Trade Policy Uncertainty and Stock Returns*

Marcelo Bianconi — Tufts
Federico Esposito — Tufts
Marco Sammon — Kellogg

April 2020

Abstract

We examine how trade policy uncertainty is reflected in stock returns. Our identification strategy exploits quasi-experimental variation in exposure to trade policy uncertainty arising from Congressional votes to revoke China's preferential tariff treatment between 1990 and 2001. More exposed industries commanded a risk premium of 6% per year. The risk premium was larger in sectors less protected from globalization, and more reliant on inputs from China. More exposed industries also had a larger drop in stock prices when the uncertainty began, and more volatile returns around key policy dates. Moreover, the effects of policy uncertainty on expected cash-flows, investors' forecast errors, and import competition from China cannot explain our results.

*Bianconi: Tufts University, 8 Upper Campus Road, Medford, MA 02155 (e-mail: marcelo.bianconi@tufts.edu); Esposito: Tufts University, 8 Upper Campus Road, Medford, MA 02155 (e-mail: federico.esposito@tufts.edu); Sammon: Northwestern University, Kellogg School of Management, Evanston, IL 60201 (e-mail: mcsammon@gmail.com). We thank Erik Loualiche for providing us the globalization factor data. We thank Scott Baker, Steve Davis, Ian Dew-Becker, Jose Fillat, Craig Furfine, Abigail Hornstein, Ravi Jagannathan, Cynthia Kinnan, Robert Korajczyk, Margaret McMillan, Dimitris Papanikolaou, Peter Schott, Martin Thyrsgaard, and numerous seminar participants at Northwestern, Midwest Trade Conference at Vanderbilt, Tufts University, London School of Economics, Atlanta Fed, ASSA 2020, MIT Sloan, for helpful suggestions.

1 Introduction

The recent threat of a trade war between US and China has brought trade policy uncertainty (henceforth TPU) to the forefront of the economic and policy debate. A growing empirical literature has analyzed the effects of TPU on employment (see e.g. Pierce and Schott (2016)), trade (see Alessandria et al. (2019), Crowley et al. (2018), Graziano et al. (2018)), investment (see Handley and Limão (2015), Pierce and Schott (2017), Caldara et al. (2020)), and welfare (see Handley and Limão (2017) and Steinberg (2019)). While this literature has focused on the impact of TPU on economic outcomes, it has remained silent on its effect on asset prices. Given the relevance that stock prices have for firms' investment decisions (see e.g. Chen et al. (2006)), household wealth (see e.g. Guiso et al. (2002), Moskowitz and Vissing-Jørgensen (2002)), and employment (see e.g. Chodorow-Reich et al. (2019)), studying how financial markets respond to policy uncertainty deserves further scrutiny.

This paper documents that TPU is a systematic risk factor that affects asset prices. We capture industries' exogenous and heterogeneous exposure to TPU arising from Congressional votes to revoke China's preferential tariff rates between 1990 and 2001, before China's accession to the World Trade Organization (WTO). Empirically, we find a large risk premium associated with exposure to TPU: investors required an additional 6% return per year on average as compensation for uncertainty about future trade policy. Moreover, the risk premium was larger in sectors more exposed to globalization and more reliant on inputs from China.

We focus on the uncertainty arising from annual votes by Congress to revoke China's "Most Favored Nation" (MFN) status between 1990 and 2001. Starting in 1980, US imports from China were subject to 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 Massacre in 1989. Starting in 1990, NTR renewal in Congress became more politically contentious, with the House passing resolutions against Chinese NTR renewal in 1990, 1991 and 1992. China's tariff status, however, did not change because the US Senate did not pass the House resolutions. Had NTR status been revoked, tariffs would have reverted to non-NTR rates, established under the Smoot-Hawley Tariff Act of 1930, which were on average 27% higher than existing tariffs. The uncertainty about tariff increases on Chinese goods ended on 12/11/2001, when China joined the WTO, eliminating the need for annual renewal votes.

We follow Pierce and Schott (2016), and quantify the heterogeneous exposure to policy 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 rates. We exploit the large cross-sectional variation in the NTR gaps across US tradeable sectors and estimate a differences-in-differences specification in which we regress monthly value-weighted industry stock returns, between 1980 and 2007, on the industry-level NTR gap, interacted with a dummy for the period of trade policy uncertainty (hereafter TPU period). The identification rests on the fact that most of the cross-sectional 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 70 years after they were set.

Our baseline results suggest that US tradeable industries more exposed to tariff uncertainty, i.e. industries that had a higher gap between non-NTR and NTR rates, experienced significantly higher stock returns than less exposed industries between 1990 and 2001. Our specification controls for unobserved industry- and time-specific characteristics, for industry-time variation in firm fundamentals, and other contemporaneous US-China policy changes, such as the global Multi-Fiber Arrangement (MFA) and the reduction in Chinese import tariffs associated with China's accession to WTO. The difference in average returns for high and low NTR gap industries is significant at the 1% level, and implies that going from an industry less exposed to TPU (at the 25th percentile of the distribution of NTR gaps in 1990), to an industry more exposed (at the 75th percentile of the distribution), increases stock returns by 4.2% per year during the uncertainty period. When we estimate a dynamic version of our baseline regression, we find that the correlation between the NTR gap and stock returns was larger in the early 1990s. This is consistent with greater uncertainty about China's NTR status between 1990 and 1992, because this is when the House of Representatives passed a resolution revoking China's preferential tariff treatment.

We then argue that the higher average returns earned by more exposed sectors can be explained by a risk premium for exposure to TPU. Intuitively, during the TPU period, investors required additional compensation to hold stocks with exposure to this policy uncertainty, as argued in the theoretical frameworks of Pastor and Veronesi (2012) and Pástor and Veronesi (2013). Using the predictions of these models to guide our empirical analysis, we document several stylized facts in support of the risk premium hypothesis.

First, we show that a value-weighted portfolio, long high-gap industries and short low-gap industries, had average excess returns of 6% per year, over the 5 factors in Fama and French (2015), during the uncertainty period 1990-2001. Our long-short portfolio's excess return remains economically large and statistically significant after controlling for the globalization factor constructed in Barrot et al. (2018), which uses industry-level shipping costs to proxy for exposure to globalization. This means that TPU was a systematic factor that could not be diversified away and could not be explained by exposure to globalization. In addition, when we repeat the portfolio analysis in the control periods 1980-1989 and 2002-2007, we find no significant difference in stock returns between high and low NTR gap industries.

Second, we investigate which, among the high-gap industries, were earning the risk premium. First, we double sort portfolios on the NTR gap in 1990 and on NTR tariff rates. The risk premium was concentrated in industries whose exposure to globalization, as measured by low NTR tariff rates, was higher. We find similar results when we double sort portfolios on the NTR gap and on industry-level shipping costs from Barrot et al. (2018). This suggests that exposure to globalization amplifies the effects of trade policy uncertainty and thus the associated risk premium. An additional amplification channel is the share of inputs sourced from China: the risk premium was larger among firms with a higher share of inputs expenditures from China, suggesting that uncertainty about the cost of production was also priced by financial markets.[1]

Third, we document a large and significant drop in stock prices for industries with higher NTR gaps around the day in which the policy uncertainty reasonably began, i.e. the day when the first resolution to revoke NTR status was proposed at the House, on 07/23/1990. This is consistent with an increase in the discount rate due to higher uncertainty on future policies that depressed prices of more exposed industries, as in Pastor and Veronesi (2012).

Fourth, we document that more exposed industries had significantly higher realized volatility around relevant policy-related events, such as the Congressional votes to revoke NTR status to China and the day Permanent Normal Trade Relations (PNTR) was granted, consistent with the evidence shown, in other contexts, in Boutchkova et al. (2012) and Baker et al. (2019).

To lend further support to our risk premium hypothesis, we discuss three other potential explanations for our results and show that they are not supported in the data. First, it could be that the differential returns of high and low NTR gap industries may have been driven by stock prices' responses to changes in expected cash-flows, instead of changes in the risk premium. We repeat the portfolio analysis, but exclude a 3-day window around the dates of NTR-related policy announcements, as well as Congressional votes to revoke China's NTR status. We find that removing these days has a negligible effect on the estimated risk premium. Second, it could be that investors initially under- or over-estimated the effect of TPU on firms' performance. If this were true, we would expect to find large stock-market responses around the dates US firms released fundamental information in their quarterly earnings announcements. Empirically, there is no evidence of systematic differences in earnings

[1] On this respect, we contribute to the literature that shows the importance of input-output linkages for economic outcomes (see e.g. Caliendo and Parro (2014), Wang et al. (2018), Adao et al. (2019) and Blaum et al. (2020)), and for stock returns (see e.g. Cohen and Frazzini (2008) and Huang et al. (2018)).

announcement returns for stocks with low and high NTR gaps. A third explanation for our results could be that more uncertainty about future tariffs offered an implicit protection against Chinese competition for firms in high-gap industries, which, as a result, enjoyed higher cash flows and higher stock returns during the 1990-2001 period. We test for this channel by double sorting portfolios on NTR gap and import penetration from China, and find that, instead, the risk premium was earned by industries *more* exposed to China.

