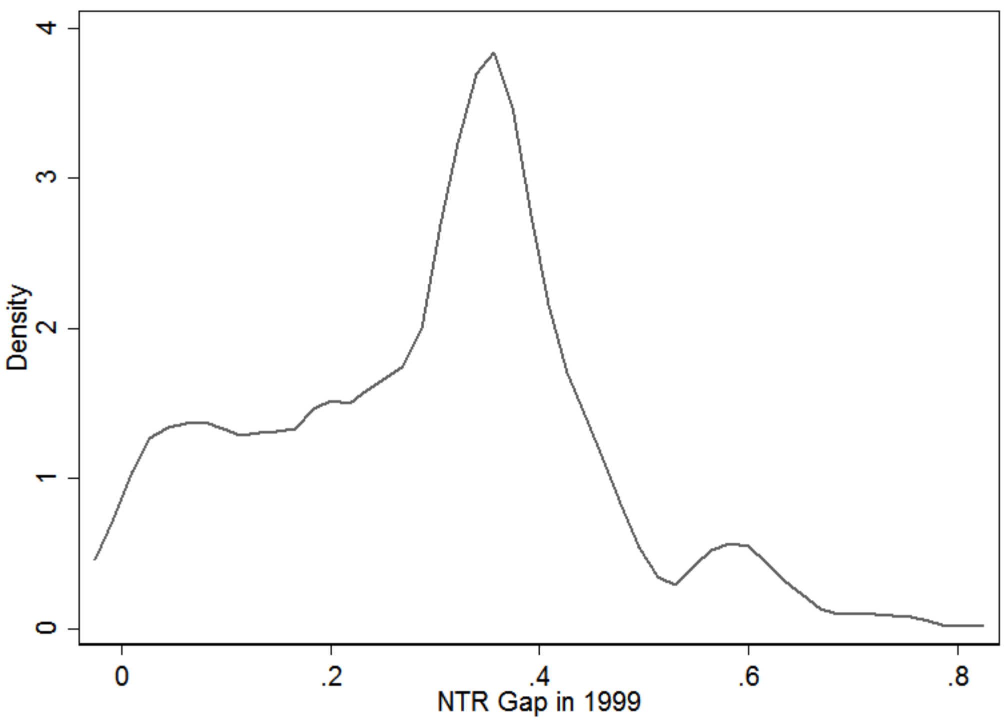

Table 1: Summary statistics

Variable	Low-Gap	High-Gap	t-Statistic
NTR Gap in 1999	0.18	0.42	-62.39
Market Capitalization ($M)	$ 2,294.99	$ 2,268.93	0.05
EV/EBITDA	1.71	3.43	-0.06
Price / Earnings per Share	12.22	19.05	-1.07
Price / Book	3.36	7.74	-7.30
Return on Equity	-0.04	-0.10	1.98
Return on Invested Capital	0.20	0.45	-0.47
Dividend Yield	0.01	0.01	2.80
Total Sales	$ 2,254.54	$ 830.28	5.42
Current Ratio	2.25	3.93	-8.78
Debt / Equity	0.73	0.29	8.80

Notes: This table contains summary statistics on high and low gap firms in 1999, the year before China was granted PNTR. A firm is classified as low-gap if it has a below median NTR gap in 1999. Each entry represents the un-weighted average within each group. The last column contains the t-Statistic from a difference of means test across groups.

Table 2: PNTR and expected returns

Dependent variable: Annual Industry Returns			
	(1)	(2)	(3)
NTR Gap 1999 x Post	-0.327***	-0.419***	-0.538***
	(0.12)	(0.15)	(0.11)
NTR Rate		-0.347	-2.02
		(0.32)	(1.56)
Chinese Tariff x Post		0.0319	-0.0442
		(0.14)	(0.11)
Observations	4,090	3,582	1,668
R^2	0.164	0.152	0.264
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Industry/Year Controls	No	No	Yes

Notes: This table contains selected estimates from the following regression, run at the industry(i)/year(t) level using data from 1990-2007:

$R_{it} = \theta PostPNTR_t \times NTRGap_i + \boldsymbol{X}'_{it}\lambda + \delta_i + \delta_t + \alpha + \epsilon_{it}$

where $PostPNTR_t$ is a dummy equal to one if the year is greater than 2000, and $NTRGap_i$ is the NTR gap for industry i in 1999. The regression also includes the following controls in $\boldsymbol{X}'_{it}$: Price/Earnings, Price/Book, Return on Invested Capital, return on Equity, EV/EBITDA, Debt/Equity, Current Ratio, Dividend Yield and Market Capitalization. All these controls are lagged one year to prevent a look-ahead bias. The regression includes industry δ_i and time δ_t fixed effects. Each observation is weighed by industry i's market capitalization in 1989. Robust standard errors, clustered at the industry level, are in parenthesis.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 3: Robustness I

	Dependent variable: Annual Industry Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
NTR Gap 1999 x Post	-0.407***	-0.371**	-0.518***	-0.469***	-0.747***	-0.522***
	(0.11)	(0.14)	(0.11)	(0.09)	(0.19)	(0.10)
NTR Rate	-1.494	-1.498	-1.981	-2.359	-3.861*	-2.238
	(1.44)	(1.82)	(1.47)	(1.50)	(2.09)	(1.57)
Chinese Tariff x Post	-0.0716	-0.036	-0.0597	-0.0348	-0.118	-0.0172
	(0.10)	(0.19)	(0.11)	(0.10)	(0.15)	(0.11)
Lagged Market Capitalization	-0.201***	-0.550***	-0.211***	-0.200***		-0.262***
	-0.0488	(0.08)	(0.05)	(0.06)		(0.06)
Log of skill intensity x Post				-0.0608		
				(0.05)		
Log of capital intensity x Post				0.00827		
				(0.02)		
MFA Quotas exposure				-1.042		
				(0.95)		
Beta						0.0171
						(0.03)
Lagged yearly return					-0.294***	
					(0.05)	
Twice Lagged yearly return					-0.235***	
					(0.05)	
Observations	1,668	1,681	1,625	1,616	1,201	1,508
R^2	0.418	0.609	0.424	0.428		0.432
Weights	1989 Cap	Prev. Yr. Cap	1989 Cap	1989 Cap	1989 Cap	1989 Cap
Constant Manufacturing	No	No	Yes	No	No	No
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry/Year Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table contains selected estimates from versions of the following regression, run at the industry(i)/year(t) level using data from 1990-2007:

$R_{it} = \theta PostPNTR_t \times NTRGap_i + \boldsymbol{X}'_{it}\lambda + \delta_i + \delta_t + \alpha + \epsilon_{it}$

where $PostPNTR_t$ is a dummy equal to one if the year is greater than 2000, and $NTRGap_i$ is the NTR gap for industry i in 1999. The regression also includes the following controls in $\boldsymbol{X}'_{it}$: Price/Earnings, Price/Book, Return on Invested Capital, return on Equity, EV/EBITDA, Debt/Equity, Current Ratio, Dividend Yield and Market Capitalization. All these controls are lagged one year to prevent a look-ahead bias. The regression includes industry δ_i and time δ_t fixed effects. In regression 1, we compute annual industry returns by summing monthly log returns, while in regressions 2-6 annual industry returns are constructed by compounding monthly returns to annual. In regressions 1 and 3-6, each observation is weighed by industry i's market capitalization in 1989. In regression 2, observations are weighed by industry i's one year lagged market capitalization. The constant manufacturing sample excludes any famlies of SIC industries that were ever classified outside of manfacturing. We compute industry betas using the previous 5 years of daily returns. Robust standard errors, clustered at the industry level, are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 4: Robustness II

	Dependent variable: Industry Returns						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NTR gap 1999 x Post	-0.619***	-0.535***	-0.540***	-0.508***		0.0371	-0.0375***
	(0.13)	(0.11)	(0.11)	(0.10)		(0.09)	(0.01)
NTR rate	-2.375	-1.937	-2.132	-1.92	-1.857	-0.127	-0.0323
	(1.50)	(1.59)	(1.56)	(1.49)	(1.54)	(1.47)	(0.02)
Chinese tariff x Post	-0.0903	-0.0443	-0.0502	-0.0375	-0.092	0.0696	0.00156
	(0.14)	(0.11)	(0.11)	(0.10)	(0.13)	(0.14)	(0.01)
Industry turnover		7.97E-06					
		(0.03)					
NTR gap 1990 x Post					-0.695***		
					(0.17)		
Observations	1,488	1,608	1,629	1,656	1,668	1,668	442,010
R^2	0.272	0.266	0.276	0.235	0.258	0.391	0.008
Observation Level	Industry/Year	Industry/Year	Industry/Year	Industry/Year	Industry/Year	Industry/Year	Firm/Month
Sample Restriction	Drop 2000/2001	None	Drop Electronics	None	None	None	None
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry/Year Controls	Yes	Yes	Yes	Yes	Yes	Yes	FL/Year Controls