Our paper is complementary to the empirical literature that investigates the effects of trade policy uncertainty, and uncertainty in general, on economic outcomes, such as Novy and Taylor (2014), Pierce and Schott (2016), Handley and Limão (2017), Crowley et al. (2018) and Esposito (2019). Differently from this literature, we focus on how TPU affects the riskiness perceived by investors, tracing down its effects on firms' stock returns. Stock returns are an important determinant of real economic variables, such as investment (see Chen et al. (2006)), household wealth (see Guiso et al. (2002)), employment (see Chodorow-Reich et al. (2019)) and business cycles (see Jordà et al. (2019)), and thus their large and heterogenous response to TPU, documented in this paper, may have exacerbated the effects of TPU on economic outcomes.

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), Kelly et al. (2016), Christou et al. (2017), Bali et al. (2017)), but the intrinsic endogeneity of policy actions makes it difficult to identify the causal effects of policy uncertainty. The methodology used in this paper presents some advantages relative to this literature. First, the identification strategy relies on non-NTR tariff rates that were set 70 years before the onset of policy uncertainty, providing the quasi-experimental variation needed to estimate the risk premium. Second, while most indicators of policy uncertainty used by the literature do not vary across industries, see e.g. Jurado et al. (2015), and Baker et al. (2016), our measure directly captures differences in exposure to TPU across sectors.[2] Third, it is an *ex-ante* measure of uncertainty, and thus is not subject to a look-ahead bias.[3] Lastly, it is directly observable, and thus its construction is not subject to measurement error, and it does not rely on assumptions about the underlying volatility process.

We contribute to the literature on the effects of globalization on stock returns, see e.g. Fillat and Garetto (2015) and Barrot et al. (2018). This literature has shown that industries more exposed to foreign competition or foreign shocks command a large risk premium. Our

[2] Brogaard and Detzel (2015) use the Baker et al. (2016) index, which does not vary across industries, but allow firms to heterogeneously load on this factor in firm-level regressions.

[3] For instance, 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. Kelly et al. (2016) and Alfaro et al. (2018) use forward-looking option-implied volatilities and realized volatilities.

double sorting exercise documents that the interaction between such "first-moment" effect and the "second-moment" effect arising from TPU amplifies the risk premium.

There is a recent literature that uses stock-market event studies to evaluate trade policies (see e.g. Breinlich (2014), Moser and Rose (2014), Huang et al. (2018), Crowley et al. (2019) and Greenland et al. (2019)). The goal of this literature is to look at the short-run response of stock returns to policy news in order to tease out the market expectations on future cash-flows. Our goal is complementary, in that we look at the long-run behavior of stock returns, which is informative of how investors perceive firms' riskiness.

The paper proceeds as follows. Section 2 documents the effect of tariff uncertainty on average stock returns across US tradeable industries during the 1990-2001 period. Section 3 argues that such effect was a risk premium for exposure to trade policy uncertainty. Section 4 discusses alternative explanations for the results. Section 5 concludes.

2 Tariff Uncertainty and US Stock Returns

In this section, we use quasi-exogenous variation in exposure to tariff uncertainty across US tradeable industries to identify the causal effect of trade policy uncertainty on stock returns. We first look at a difference-in-differences specification, that shows that industries more exposed to TPU in 1990-2001 had higher average returns relative to low-gap industries. We then show that such positive differential return was absent in the control periods 1980-1989 and 2002-2007.

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).[4] From 1980 to 1989, renewal of these NTR rates for China was essentially automatic. After the Tiananmen Square Massacre in 1989, however, the US House of Representatives introduced and voted on legislation to revoke China's temporary NTR tariffs 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. The renewal process was politically contentious. In fact, the House passed resolutions against Chinese NTR renewal in 1990, 1991 and 1992, despite being disapproved by the Senate later

[4] US president Jimmy Carter began granting such waiver to China annually in 1980, under the premises of the US Trade Act of 1974.

on.[5] 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 this source of tariff uncertainty by fixing US taxes on Chinese imports at NTR levels.

We argue that the annual Congressional votes generated uncertainty because: (i) investors were uncertain about whether China's NTR status would be revoked, and (ii) they were uncertain about the future performance of US industries if NTR status was revoked. As in Pastor and Veronesi (2012), we refer to the former type of uncertainty as ''political uncertainty'', while to the latter as ''policy uncertainty''. While the likelihood of a policy change (i.e. revoking NTR status to China) was the same for all industries, since either all would revert to Smoot-Hawley rates, or all would keep lower NTR rates, the potential impact of such policy change could have been different across industries.

To capture the exposure of each sector to such ''policy uncertainty'', we follow Pierce and Schott (2016) and construct 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:

$$NTRGap_{it} = NonNTR_i - NTR_{it} \tag{1}$$

where i stands for industry and t for year.[6] 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. As in Pierce and Schott (2016), we exclude all industries that have missing NTR gaps, i.e. non-tradeable industries. This practically excludes also industries that had positive NTR rates but missing non-NTR rates.

Our identification relies on the fact that most of the variation in the NTR gap across tradeable industries arises from variation in non-NTR rates, set 70 years prior to passage of PNTR.[7] This feature mitigates concerns of 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 varia-

[5]See Online Appendix of Pierce and Schott (2016) for several pieces of anecdotal evidence suggesting how the renewal of China's NTR status was perceived as uncertain.

[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 Harmonized System (HS) level. Industry-level NTR gaps are then computed using concordances provided by the US Bureau of Economic Analysis (BEA), such that the gap for an industry is the average NTR gap across the eight-digit HS tariff lines belonging to that industry.

[7]A regression of the NTR gap in 1990 on the non-NTR rate across industries gives a R^2 of 0.96, while a regression of the NTR gap in 1990 on the NTR rate in 1990 gives a R^2 of only 0.15.

tion in the NTR gaps across US tradeable industries in the years 1990-2001, *before* China was granted PNTR. We compare the stock returns of US firms in high NTR gap industries to low NTR gap industries (first difference), during the uncertainty period, 1990-2001, versus the years 1980-1989 and 2002-2007 (second difference). These potential tariff increases were substantial: in 1990 the average NTR gap across the tradeable industries in our sample was 27% with a standard deviation of 14%. The distribution of NTR gaps in 1990 is displayed in Figure A.1 in Appendix 6.1.

To compute market-adjusted stock returns, we start with the universe of publicly listed US firms in CRSP that can be matched to Compustat, from where we download all the firm-level variables used as controls in the regressions. We then filter for ordinary common shares traded on major exchanges (NYSE, AMEX and NASDAQ). We match the SIC code in Compustat, which assigns a single SIC code to each firm, to the Pierce and Schott (2012) families of industries and only keep the matched firms. Each month, we construct value-weighted portfolios at the industry level, where the weights are proportional to each firm's 1-month lagged market capitalization. We value-weight the portfolios to reduce the influence of small firms (see e.g. Hou et al. (2017)). Table A.1 in Appendix 6.1 reports some summary statistics about our final sample. Table A.2 further documents that our sample does not significantly differ in terms of firms' average size from the original populations in both CRSP and CRSP/Compustat Merged (CCM).

2.2 Diff-in-Diff specification

We begin our analysis by estimating the following regression at the US industry/month level:

$$r_{it} = \alpha + \beta_1 Uncertainty_t \times Gap_{i,y-1} + \delta_i + \delta_t + \boldsymbol{X}'_{iy-1}\lambda + \epsilon_{it} \tag{2}$$

where the dependent variable is the return of value-weighted industry portfolio i in month t and year y, for the years 1980 to 2007. The first term on the right-hand side is the Difference-in-Differences (DID) term of interest, an interaction of the one year-lagged NTR gap and an indicator for the uncertainty period, i.e. equal 1 in the years characterized by tariff uncertainty, 1990-2001.[8] Therefore, the DID term of interest equals zero in the control periods, 1980-1989 and 2002-2007. $\boldsymbol{X}_{it-1}$ is a vector of lagged industry-time controls, to be specified below, while δ_i and δ_t are industry and month fixed effects, which control for industry specific components of systematic risk and for time trends in stock returns.

We use time-varying NTR gaps to prevent a look-ahead bias and to allow for time

[8]Although President Clinton signed the law granting PNTR in October 2000, China actually entered the WTO in December 2001, thus Congress voted also in 2001 on whether to revoke China's NTR rates.

variation in the measure of uncertainty, in order to identify more precisely the response of stock returns over time.[9] We use the lagged NTR gaps to avoid endogeneity issues, which may arise if NTR tariff rates responded to contemporaneous changes in stock returns. In addition, the implicit assumption is that every year, investors' used previous-year NTR gaps to assess the level of each industry's tariff uncertainty. Regression estimates are weighted by industry stock market capitalization in 1979, before the beginning of our sample period. Standard errors are clustered at the industry level to allow for arbitrary error correlations within industries over time. The final sample consists of 123 tradeable industries over 336 months, for a total of 40,400 observations.

The baseline results are shown in Table 1. Columns (1)-(2) report the results for the period 1980-2001, columns (3)-(4) report the results for the period 1990-2007, while columns (5)-(6) consider the entire period 1980-2007. For each sample period, we first consider a simple specification that includes only the DID term, the un-interacted NTR gap in 1990, and month fixed effects. We can see that, irrespective of the control period used, the DID term is positive and 1% significant, suggesting that high-gap industries had higher average monthly returns than low-gap industries during the uncertainty period 1990-2001.