Notes: This table contains selected estimates from the following regression, using data from 1990-2007:
$R_{it} = \theta PostPNTR_t \times NTRGap_i + \boldsymbol{X}'_{it}\lambda + \delta_i + \delta_t + \alpha + \epsilon_{it}$
where $PostPNTR_t$ is a dummy equal to one if the year is greater than 2000. For regressions 1-6, the unit of observation is industry/year, while for regression 7 it is firm/month. $NTRGap_i$ is the NTR gap for industry/firm i in 1999. The regression also includes the following controls in $\boldsymbol{X}'_{it}$: Price/Earnings, Price/Book, Return on Invested Capital, return on Equity, EV/EBITDA, Debt/Equity, Current Ratio, Dividend Yield and Market Capitalization. All these controls are lagged one year to prevent a look-ahead bias. The regression includes industry δ_i and time δ_t fixed effects. For regressions 1-6, each observation is weighed by industry i's market capitalization in 1989. In regression 7, each observation is weighed by firm i's market capitalization in the previous year. The exclude electronics sample removes industry famlies 409, 410, 411 and 412, which map to the 4-digit NAICS code for Computer and Peripheral Equipment Manufacturing. Industry turnover is calculated as a value-weighted average of trading volume/shares outstanding. Robust standard errors, clustered at the industry level, are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 5: Portfolio analysis

	Dependent variable: Monthly Portfolio Returns						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Lowest	2	3	4	Highest	High minus Low	High minus Low
Post PNTR	0.00971**	0.00572*	-0.00153	0.000247	-0.00399*	-0.0137***	-0.00989**
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Market	0.716***	0.889***	1.192***	1.140***	0.939***	0.223***	0.291***
	(0.06)	(0.05)	(0.07)	(0.10)	(0.04)	(0.07)	(0.09)
Size	0.00585	-0.0669	-0.0518	-0.0346	-0.0472	-0.053	0.0702
	(0.07)	-0.07	(0.08)	(0.12)	(0.06)	(0.09)	(0.10)
Value	0.472***	0.081	-0.121	-0.276	-0.638***	-1.110***	-1.186***
	(0.11)	(0.09)	(0.13)	(0.18)	(0.09)	(0.15)	(0.20)
Profitability	0.108	-0.178*	-0.404***	-0.311***	0.177***	0.0686	0.18
	(0.08)	(0.09)	(0.12)	(0.11)	(0.07)	(0.12)	(0.13)
Investment	0.05	0.213	-0.0998	-0.435	0.320***	0.270*	0.265
	(0.13)	(0.13)	(0.17)	(0.27)	(0.09)	(0.16)	(0.25)
Market X Post							-0.360**
							(0.16)
Size X Post							-0.507***
							(0.18)
Value X Post							0.497*
							(0.27)
Profitability X Post							-0.635***
							(0.24)
Investment X Post							0.014
							(0.31)
Observations	216	216	216	216	216	216	216
R^2	0.488	0.742	0.811	0.784	0.851	0.529	0.575

Notes: This table contains selected estimates from the following regression, using data from 1990-2007:
$R_{pt} = \theta PostPNTR_t + \boldsymbol{F}_t'\lambda + \alpha + \epsilon_{pt}$
Where R_{pt} is the return on portfolio p in month t and $PostPNTR_t$ is a dummy equal to one if the year is greater than 2000. $\boldsymbol{F}_t'$ is a vector containing the 5 Fama-French factors: Market, Size, Value, Profitability and Investment. Column 7 augments this regression, by including the terms for the interaction between the $PostPNTR_t$ dummy and each of the five factors. Robust standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 6: Congressional votes