In columns (2), (4) and (6) we control for contemporaneous policy changes related to China's accession to the WTO that could have influenced the performance of US industries over our sample period. To this end, we include the NTR tariff rates, Chinese import tariffs from Brandt et al. (2012), and data on US textile and clothing quotas from Khandelwal et al. (2013). We also add some industry-level financial characteristics known to be correlated with expected returns, such as the one-year lagged industry-level price/earnings ratio (see Shiller (2000)), price/book ratio (see Fama and French (1995)), dividend yield (see Black and Scholes (1974)), and market capitalization (see Banz (1981)). In Appendix 6.2 we describe the methodology used to compute these variables. We also add the industry fixed effects to account for unconditional difference in average returns across industries over time.

[9]In Table A.3 we show that results are similar if we fix the NTR gap to its value in 1990.

Table 1: TPU and Stock Returns

Dep. variable:	Monthly returns, r_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
$Gap_{i,y-1} \times D_t$	0.011***	0.012**	0.019***	0.027***	0.015***	0.020***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
$Gap_{i,1990}$	(0.01)		-0.014**		-0.009**	
	(0.00)		(0.01)		(0.00)	
R^2	0.124	0.130	0.160	0.166	0.127	0.131
Observations	32,080	31,822	25,680	25,448	40,400	40,064
Sample Period	1980-2001	1980-2001	1990-2007	1990-2007	1980-2007	1980-2007
Industry FE	N	Y	N	Y	N	Y
Month FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y

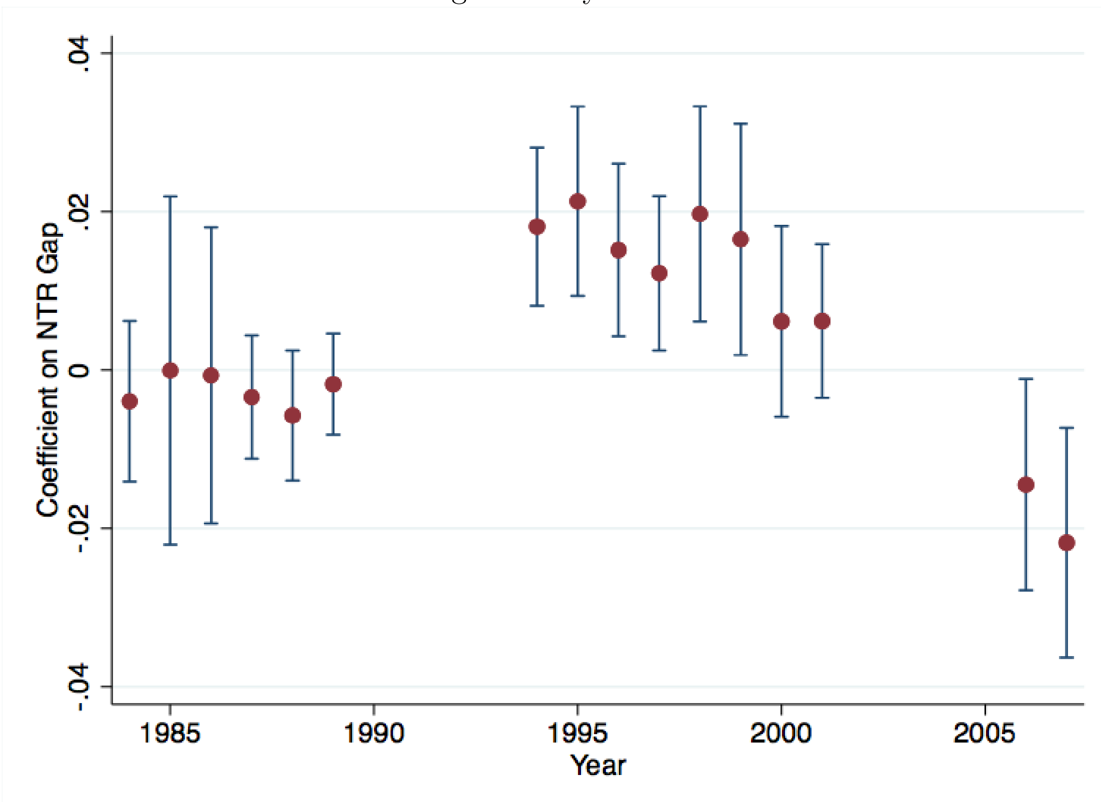
Notes: This table contains selected estimates from versions of the following regression, run at the industry(i)/month(t) level:
$r_{it} = \alpha + \beta_1 D_t \times Gap_{i,y-1} + \delta_i + \delta_t + \boldsymbol{X}'_{iy-1}\lambda + \epsilon_{it}$
where D_t is a dummy equal to one if the year is between 1990 and 2001, r_{it} is the return of value-weighted industry portfolio i in month t. The regression also includes the following controls in $\boldsymbol{X}'_{it}$: NTR tariff rates, Chinese import tariffs, quotas, Price/Earnings, Price/Book, Dividend Yield, and Market Capitalization. δ_i and δ_t are industry and month fixed effects. Observations are weighted by industry i's market capitalization in January, 1979. Robust standard errors, clustered at the industry level, are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

We can see that the coefficient on the DID term of interest remains positive and statistically significant throughout all the specifications. The last column of Table 1, which uses all controls and the entire sample period, represents the "baseline" specification to which we refer throughout the remainder of the paper. The difference-in-differences coefficient of 0.020 in the baseline specification is significant at 1% level, and it implies that going from an industry less exposed from trade policy uncertainty (at the 25th percentile of the distribution of NTR gaps in 1990), such as "Aluminum Sheet, Plate, and Foil Manufacturing", to an industry more exposed to trade policy (at the 75th percentile of the distribution), such as "Heating Equipment Manufacturing", increases stock returns by 4.2% per year during the uncertainty period.

2.3 Dynamics

For the differential stock performance of high-gap industries to be attributable to exposure to TPU, our policy measure, the NTR gap, should be positively correlated with stock returns only during the 1990-2001 period, but not in the control periods. To determine whether there is a relationship between the NTR gap and stock returns in the years 1980-1989 and 2002-2007, we estimate rolling windows regressions. We start by running a first-stage regression of stock returns on the baseline set of control variables, and take the residuals. We then regress these residuals on the NTR gap in 5-year rolling windows. The use of 5-year rolling windows is common in the finance literature, see e.g. Frazzini and Pedersen (2014), and it allows to flexibly look at the dynamics of stock returns while guaranteeing enough precision of the estimates.

Figure 1: Dynamics



Notes: This figure is constructed in two steps: First, we run a regression of industry level returns on the set of controls in the baseline regression, as well as industry fixed-effects and month-fixed effects. The second stage takes the residuals from the first stage, and regresses them on the NTR gap in 5-year rolling windows. For example, the datapoint for 1994 uses data from 1990 to 1994. The blue lines surrounding the point estimates (red dots) are 95% confidence intervals, calculated based on standard errors clustered at the industry-level.

The graph shows that the positive association between the NTR gap and stock returns was significant throughout the entire 1990-2001 period, but it was stronger in the first years of the decade (although the coefficient are not statistically different from each other). This is consistent with the fact that there was greater uncertainty about the legislation passage in the years 1990-1992, as suggested by the fact that in those years the House voted in favor of revoking NTR status to China.

In contrast, in the 1980-1989 control period the relationship between NTR gap and stock returns was not significantly different from zero, while after 2001 the coefficient is negative and significant. This negative relationship in the post period can likely be explained with a negative effect of PNTR on high-gap firms cash-flows, as documented by Greenland et al.

(2019). This may also explain the larger DID coefficient that we find in Table 1 when we use the 2002-2007 control period. We discuss in detail in Section 4 how the cash-flow effect could affect our results. However, it is important to note that the negative relative returns observed in the post period do not alter the main conclusions of the paper, since the portfolio analysis we undertake in Section 3 documents a TPU risk factor *only* in the uncertainty period 1990-2001.

2.4 Robustness

In Table A.3 in Appendix 6.1 we perform several exercises to gauge the robustness of our baseline results. First, we control for the possibility that high-gap and low-gap industries may load differently on risk factors known to predict returns. To this end, we first run regressions using daily data in 5-year rolling windows to estimate the betas of each industry portfolio on the Fama and French (2015) factors. We then interact the estimated betas, lagged by one month, with the uncertainty dummy, and add them to the baseline regression. Column (1) shows that the DID coefficient is very close to the baseline. Column (2) reports the results of the baseline specification, but with standard errors clustered at both industry and month level, as in Petersen (2009), to account for the potential autocorrelation of the residuals. With double clustering, the coefficient of interest is still significant at the 5% level.[10] Column (3) weighs observations by the industry's previous year market capitalization, as in standard portfolio analysis; column (4) uses an equally weighted regression; column (5) includes an interaction between all control variables and the treatment period dummy, to ensure that the other covariates do not generate differential average returns during the uncertainty period (see e.g. Gagliardini et al. (2016)). We can see that in all these specifications the DID coefficient is very similar to the baseline. In addition, column (4) suggests that weighting the observations leads to a more precise point estimate, which is smaller but not statistically different from the baseline.