	Dependent variable: Returns in from t-1 to t+3						
MFN-Status Voting Date	10/18/1990	7/10/1991	7/21/1992	6/8/1993	8/9/1994	7/20/1995	6/27/1996
Vote Result:	House/Pass	House/Pass	House/Pass	House/Reject	House/Reject	House/Table	House/Reject
NTR Gap 1999	0.0739***	0.00962	-0.0189*	-0.0369*	0.0612***	-0.0508*	-0.031
	(0.0155)	(0.0102)	(0.0114)	(0.0195)	(0.0212)	(0.0277)	(0.0202)
Observations	253	251	246	244	242	243	241
R-squared	0.153	0.01	0.029	0.059	0.199	0.101	0.073
MFN-Status Voting Date	6/24/1997	7/16/1997	7/22/1998	7/20/1999	7/27/1999	7/18/2000	
Vote Result:	House/Reject	Senate/Reject	House/Reject	House/Reject	Senate/Reject	House/Reject	
NTR Gap 1999	-0.0274	0.0356	-0.0856**	-0.0973***	-0.0306	-0.0803*	
	(0.0268)	(0.0352)	(0.0396)	(0.0288)	(0.0207)	(0.0408)	
Observations	238	239	237	235	235	224	
R^2	0.041	0.028	0.141	0.195	0.041	0.091	

Notes: This table contains selected estimates from the following regression:
$R_{i,(t-1,t+3)} = \theta NTRGap_i + \alpha + \epsilon_{it}$
Where $R_{i,(t-1,t+3)}$ is the cumulative return for industry i from $t-1$ to $t+3$, where t is the event-date of interest. Event dates are all days where US Congress voted to revoke China's MFN status. Observations are weighed by each industry's one year lagged market capitalization. Robust standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 7: Pre- and post-trends in expected returns (Baseline)

Dependent variable: Annual Industry Returns		
	(1)	(2)
NTR Gap 1999 x Uncertainty	0.278**	0.297***
	(0.12)	(0.09)
NTR Gap 1999 x Pre	0.108	0.172
	(0.17)	(0.18)
Observations	4,342	1,870
R^2	0.362	0.45
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Industry/Year Controls	No	Yes

Notes: This table contains selected estimates from the following regression, run at the industry(i)/year(t) level using data from 1981-2007:
$R_{it} = \theta_1 PrePNTR_t \times NTRGap_i + \theta_2 Uncertainty_t \times NTRGap_i + \boldsymbol{X}'_{it}\lambda + \delta_i + \delta_t + \alpha + \epsilon_{it}$
where $PrePNTR_t$ is a dummy equal to one for the years 1981-1989, $Uncertainty_t$ is a dummy equal to one for the years 1990-2000 and $NTRGap_i$ is the NTR gap for industry i in 1999. The regression also includes the following controls in $\boldsymbol{X}'_{it}$: Price/Earnings, Price/Book, Return on Invested Capital, return on Equity, EV/EBITDA, Debt/Equity, Current Ratio, Dividend Yield and Market Capitalization. All these controls are lagged one year to prevent a look-ahead bias. The regression includes industry δ_i and time δ_t fixed effects. Each observation is weighed by industry i's market capitalization in 1989. Robust standard errors, clustered at the industry level, are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 8: Pre- and post-trends in expected returns (Portfolios)

	Dependent variable: Monthly Industry Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
	Lowest	2	3	4	Highest	High minus Low
Pre Dummy	-0.00447	-0.00392	-0.000976	-0.00309	0.00295	0.00742
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Uncertainty Dummy	-0.0101**	-0.00685**	0.00201	0.000216	0.00404*	0.0142***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	336	336	336	336	336	336
R-squared	0.562	0.691	0.838	0.819	0.867	0.487
Fama-French 5-Factors	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table contains selected estimates from the following regression, using data from 1981-2007:

$R_{pt} = \theta_1 PrePNTR_t + \theta_2 Uncertainty_t + \boldsymbol{F}'_t\lambda + \alpha + \epsilon_{pt}$

Where R_{pt} is the return on portfolio p in month t, $PrePNTR_t$ is a dummy equal to one for the years 1981-1989 and $Uncertainty_t$ is a dummy equal to one for the years 1990-2000. $\boldsymbol{F}'_t$ is a vector containing the 5 Fama-French factors: Market, Size, Value, Profitability and Investment. Robust standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 9: PNTR and Chinese competition