One concern with our identification strategy is that the US government could have set high NTR tariff rates to protect industries that they expected to perform poorly. In this case, while the non-NTR rates are exogenous because they were set by the Smoot-Hawley act, NTR rates are not. A second related concern is that the decision to vote on legislation to revoke China's temporary NTR status could have motivated by economic reasons, rather than geo-political reasons, i.e. the Tiananmen Square Massacre. This could generate an omitted variable problem in our regressions, leading to biased estimates. To mitigate these concerns,

[10]We do not weight observations when we double cluster the standard errors, because that leads to a not well-defined covariance matrix. This could be the result of a particular correlation structure within clusters.

we follow Pierce and Schott (2016) and estimate a two-stage least squares specification in which we instrument the baseline DID term, $Uncertainty_t \times Gap_{i,y-1}$, with an interaction of the uncertainty indicator and the Smoot-Hawley non-NTR rates, $Uncertainty_t \times NNTR_i$. As reported in column (6) of Table 3, the DID coefficient is positive, statistically significant and close to the baseline. Finally, column (6) reports the results when holding the NTR gap at its level in 1990, the year the uncertainty started, with similar results.[11]

3 A Risk Premium for Tariff Uncertainty

Our empirical results show that high gap industries had higher average returns, relative to low gap industries, between 1990 and 2001. In this section, we argue that this difference in returns was a risk premium for exposure to tariff uncertainty. We first perform a portfolio analysis which shows that, *only* in the uncertainty period 1990-2001, a portfolio long high-gap sectors and short low gap industries had positive and significant returns. We then present additional empirical evidence on discount rate effects and realized volatility that support our risk premium hypothesis.

3.1 Conceptual framework

In any asset pricing model (see e.g. Cochrane (2009) and Duffie (2010)), the maximization problem of the representative investor implies the following relationship:

$$E\left(r_{it} - r_f\right) \propto -Cov\left(SDF_t, r_{it}\right) \tag{3}$$

Equation (3) states that the expected excess return of any asset i is inversely proportional to the covariance of the asset's return with the Stochastic Discount Factor (SDF). Intuitively, stocks that covary negatively with the SDF are riskier because they pay less in bad states of the world, and thus require higher expected returns as compensation for risk-averse investors.[12] Empirically, expected returns are estimated using average returns, computed over long periods of time.

To fully characterize the SDF, further assumptions about the economy are needed. The key elements in defining the SDF are the factors that affect the marginal utility of consumption.

[11] Additional results not reported for brevity show that our findings are robust if i) we use the industry classification in CRSP, and ii) we exclude the computer and electronics industries that experienced the dot-com crash in 2000-2001, iii) we extend the sample to 2017.

[12] For example, with CRRA utility and time-separable preferences, the SDF is proportional to the marginal utility of consumption. See also footnote 16.

Given our setting, we think it is appropriate to start with the well-known frameworks in Pastor and Veronesi (2012) and Pástor and Veronesi (2013). In these models, stock dividends depend on the government policy, which is uncertain, and thus any policy change affects the future marginal utility. This implies that government policy enters the SDF, i.e. investors require an additional compensation for exposure to policy uncertainty. In the context of our analysis, this means that stocks more exposed to TPU, i.e. stocks with higher NTR gap, should have a higher (in absolute value) covariance with the component of the SDF associated with TPU. From equation (3), this implies higher expected returns.[13]

In the next section, we follow the vast literature on empirical asset pricing (see e.g. Nagel (2013) and Fama and French (2015)) and test this hypothesis by ranking stocks according to their exposure to TPU and forming value-weighted portfolios. We then present additional empirical evidence, consistent with the predictions of the Pastor and Veronesi (2012) model, that supports our risk premium hypothesis.

3.2 Portfolio analysis

In order to estimate the risk premium associated with exposure to TPU, we rank the industries in our sample in 3 sub-groups, based on their NTR gap in 1990, the year the uncertainty began. The groups are above/below/between the 33rd and 66th percentiles. We then construct value-weighted portfolios, with weights proportional to each firm's market capitalization in the previous month, and calculate monthly returns between 1990 and 2001. We then construct a "Trade Policy Uncertainty" (TPU) portfolio, which is the difference in returns between the portfolios containing firms with the highest and lowest gaps, divided by two. We then run the following regression, separately for each portfolio p:[14]

$$r_t^p = \alpha^p + \boldsymbol{F'}_t \beta + \epsilon_t \tag{4}$$

where r_t^p is the excess return on portfolio p in month t, and $\boldsymbol{F}_t$ is a vector containing the 5 Fama and French (2015) factors: the market portfolio minus the risk-free rate, the size

[13]This conclusion implicitly assumes that: i) the covariance between the component of the SDF associated with jumps in TPU and stock returns is negative, i.e. increases in TPU are perceived as bad states of the world by investors, and ii) the loading on the TPU factor in the SDF is positive. Both endogenously hold in Pastor and Veronesi (2012) (see Proposition 6), and are consistent with a vast literature arguing that increases in uncertainty are detrimental for the economy (see e.g. Bloom et al. (2007), Bloom (2009) and Bachmann et al. (2013)).

[14]The implicit assumption is that the loadings on other risk-factors, such as the Fama and French (2015) factors, are randomly distributed across high and low gap firms. In addition, under standard assumptions on the stochastic process for the returns, one can show that the SDF is linear in its arguments (see e.g. Pastor and Veronesi (2012)). This implies that by constructing a portfolio that goes long high-gap firms, and short low-gap firms, we can effectively isolate exposure to TPU.

factor (small minus big), the value factor (high minus low), the profitability factor (robust minus weak), and the investment factor (conservative minus aggressive).[15] Our hypothesis is that industries more exposed to policy uncertainty should command higher expected returns, because investors require compensation for such exposure, as in Pastor and Veronesi (2012). If our hypothesis is correct, then the estimated constant α^p in equation (4) should be: i) monotonically increasing as we go from low to high gap portfolios, and ii) positive and significant for the TPU portfolio.

Our results in Table 2 show that the TPU portfolio had an α^p of 0.005 per month during the uncertainty period, significant at the 1% level. Furthermore, the constant is monotonically increasing as we go from the low gap to high gap portfolios. The estimated coefficient implies that the TPU portfolio, long high-gap firms and short low-gap firms, would have earned 6% per year throughout the 1990-2001 period. Therefore, trade policy uncertainty was a systematic factor that could *not* be diversified away across stocks with similar NTR gaps.[16]

[15] We obtain the monthly returns on these factors from Ken French's website: `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

[16] Additional evidence in favor of the risk premium hypothesis comes from the consumption-based capital asset pricing model. Under power utility, the risk premium is simply proportional to $-Cov\left(\beta\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}, r_{it}\right)$, where γ is the relative risk aversion of the representative consumer, r_{it} is the return of asset i, and $\frac{C_{t+1}}{C_t}$ is the growth rate of aggregate consumption. We estimate this correlation with a range of relative risk aversion from 1 to 30, gross growth of US private consumption expenditure from the FRED database, the S&P500 market portfolio, and the TPU portfolio constructed as described above. We find that the correlation between the stochastic discount factor and the TPU portfolio payoff is between -0.20 and -0.22, and statistically significant between 1990 and 2001. Instead, in the 1980-1989 and 2001-2007 periods such correlation is not statistically significant.

Table 2: Portfolio analysis

Dep. variable:	Monthly returns, R_t^p			
	Low Gap	Medium Gap	High Gap	TPU
Market	0.849***	1.098***	0.983***	0.067
	(0.05)	(0.06)	(0.08)	(0.05)
Size	-0.131**	0.220***	0.133	0.132**
	(0.05)	(0.08)	(0.08)	(0.06)
Value	-0.237**	-0.031	-0.294**	-0.029
	(0.09)	(0.11)	(0.12)	(0.09)
Profitability	0.243***	-0.076	-0.240**	-0.241***
	(0.07)	(0.08)	(0.11)	(0.08)
Investment	0.742***	-0.310*	-0.601***	-0.671***
	(0.15)	(0.17)	(0.16)	(0.13)
α^p	-0.002	-0.001	0.008***	0.005***
	(0.00)	(0.00)	(0.00)	(0.00)
Realized Volatility	0.034	0.061	0.072	0.032
R^2	0.713	0.881	0.878	0.694
Observations	144	144	144	144
Sample Period	1990-2001	1990-2001	1990-2001	1990-2001

Notes: This table contains selected estimates from the following regression, using data from 1990-2001:
$r_t^p = \boldsymbol{F'}_t\beta + \alpha^p + \epsilon_t$
where r_t^p is the return on portfolio p in month t. $\boldsymbol{F'_t}$ 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 2 also reports the realized volatility of each portfolio computed during the same period. We can see that the realized volatility increases monotonically as we go from the low gap to the high gap portfolio. This is also consistent with the Pastor and Veronesi (2012) model, which predicts a positive relationship between exposure to uncertainty and volatility.

Table 3 repeats the same portfolio analysis but using the 1980-1989 and 2001-2007 periods. The table documents that during the control periods, high-gap industries did not have economically large or statistically significant alphas, suggesting that the risk premium was earned only during the uncertainty period, consistent with our hypothesis.

Table 3: Portfolio analysis, control periods

Dep. variable:	Monthly returns, R_t^p	
	TPU	TPU
Market	-0.014	0.074
	(0.04)	(0.07)
Size	0.229***	0.114*
	(0.07)	(0.06)
Value	-0.343***	-0.294**
	(0.10)	(0.12)
Profitability	-0.296***	-0.323**
	(0.10)	(0.14)
Investment	-0.02	0.093
	(0.13)	(0.14)
α^p	0.002	0
	(0.00)	0.00
Realized Volatility	0.018	0.019
R^2	0.419	0.544
Observations	120	72
Sample Period	1980-1989	2002-2007

Notes: This table contains selected estimates from the following regression:
$r_t^p = \boldsymbol{F'}_t\beta + \alpha^p + \epsilon_t$
where r_t^p is the return on portfolio p in month t. $\boldsymbol{F}'_t$ is a vector containing the 5 Fama-French factors: Market, Size, Value, Profitability and Investment. Robust standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

3.2.1 The determinants of the risk premium

We now investigate which economic forces interact with exposure to TPU and determine the expected returns. We first examine how the level of trade protection interacts with the exposure to trade policy uncertainty. Specifically, we form portfolios by double-sorting the industries according to both the NTR gap in 1990 and the NTR tariff rate in 1990. To do this, we calculate the median of the NTR gap in 1990, and the median of the NTR rate in 1990. We then do a 2 by 2 sort to form 4 total portfolios. Table 4 shows that the risk premium was earned mostly by industries with a low level of NTR rate, i.e. industries less protected by trade policy from foreign competition. This suggests that a lack of protection from import competition can amplify the risk premium for TPU.

Table 4: TPU and NTR rates

Dep. variable:	Monthly returns, R_t^p	
	TPU-Low	TPU-High
Market	0.028	0.085
	(0.07)	(0.08)
Size	0.078	0.1
	(0.08)	(0.09)
Value	-0.057	0.137
	(0.12)	(0.13)
Profitability	-0.278***	-0.18
	(0.10)	(0.11)
Investment	-0.683***	-0.264
	(0.17)	(0.22)
α^p	0.007***	-0.001
	(0.00)	(0.00)
R^2	0.552	0.203
Observations	144	144
Sample Period	1990-2001	1990-2001

Notes: This table contains selected estimates from the following regression, using data from 1990-2001:
$r_t^p = \boldsymbol{F}_t'\beta + \alpha^p + \epsilon_t$
where r_t^p is the return on portfolio p in month t. $\boldsymbol{F}_t'$ is a vector containing the 5 Fama-French factors: Market, Size, Value, Profitability and Investment. Robust standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Motivated by this result, we examine the relationship between our TPU factor and the globalization risk premium, estimated in Barrot et al. (2018) with data on industry-level shipping costs. We first simply add their factor as control in addition to the baseline 5 factors. Table 5 shows that the high-gap portfolio loads positively on the globalization factor, but the alpha remains highly significant and very close to the baseline, suggesting that the TPU risk premium is not explained by exposure to globalization.

Table 5: TPU and Globalization Risk Factor

	Low Gap	Medium Gap	High Gap	TPU
Market	0.841***	1.093***	0.947***	0.053
	(0.05)	(0.07)	(0.07)	(0.05)
Size	-0.123**	0.225***	0.169**	0.146**
	(0.06)	(0.08)	(0.08)	(0.06)
Value	-0.193*	-0.001	-0.093	0.05
	(0.10)	(0.12)	(0.11)	(0.09)
Profitability	0.262***	-0.063	-0.153	-0.207***
	(0.07)	(0.08)	(0.10)	(0.08)
Investment	0.753***	-0.303*	-0.552***	-0.653***
	(0.15)	(0.17)	(0.15)	(0.13)
Globalization	0.057	0.037	0.256***	0.100**
	(0.05)	(0.07)	(0.05)	(0.05)
α^p	-0.002	-0.001	0.005**	0.004**
	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.718	0.881	0.898	0.710
Observations	144	144	144	144
Sample Period	1990-2001	1990-2001	1990-2001	1990-2001

Notes: This table contains selected estimates from the following regression, using data from 1990-2001:
$r_t^p = \boldsymbol{F'}_t\beta + \alpha^p + \epsilon_t$
where r_t^p is the return on portfolio p in month t. $\boldsymbol{F}'_t$ is a vector containing the 5 Fama-French factors: Market, Size, Value, Profitability and Investment, plus the Globalization Factor estimated in Barrot et al (2018). Robust standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

In addition, we double sort portfolios on the NTR gap in 1990 and on the shipping costs from Barrot et al. (2018). Table 6 reports that, within high-gap industries, the TPU risk premium was earned by industries with lower shipping costs, i.e. sectors that were exposed more to globalization. This suggests another amplifying factor of the risk premium for trade policy uncertainty.

Table 6: TPU and Shipping costs

Dep. variable:	Monthly returns, R_t^p	
	TPU-Low	TPU-High
Market	0.003	0.123**
	(0.09)	(0.05)
Size	0.115	0.126**
	(0.10)	(0.05)
Value	0.432**	-0.393***
	(0.17)	(0.08)
Profitability	-0.441***	0.038
	(0.12)	(0.07)
Investment	-1.087***	0.214*
	(0.21)	(0.12)
α^p	0.006**	0.001
	(0.00)	(0.00)
R^2	0.453	0.462
Observations	144	144
Sample Period	1990-2001	1990-2001

Notes: This table contains selected estimates from the following regression, using data from 1990-2001:
$r_t^p = \boldsymbol{F'}_t\beta + \alpha^p + \epsilon_t$
where r_t^p is the return on portfolio p in month t. $\boldsymbol{F'_t}$ is a vector containing the 5 Fama-French factors: Market, Size, Value, Profitability and Investment. Robust standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Lastly, we study another channel through which TPU may have affected the riskiness of US firms. Table 7 documents that, within high-gap industries, industries with a higher share of inputs expenditures from China throughout the 1990-2001 period earned a larger risk premium.[17] This suggests that uncertainty about the cost of production, deriving from uncertainty on the tariffs imposed on intermediate inputs from China, is a risk factor that was also priced by financial markets.

[17]We use data from WIOD to compute the share of expenditures of each downstream US industry on each upstream industry from China. Since the sectors in the WIOD are more aggregated than the industries in our sample, we assume that this share is constant across industries within each WIOD sector.

Table 7: TPU and inputs from China

Dep. variable:	Monthly returns, R_t^p	
	TPU-Low	TPU-High
Market	0.037	0.043
	(0.07)	(0.07)
Size	0.116	0.124*
	(0.09)	(0.07)
Value	0.047	0.047
	(0.10)	(0.12)
Profitability	-0.095	-0.260***
	(0.08)	(0.09)
Investment	-0.146	-0.770***
	(0.15)	(0.16)
α^p	0.002	0.005***
	(0.00)	(0.00)
R^2	0.117	0.620
Observations	144	144
Sample Period	1990-2001	1990-2001

Notes: This table contains selected estimates from the following regression, using data from 1990-2001:
$r_t^p = \boldsymbol{F}_t' \beta + \alpha^p + \epsilon_t$
where r_t^p is the return on portfolio p in month t. $\boldsymbol{F}_t'$ is a vector containing the 5 Fama-French factors: Market, Size, Value, Profitability and Investment. Robust standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

3.3 Discount rate effect

In Section 3.1, we argue that high-gap firms had higher average returns than low-gap firms between 1990 and 2001 because investors required a risk premium for exposure to trade policy uncertainty. In any asset pricing model, the stock price of firm i in period t equals:

$$P_{i,t} = \frac{D_{i,t+1}}{r_i - g_i}, \tag{5}$$

where $D_{i,t+1}$ is the cash-flow at $t+1$, r_i is a weighted-average of all future discount rates, and g_i is a weighted-average of all future growth rates (see e.g. Campbell and Shiller (1988)). The discount rate embeds firm i's loadings on all priced risk factors which, as argued in Section 3.1, should include trade policy uncertainty. Equation (5) implies that if there is a sudden jump in TPU, the discount rate increases and the stock price decreases. Thus, if we could identify the date when the uncertainty on China's NTR status began, we should observe a sudden decrease in stock prices for exposed industries. As shown in Pastor and

Veronesi (2012), this discount rate effect at the announcement of a new policy should be stronger for industries more exposed to TPU, i.e. the ones with higher NTR gap.