	Dependent variable: Annual Industry Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
NTR gap 1999 x Post	-0.374**	-0.447***	-0.371**	-0.462***	-0.477**	-0.553***
	(0.17)	(0.14)	(0.17)	(0.13)	(0.18)	(0.12)
NTR gap 1999 x Post x Import	0.0106	-0.208	0.275	-0.0726	0.311	0.0897
	(0.27)	(0.31)	(0.28)	(0.32)	(0.22)	(0.17)
Post x Import	0.0208	0.00893	-0.0969	-0.0425	-0.0277	-0.0355
	(0.08)	(0.10)	(0.09)	(0.11)	(0.06)	(0.07)
NTR rate		-0.916		-0.968		-1.976
		(1.87)		(1.89)		(1.62)
Chinese tariff x Post		-0.0788		-0.102		-0.0541
		(0.18)		(0.18)		(0.11)
Observations	3,154	1,349	3,154	1,349	3,533	1,615
R^2	0.188	0.292	0.188	0.292	0.164	0.268
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry/Year Controls	No	Yes	No	Yes	No	Yes
Competition Computed With	Final Goods	Final Goods	+ Intermediate	+ Intermediate	w/o Dom. Sales	w/o Dom. Sales

Notes: Notes: This table contains selected estimates from the following regression, run at the industry(i)/year(t) level using data from 1990-2007:
$R_{it} = \theta PostPNTR_t \times NTRGap_i + \beta Import_{it} + \boldsymbol{X}'_{it}\lambda + \delta_i + \delta_t + \alpha + \epsilon_{it}$
where $PostPNTR_t$ is a dummy equal to one if the year is greater than 2000, and $NTRGap_i$ is the NTR gap for industry i in 1999. We use three different methods to compute the industry-level import shares from China, $Import_{it}$: (1) Compute import share from WIOD data as industry-level imports from China divided by total US expenditures in that industry, using only trade flows in final goods (2) Everything the same as method 1, except we include trade flows in both intermediate and final goods (3) We use trade flows data at the HS-6 level from UN Comtrade and aggregate them to the industry level. Unlike methods 1 and 2, we compute the share of imports from China as a share of US industry imports, rather than US industry expenditures. The regression also includes the following controls in $\boldsymbol{X}'_{it}$: Price/Earnings, Price/Book, Return on Invested Capital, return on Equity, EV/EBITDA, Debt/Equity, Current Ratio, Dividend Yield and Market Capitalization. All these controls are lagged one year to prevent a look-ahead bias. The regression includes industry δ_i and time δ_t fixed effects. Each observation is weighed by industry i's market capitalization in 1989. Robust standard errors, clustered at the industry level, are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 10: PNTR and Realized Returns

Dependent variable: Event-Day Returns					
	(1)	(2)	(3)	(4)	(5)
	PNTR Dates			Congress votes	Earnings ann.
	10/10/2000	12/11/2001	1/2/2002		
NTR gap 1999	-0.151**	-0.00462	0.04	-0.0425***	
	(0.06)	(0.03)	(0.02)	(0.01)	
NTR gap 1999 x Post					-0.0148**
					(0.01)
Observations	225	224	221	6,790	125,131
R^2	0.11	0	0.022	0.036	0.011
Event Window	t-1 to t+3	t-1 to t+3	t-1 to t+3	t-1 to t+3	t-5 to t+1

Notes: This table contains selected estimates from the following regression:
$R_{i,(t-n,t+m)} = \theta NTRGap_i + \alpha + \epsilon_{it}$
Where $R_{i,(t-n,t+m)}$ is the cumulative return for industry i from $t-n$ to $t+m$, where t is the event-date of interest. 10/10/2000 is the day President Clinton signed the law which gave China PNTR conditional on joining the WTO. 12/11/2001 is the day China joined the WTO. 1/2/2002 is the day PNTR went into effect. Regression 4 pools across across all dates where the US Senate or House of Representatives voted on propositions to revoke China's MFN status. Observations are weighed by each industry's one year lagged market capitalization. Regression 5 is run at the firm, rather than industry level, and obeservations are weighed by each firm's one year lagged market capitalization. Regression 5 also includes industry and year fixed effects. Robust standard errors, which for regression 5 are clustered at the industry level, are in parenthesis.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 11: Robustness - Excluding event days

Dependent variable: Annual Industry Returns (Log Aggregation)