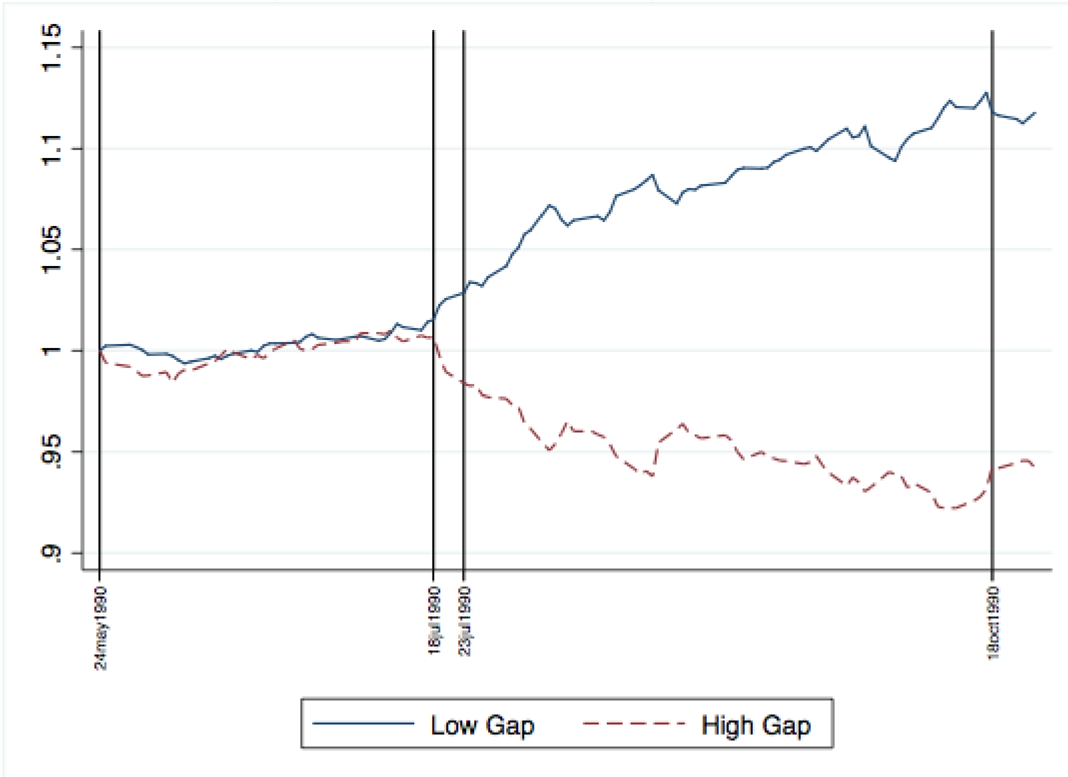
We look at the stock price responses around the days in which the uncertainty about China's tariff status reasonably began. In particular, while the Tiananmen Square Massacre happened on June 4, 1989, the first resolution to revoke China's NTR status was introduced in the House on May 24, 1990, by Rep. Donald Pease (H.R. 4939), and it was reported by the Committee on Ways and Means on July 23, 1990 (H. Rept. 101-620).[18] As introduced, the bill would have directed the President to take new conditions – involving substantial progress on human rights violations – into account when extending China's MFN status beginning in 1991 (see Dumbaugh (1998)).[19]

We examine value-weighted portfolios of high-gap and low-gap firms, defined as having NTR gaps above/below the median in 1990. We work with market-adjusted returns of these portfolios to take out a common mean component over the period of interest. Figure 2 documents the value of $1 invested in each of these portfolios on May 24, 1990. We can see that, from when the bill was introduced until July, 1990, high and low gap firms were following the same trend. On July 18, 1990 the bill was ordered to be reported by the Committee on Ways and Means, and it was actually reported by the Committee on July 23, 1990 (H. Rept. 101-620). Since then, i.e. when it became known to the public that the House was considering revoking China's NTR status, high-gap firms' market-adjusted stock returns started to decrease relative to low-gap firms. This suggests a strong discount rate effect pushing down prices for tradeable sectors more exposed to the newly introduced trade policy uncertainty. Interestingly, when the bill was actually approved by the House on October 18, 1990, there was no significant impact on stock prices, suggesting that the markets had already priced in the increased TPU.

[18]The Tiananmen Square Massacre happened 3 days after President Bush's MFN extension recommendation for 1989, and no resolution was introduced in the Congress in 1989 to disapprove the President's recommendation. The U.S. response to Tiananmen Square that year consisted of two sets of non-MFN-related sanctions announced by President Bush (on June 5 and June 20, 1989), and a series of bills that Congress considered which were designed to codify the President's actions and expand their scope. See Dumbaugh (1998).

[19]See https://www.congress.gov/bill/101st-congress/house-bill/4939.

Figure 2: Effect of Introducing Uncertainty



Notes: The figure plots the value of 1 dollar invested in value-weighted portfolios of high and low gap industries on 5/24/1990.

Another explanation for the drop in stock prices for high NTR gap firms could have been a decrease in g_i.[20] This may have occurred, for example, if investors believed that increased policy uncertainty would have led high-gap firms to hold cash, instead of paying dividends or buying back shares, relatively more than low-gap firms. If investors had perfect foresight, the effect of increased uncertainty on all future expected dividend growth rates should have been reflected in prices. To test this hypothesis, we calculate realized dividend growth rates for the 3 portfolios formed in Section 3.2. We find that between 1990 and 2001, the dividend growth rate of high-gap firms was not statistically significantly different from the one of low-gap firms. This suggests that, even in the perfect foresight case, a change in g_i was likely not responsible for the price drop in Figure 2.

[20] Of course, another reason for the drop in stock price could have been a relative decrease in the next period's dividends, $D_{i,t+1}$. However, the literature has shown that uncertainty typically has long-run effects that would not show up instantaneously on dividends (see e.g. Bloom (2009) and Barrero et al. (2017)). In fact, when we look at dividends paid in 1991, they actually increased relatively more for high-gap firms.

3.4 Realized Volatility

We investigate whether uncertainty about China's trade status was also associated with more volatile stock prices around days where policy-related news was released. Intuitively, regardless of whether the policy change is perceived as good or bad by investors, firms more exposed to such policy changes should have larger responses (in absolute terms) than less exposed firms, as argued both theoretically and empirically in Pastor and Veronesi (2012), Boutchkova et al. (2012) and Baker et al. (2019).

We test this hypothesis with the following regression:

$$RV_{it} = \alpha + \theta_1 \cdot NTRGap_{i,1990} + \theta_2 \cdot D_t + \theta_3 \cdot D_t \cdot NTRGap_{i,1990} + \epsilon_{it} \tag{6}$$

where RV_{it} is the realized volatility of firm i in day t, computed as the sum of the squared daily returns, D_t is a dummy equal to 1 if t is between 3 days before and 3 after a policy event, and $NTRGap_{i,1990}$ is the NTR gap in 1990 of the firm's industry. We estimate this regression at the firm-day level so we can i) account for unconditional differences in volatility among high and low gap firms between 1990 and 2001, and ii) cluster the standard errors at the firm level. We do not control for differences in firm fundamentals as, given that we are only including a tight window around the announcement, we expect the announcement to be the main factor driving differences in volatility.

We focus on three key policy announcements: i) 10/10/2000, when China was granted permanent 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 also include all days in which the US Congress voted to revoke the NTR status to China, from 1990 to 2001.

Table 8 documents that, during the tariff uncertainty period, i) firms in high-gap industries had significantly higher average realized volatility than firms in low-gap industries, and ii) this difference was larger around relevant policy days. To ensure that the higher unconditional volatility of high-gap firms does not drive the result on the event dates, we select random placebo announcement days each year. The interaction term on these placebo days is not significant, confirming that the increased volatility of high-gap firms is specific to key policy days.

Table 8: Realized Volatility around Policy Days

Dep. variable:	Realized Volatility, RV_{it}	
	Actual days	Placebo days
Day	-0.0189	0.0645***
	(0.00)	(0.00)
$Gap_{i,1990}$	2.17***	2.16***
	(0.00)	(0.00)
$Gap_{i,1990} \times Day$	0.547***	-0.22
	(0.00)	(0.00)
Constant	0.309***	0.307***
	(0.00)	(0.00)
R^2	0.004	0.004
Observations	8,730,368	8,288,900

Notes: This table contains selected estimates from versions of the following regression, run at the industry(i)/month(t) level using data from 1980-2007:
$RV_{it} = \alpha + \theta_1 \cdot NTRGap_{i,1990} + \theta_2 \cdot D_t + \theta_3 \cdot D_t \cdot NTRGap_{i,1990} + \epsilon_{it}$
where RV_{it} is the sum of squared daily returns for firm i from $t-3$ to $t+3$ where t is the event-date of interest. Robust standard errors, clustered at the firm level, are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

4 Alternative Explanations

In this section we discuss a number of alternative explanations that could potentially rationalize our results, and show that they are not consistent with the empirical evidence. This additional set of results provides strong evidence in favor of our explanation that exposure to TPU is a source of risk that is priced in the cross-section of stock returns.

4.1 Expected Cash-flow Effect

A potential explanation for our results could be that the higher returns for high-gap industries in the uncertainty period were driven by the response of stock prices to news and policy-related events, rather than by a change in the risk premium. If capital markets are efficient, stock prices adjust quickly after a news announcement, incorporating any changes in expected future cash-flows, as recently shown by Breinlich (2014) and Greenland et al. (2019).

In order to disentangle the effect of expected cash flows on stock returns, we repeat our portfolio analysis but exclude a window of 3 days before and after each policy-related event. We use the same days as in the previous section: all the Congressional voting days, and three key policy announcements days. We sum daily log-returns to compute monthly returns.

Table 9: Portfolio analysis excluding policy days

Dep. variable:	Monthly returns, r_t^p			
	Low Gap	Medium Gap	High Gap	TPU
Market	0.848***	1.095***	0.963***	0.057
	(0.05)	(0.07)	(0.09)	(0.06)
Size	-0.098*	0.289***	0.215**	0.156**
	(0.06)	(0.09)	(0.09)	(0.06)
Value	-0.222**	-0.095	-0.338**	-0.058
	(0.09)	(0.13)	(0.16)	(0.10)
Profitability	0.251***	0.031	-0.172	-0.211**
	(0.07)	(0.11)	(0.13)	(0.09)
Investment	0.725***	-0.218	-0.536***	-0.631***
	(0.15)	(0.19)	(0.20)	(0.15)
Constant	-0.001	0.001	0.009***	0.005***
	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.693	0.842	0.832	0.654
Observations	144	144	144	144
Sample Period	1990-2001	1990-2001	1990-2001	1990-2001

Notes: This table contains selected estimates from the following regression, using data from 1990-2001:
$r_t^p = \boldsymbol{F}'_t\beta + \alpha^p + \epsilon_t$
where r_t^p is the return on portfolio p in month t. $\boldsymbol{F}'_t$ 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 documents that excluding days around key policy dates does not significantly alter the estimated risk premium, which is still 6% per year. Therefore, this differential return between high and low gap industries was not due to differential expectations of investors on future cash-flows.

4.2 Realized Returns at Earnings Announcements

A potential concern with our results is that the differences in stock returns we pick up across high and low gap industries are driven by returns around quarterly earnings announcements, reflecting investors' forecast errors on firms' performance after the policy change in 1990. To mitigate this concern, we follow Barrot et al. (2018) and test whether the differential returns of our high and low gap portfolios were concentrated around earnings announcements. We identify earnings days using the Institutional Brokers Estimates System (I/B/E/S) database.[21]

[21] 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.

We look at the cumulative returns from t-3 to t+3, where t is an earnings announcement date.

Table 10: TPU factor around Earnings Announcements

Dep. variable:	Monthly returns, r_t^p			
	Low Gap	Medium Gap	High Gap	TPU
Market	0.171*	0.313*	0.236	0.032
	(0.09)	(0.17)	(0.20)	(0.12)
Size	-0.125	0.545**	0.379*	0.252**
	(0.10)	(0.22)	(0.21)	(0.12)
Value	-0.144	0.099	0.407	0.275
	(0.18)	(0.39)	(0.28)	(0.17)
Profitability	-0.117	-0.043	-0.119	-0.001
	(0.12)	(0.37)	(0.38)	(0.19)
Investment	-0.062	-0.514	-0.628	-0.283
	(0.23)	(0.67)	(0.52)	(0.30)
Constant	0.002	0.001	0.001	-0.001
	(0.00)	(0.01)	(0.01)	(0.00)
R^2	0.130	0.195	0.132	0.062
Observations	144	143	144	144

Notes: This table contains selected estimates from the following regression, using data from 1990-2001:
$r_t^p = \boldsymbol{F}'_t\beta + \alpha^p + \epsilon_t$
where r_t^p is the return on portfolio p in month t. $\boldsymbol{F}'_t$ is a vector containing the 5 Fama-French factors: Market, Size, Value, Profitability and Investment. Robust standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

We repeat the baseline portfolio analysis shown in Section 3.2, but only including the days of firms' earnings announcements. Table 10 documents that the difference in returns around earnings announcement days for stocks in the low and high gap portfolios is not statistically significant.[22] These findings provide evidence against the hypothesis that the ex-post average realized returns that we measure in the data deviate in a systematic way from the unobserved ex-ante expected returns for investors.

4.3 Protection from China

One possible explanation for the baseline results is that high-gap industries were receiving higher de-facto protectionism from China via the uncertainty generated by the trade policy status. There is in fact evidence that these industries suffered in terms of employment and

[22]These results also also confirmed by a simple regression of stock returns around earnings days in the period 1990-2001 on the NTR gap in 1990. We find an insignificant effect of more exposure to TPU on stock returns around earning days.

investment relatively more when the uncertainty was eliminated in 2001 (see Pierce and Schott (2016), Handley and Limão (2017) and Pierce and Schott (2018)). This would have translated into higher expected cash flows for high-gap sectors, and thus in higher average returns between 1990 and 2001.

To assess this alternative hypothesis, we double sort portfolios on NTR gap in 1990 and on Chinese import penetration. We measure import exposure as the industry-year level import share from China.[23] If this alternative hypothesis is correct, we should observe that the risk premium we estimate is concentrated in industries that were more protected from China, i.e. industries that had a lower import share from China throughout 1990-2001. Instead, Table 11 documents the opposite: during the uncertainty period, the risk premium was concentrated in industries *less* protected from China, so industries that were importing relatively more. This is also consistent with the previous findings in Table 4, which shows that the risk premium was earned mostly by industries more vulnerable to globalization. Therefore, this evidence suggests that the higher returns of high-gap sectors we observe in the 1990-2001 period were not due to more implicit protection from China.

[23]We use US import data at the HS-6 level downloaded from the Center for International Data at UC Davis, https://cid.econ.ucdavis.edu/usix.html. We aggregate the data at the industry level, and then compute the imports from China as share of total production, obtained from the NBER Manufacturing database. Results are very similar if we divide the import from China by total imports.

Table 11: TPU factor and Imports from China

Dep. variable:	Monthly returns, r_t^p	
	TPU-Low	TPU-High
Market	0.139**	-0.017
	(0.06)	(0.05)
Size	0.183**	-0.032
	(0.08)	(0.07)
Value	-0.195*	0.220**
	(0.11)	(0.10)
Profitability	0.001	-0.139*
	(0.12)	(0.07)
Investment	0.152	-0.781***
	(0.17)	(0.13)
α^p	-0.001	0.005***
	(0.00)	(0.00)
R^2	0.255	0.410
Observations	144	144
Sample Period	1990-2001	1990-2001

Notes: This table contains selected estimates from the following regression, using data from 1990-2001:
$r_t^p = \boldsymbol{F}'_t\beta + \alpha^p + \epsilon_t$
where r_t^p is the return on portfolio p in month t. $\boldsymbol{F}'_t$ is a vector containing the 5 Fama-French factors: Market, Size, Value, Profitability and Investment. Robust standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

5 Conclusions

We use quasi-experimental variation arising from China's temporary NTR status to show that US tradeable industries more exposed to trade policy uncertainty had significantly higher stock returns than less exposed industries between 1990 and 2001. Our measure of uncertainty, which relies on the difference between current NTR and non-NTR tariff rates, has the advantage of being directly observable, quasi-exogenous, and ex-ante. As such, it is not subject to the concerns associated with ex-post measures of uncertainty typically used in the finance literature.

Our estimated risk premium is substantial, even after accounting for the response of stock prices at key policy-related dates, and for the effect of Chinese import competition on stock returns. Industries highly exposed to policy uncertainty earned a risk premium of 6% per year relative to less exposed sectors, suggesting a large impact of trade policy uncertainty on the perceived riskiness of exposed stocks. Among industries more exposed to trade policy uncertainty, the risk premium was larger if shipping costs were low, the NTR tariff rate was low, or if the industry relied more heavily on imports from China. These amplification channels make intuitive sense: uncertainty about trade policy matters more if you are directly exposed to globalization, either through low trade barriers or through the supply chain.

Our focus in this paper is on trade policy uncertainty before China entered the WTO, but currently the U.S.-China trade relationships are also unstable. The large risk premia should have informed policy makers at the time, and today. Our approach is general: policy makers and practitioners can use risk premia to understand the effect of protracted uncertainty on investor's beliefs and stock market behavior.

References

Adao, R., Arkolakis, C., Esposito, F., 2019. Spatial linkages, global shocks, and local labor markets: Theory and evidence. Tech. rep., National Bureau of Economic Research.

Alessandria, G., Khan, S., Khederlarian, A., 2019. Taking stock of trade policy uncertainty: Evidence from china. Tech. rep., National Bureau of Economic Research.

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

Bachmann, R., Elstner, S., Sims, E. R., 2013. Uncertainty and economic activity: Evidence from business survey data. American Economic Journal: Macroeconomics 5 (2), 217--49.

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

Baker, S. R., Bloom, N., Davis, S. J., Kost, K. J., 2019. Policy news and stock market volatility. Tech. rep., National Bureau of Economic Research.

Bali, T. G., Brown, S. J., Tang, Y., 2017. Is economic uncertainty priced in the cross-section of stock returns? Journal of Financial Economics 126 (3), 471--489.

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

Barrero, J. M., Bloom, N., Wright, I., 2017. Short and long run uncertainty. Tech. rep., National Bureau of Economic Research.

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

Black, F., Scholes, M., 1974. The effects of dividend yield and dividend policy on common stock prices and returns. Journal of financial economics 1 (1), 1--22.

Blaum, J., Esposito, F., Heise, S., 2020. Input sourcing under risk: Evidence from u.s. firms. Working paper.

Bloom, N., 2009. The impact of uncertainty shocks. econometrica 77 (3), 623--685.

Bloom, N., Bond, S., Van Reenen, J., 2007. Uncertainty and investment dynamics. The review of economic studies 74 (2), 391--415.

Boutchkova, M., Doshi, H., Durnev, A., Molchanov, A., 2012. Precarious politics and return volatility. The Review of Financial Studies 25 (4), 1111--1154.

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.

Breinlich, H., 2014. Heterogeneous firm-level responses to trade liberalization: A test using stock price reactions. Journal of International Economics 93 (2), 270--285.

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

Caldara, D., Iacoviello, M., Molligo, P., Prestipino, A., Raffo, A., 2020. The economic effects of trade policy uncertainty. Journal of Monetary Economics 109, 38--59.

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

Campbell, J. Y., Shiller, R. J., 1988. Stock prices, earnings, and expected dividends. The Journal of Finance 43 (3), 661--676.