	(1)	(2)	(3)	(4)
NTR gap 1999 x Post	-0.475***	-0.486***	-0.395***	-0.470***
	(0.11)	(0.10)	(0.08)	(0.11)
NTR rate	-1.744	-1.681	-1.562	-1.707
	(1.47)	(1.35)	(1.23)	(1.53)
Chinese tariff x Post	-0.0519	-0.0406	0.0471	-0.0393
	(0.09)	(0.07)	(0.06)	(0.10)
Observations	1,668	1,668	1,668	1,668
R^2	0.282	0.293	0.349	0.279
Exclude PNTR Dates	Yes	Yes	Yes	No
Exclude MFN Voting Dates	No	Yes	Yes	No
Exclude Earnings Dates	No	No	Yes	No
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry/Year Controls	Yes	Yes	Yes	Yes

Notes: This table contains selected estimates from the following regression, run at the industry(i)/year(t) level using data from 1990-2007:

$R_{it} = \theta PostPNTR_t \times NTRGap_i + \boldsymbol{X}'_{it}\lambda + \delta_i + \delta_t + \alpha + \epsilon_{it}$

where $PostPNTR_t$ is a dummy equal to one if the year is greater than 2000, and $NTRGap_i$ is the NTR gap for industry i in 1999. Monthly industry returns are computed by adding up log daily returns. These monthly returns are then compounded up to compute annual industry returns. In column 1, we exclude the t-1 to t+3 window around the following dates when computing monthly returns: 10/10/2000, 12/11/2001 and 1/2/2002. In column 2, we also exclude the t-1 to t+3 window around all the dates where US Congress voted on revoking China's MFN status. In column 3 we also exclude the t-5 to t+1 window around each firm's annual and quarterly earnings announcement days. Column 4 is a replication of our baseline regression, but constructing the initial monthly returns by adding up log daily returns, instead of directly using monthly returns from CRSP.

The regression also includes the following controls in $\boldsymbol{X}'_{it}$: Price/Earnings, Price/Book, Return on Invested Capital, return on Equity, EV/EBITDA, Debt/Equity, Current Ratio, Dividend Yield and Market Capitalization. All these controls are lagged one year to prevent a look-ahead bias. The regression includes industry δ_i and time δ_t fixed effects. Each observation is weighed by industry i's market capitalization in 1989. Robust standard errors, clustered at the industry level, are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 12: IO Linkages and Stock Returns

Dependent variable: Annual Industry Returns			
	(1)	(2)	(3)
Upstream China x Post	-0.878***		
	(0.30)		
Downstream x Post		0.114	
		(0.29)	
Upstream x Post		-1.045*	
		(0.60)	
Downstream Leontief x Post			-0.2
			(0.22)
Upstream Leontief x Post			-1.199***
			(0.28)
NTR rate	-0.853	-0.445	-1.428
	(1.50)	(1.31)	(1.37)
Chinese tariff x Post	-0.0679	-0.163	-0.255
	(0.15)	(0.18)	(0.18)
Observations	1,650	1,571	1,571
R^2	0.249	0.225	0.241
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Industry/Year Controls	Yes	Yes	Yes

Notes: This table contains selected estimates from the following regression, run at the industry(i)/year(t) level using data from 1990-2007:
$R_{it} = \theta PostPNTR_t \times NTRGap_i + \beta IOLinkages_{it} + \boldsymbol{X}'_{it}\lambda + \delta_i + \delta_t + \alpha + \epsilon_{it}$
where $PostPNTR_t$ is a dummy equal to one if the year is greater than 2000, and $NTRGap_i$ is the NTR gap for industry i in 1999. The following terms are part of $IOLinkages_{it}$: $UpstreamChina$ is a a weighted average of NTR gaps for upstream Chinese industries, where the weights are proportional to the share of input expenditures in those industries. $Upstream/Downstream$ are also weighted averages of NTR gaps for upstream/downstream US industries, where the weights are proportional to the expenditures/sales in those industries. $Upstream/DownstreamLeontief$ are calculated from the inverse of the Leontief matrix for all upstream/downstream linkages.
The regression also includes the following controls in $\boldsymbol{X}'_{it}$: Price/Earnings, Price/Book, Return on Invested Capital, return on Equity, EV/EBITDA, Debt/Equity, Current Ratio, Dividend Yield and Market Capitalization. All these controls are lagged one year to prevent a look-ahead bias. The regression includes industry δ_i and time δ_t fixed effects. Each observation is weighed by industry i's market capitalization in 1989. Robust standard errors, clustered at the industry level, are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$