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

Chen, Q., Goldstein, I., Jiang, W., 2006. Price informativeness and investment sensitivity to stock price. The Review of Financial Studies 20 (3), 619--650.

Chodorow-Reich, G., Nenov, P. T., Simsek, A., 2019. Stock market wealth and the real economy: A local labor market approach. Tech. rep., National Bureau of Economic Research.

Christou, C., Cunado, J., Gupta, R., Hassapis, C., 2017. Economic policy uncertainty and stock market returns in pacificrim countries: Evidence based on a bayesian panel var model. Journal of Multinational Financial Management 40, 92--102.

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

Cohen, L., Frazzini, A., 2008. Economic links and predictable returns. The Journal of Finance 63 (4), 1977--2011.

Crowley, M., Meng, N., Song, H., 2018. Tariff scares: Trade policy uncertainty and foreign market entry by chinese firms. Journal of International Economics 114, 96--115.

Crowley, M. A., Meng, N., Song, H., 2019. Policy shocks and stock market returns: Evidence from chinese solar panels. Journal of the Japanese and International Economies 51, 148--169.

Duffie, D., 2010. Dynamic asset pricing theory. Princeton University Press.

Dumbaugh, K., 1998. China's most-favored-nation (mfn) status: Congressional consideration, 1989-1998. Congressional Research Service, the Library of Congress.

Esposito, F., 2019. Demand risk and diversification through trade. Available at SSRN 3498593.

Fama, E. F., French, K. R., 1995. Size and book-to-market factors in earnings and returns. The journal of finance 50 (1), 131--155.

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

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

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.

Gagliardini, P., Ossola, E., Scaillet, O., 2016. Time-varying risk premium in large cross-sectional equity data sets. Econometrica 84 (3), 985--1046.

Graziano, A., Handley, K., Limão, N., 2018. Brexit uncertainty and trade disintegration. Tech. rep., National Bureau of Economic Research.

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

Guiso, L., Haliassos, M., Jappelli, T., et al., 2002. Household portfolios. MIT press.

Handley, K., Limão, 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.

Hou, K., Xue, C., Zhang, L., 2017. Replicating anomalies. Tech. rep., National Bureau of Economic Research.

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

Jordà, Ò., Schularick, M., Taylor, A. M., Ward, F., 2019. Global financial cycles and risk premiums. IMF Economic Review 67 (1), 109--150.

Jurado, K., Ludvigson, S. C., Ng, S., 2015. Measuring uncertainty. American Economic Review 105 (3), 1177--1216.

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.

Moser, C., Rose, A. K., 2014. Who benefits from regional trade agreements? the view from the stock market. European Economic Review 68, 31--47.

Moskowitz, T. J., Vissing-Jørgensen, A., 2002. The returns to entrepreneurial investment: A private equity premium puzzle? American Economic Review 92 (4), 745--778.

Nagel, S., 2013. Empirical cross-sectional asset pricing. Annu. Rev. Financ. Econ. 5 (1), 167--199.

Novy, D., Taylor, A. M., 2014. Trade and uncertainty. Review of Economics and Statistics, 1--50.

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.

Petersen, M. A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. The Review of Financial Studies 22 (1), 435--480.

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.

Pierce, J. R., Schott, P. K., 2018. Investment responses to trade liberalization: Evidence from us industries and establishments. Journal of International Economics 115, 203--222.

Shiller, R. J., 2000. Irrational exuberance princeton. Princeton University Paper.

Steinberg, J. B., 2019. Brexit and the macroeconomic impact of trade policy uncertainty. Journal of International Economics 117, 175--195.

Wang, Z., Wei, S.-J., Yu, X., Zhu, K., 2018. Re-examining the effects of trading with china on local labor markets: A supply chain perspective. Tech. rep., National Bureau of Economic Research.

6 Appendix

6.1 Additional Tables and Figures

Table 1: Summary Statistics

Variable	Low-Gap	High-Gap	t-Statistic
NTR Gap in 1990	0.09	0.36	14.66
Market Capitalization ($M)	$ 14.16	$ 8.59	-1.08
Price / Earnings per Share	14.59	13.55	-0.43
Price / Book	2.70	2.60	-0.23
Dividend Yield	0.04	0.02	-5.80

Notes: This table contains summary statistics on high and low gap firms in 1990. A firm is classified as low-gap if it has a below median NTR gap in 1990. 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: Sample Selection

	1980-1989		1990-2001		2002-2007	
	# Firms/Month	Mkt. Cap ($B)	# Firms/Month	Mkt. Cap ($B)	# Firms/Month	Mkt. Cap ($B)
All Firms in CRSP	5719	$ 0.34	6876	$ 1.16	5327	$ 2.83
CRSP/Compustat Merged (CCM)	5190	$ 0.37	6751	$ 1.18	5291	$ 2.84
CCM, PS Families	3578	$ 0.38	4658	$ 1.20	3628	$ 2.85

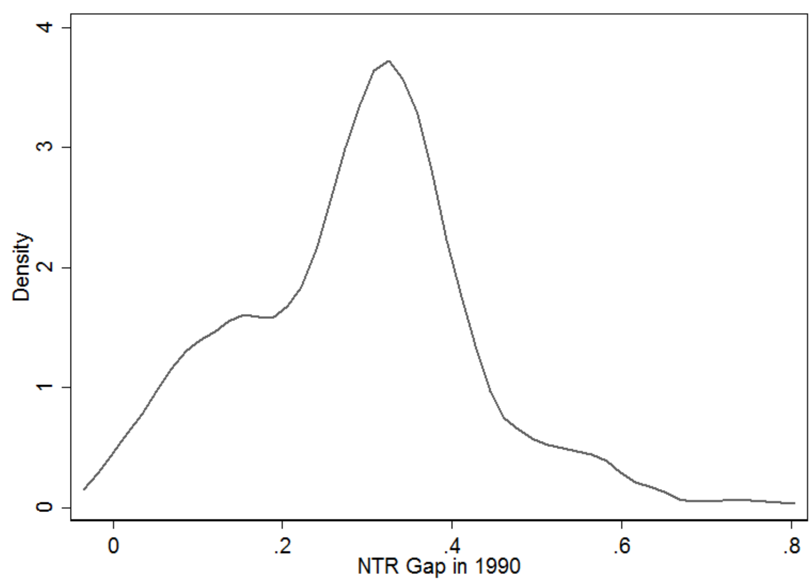
Notes: This table has three groups of firms: (1) All firms in CRSP: this includes all firms with ordinary common shares traded on major exchanges; (2) CRSP/Compustat Merged (CCM): this includes all firms from the first group, that can also be matched to Compustat; (3) CCM, PS Families: this includes all the firms from the second group that have a non-missing SIC industry, and can be matched to one of the families of industries in Pierce and Schott (2012). The market capitalization is an equal-weighted average.

Table 3: TPU and Stock Returns, Robustness

Dep. variable:	Monthly returns, r_{it}						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Gap_{i,y-1} \times D_t$	0.016***	0.014**	0.019**	0.014**	0.018***		0.022***
	(0.01)	(0.01)	(0.01)	(0.01)			(0.01)
$Gap_{i,1990} \times D_t$						0.018***	
						(0.01)	
R^2	0.133	0.068	0.049	0.068	0.129	0.131	0.129
Observations	39,974	40,064	40,064	40,064	40,064	40,100	40,052
Industry FE	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y

Notes: Column (1) controls for betas on 5 factors, column (2) clusters errors at industry and month level, column (3) uses previous year weights, column (4) use equal weights, column (5) adds an interaction between the controls and the uncertainty dummy, column (6) uses an IV methodology, column (7) uses the NTR Gap in 1990. Observations are weighted by industry i's market capitalization in 1979, except in columns (3) and (4). Robust standard errors, clustered at the industry level, are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Figure 1: Distribution of NTR gaps in 1990



6.2 Construction of valuation variables

The price-to-earnings ratio (P/E ratio) is measured at the firm level as current share price relative to earnings per-share. To aggregate this to the industry level, we take the value-weighted average at the industry/fiscal-year level. We construct this using annual Compustat data.

The Price-to-book ratio is measured at the firm level as the ratio of price to book value per-share. We also take a value-weighted average at the industry/fiscal-year level of market capitalization, divided by total book value of equity. We exclude firms with negative book values from this calculation.

The dividend yield (D/P) for each industry is computed as total cash dividends paid over the past 12 months, divided by total market capitalization.

Computing betas. We start by constructing daily returns for industry portfolios across all the industries. Each day, we merge in market capitalizations from the end of the previous month, and calculate value-weighted portfolio returns. Then, in 5-year rolling windows, we run a regression of industry-level excess returns on the 5 Fama French factors. We retain the betas, and lag them by one month for use in the baseline regression. All our results are similar if we use 1-year rolling windows.

Aggregating controls at the industry level. In our baseline specification, our unit of observation is industry-month. As mentioned above, we computed the ratio for each firm/fiscal-year, and then taken a value-weighted average (weights proportional to the previous year's market capitalization) at the industry level. Alternatively, we could have constructed the controls by summing each part of each ratio within each industry/year, and then computing the ratio. In unreported results, we show that this alternative approach delivers similar results. We have also estimated the regressions at the firm level to avoid the issue of aggregating controls, and results are close to the baseline.