Taking Stock of Trade Policy Uncertainty: Evidence from China's Pre-WTO Accession*

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Abstract

We study the effects on trade from the annual tariff uncertainty about China's MFN status renewal prior to joining the WTO. We have four main findings. First, in monthly data trade increases significantly in anticipation of uncertain future increases in tariffs. Second, the probability of a tariff increase was perceived to be relatively small, with an average annual probability of non-renewal of about 6 percent. Third, what matters more is the expected future tariff rather than the uncertainty around it. We identify these effects using within-year variation in the risk of trade policy changes around the renewal vote and trade flows. We show that an (s, s) inventory model generates this behavior and that variation in the strength of the stockpiling in advance of the vote is increasing in the storability of goods. Fourth, the costs associated with within year trade policy induced stockpiling account for around 30% of the trade dampening effects of uncertainty found in annual data. Our results explain why trade may hold up in advance of a prospective policy change such as Brexit or the US-China escalating tariff war of 2018-19, but may fall off sharply even if expected tariff increases do not materialize.

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1 Introduction

As the world rethinks the benefits of globalization, the path of future trade policy has become increasingly uncertain. This uncertainty requires firms making long-lived decisions to participate in foreign markets to form expectations over the future path of tariffs. Forecasting this path can be challenging as the timing, size, and likelihood of policy changes are all uncertain. Yet firms do form these expectations and move on. In this paper, we show how to estimate the path of expected future tariffs based on the behavior of firms in advance of a possible policy change whose size and timing is known but whose probability is not. We apply these ideas to China's annual renewal of normal trade relations (NTR) status in the US prior to access to the World Trade Organization (WTO).

We have four main findings. First, we find that trade increases significantly in anticipation of uncertain future increases in tariffs in monthly data. Second, the probability of a tariff increase is estimated to be relatively small, with an average probability of non-renewal of about 6 percent and annual probabilities that ranges from 2.4 to 11 percent. Third, the expected future tariff is the primary driver of trade dynamics instead of uncertainty about the path of tariffs. The "wait-and-see" real option force from uncertainty only slightly weakens the incentives to anticipate the future tariff increase. Fourth, we find that costs associated with trade policy induced stockpiling are responsible for a sizeable 30% of the total annual trade dampening effect reported in the literature (Pierce and Schott (2016), Handley and Limao (2017), Graziano et al. (2018)).

We use the timing of the annual renewal of China's NTR status and within-year variation in trade flows around this renewal to identify the impact of uncertain future changes in trade policy. Our identification leverages the fact that the NTR status renewal decision was legislated to occur in the summer of each year. Thus, prior to renewal firms faced greater near-term risk about trade policy than immediately after Congress renewed NTR. Using a generalized triple difference approach, we show that trade flows rise when facing a risk of higher tariffs in the months in advance of the renewal decision but then fall off sharply when renewal occurs. Essentially, trade policy risk induces a seasonal component into trade flows that is related to the expected change in trade policy and the ability of products to be stored.

Our findings can be best understood through the lens of an $(\underline{s},\overline{s})$ inventory model applied to international trade as in Alessandria et al. (2010b). In this model, firms purchase a storable commodity infrequently to economize on a fixed ordering cost and as a buffer in the presence of demand uncertainty. Firms trade off higher inventory costs against lower international transaction costs. Facing an uncertain future increase in tariffs firms shift the timing of their purchases so they have relatively high purchases and stocks of inventories in advance of the possible tariff increase. Upon a successful renewal and fixed tariffs for the next 12 months, firms already hold large stocks in inventory and hence are less likely to purchase until they have run down their stockpile. These effects are larger for goods for which holding inventories is less costly in the model and the data.

The finding that prospective future increases in tariffs increase trade stands in contrast to previous findings in the literature because we are using within-year variation in trade flows rather than annual trade flows. Our approach is complementary to other approaches that identify the role of trade policy uncertainty but operates at a different frequency since it is based on within-year variation of firms already active in the export market who are deciding when to send their shipments. This analysis generates a time-varying path of the probability of non-renewal that can then be plugged into models of the export decision. By compounding these probabilities, we find that nearing its access to the WTO in 2002, China's probability of retaining its MFN status to the US market is much higher than those estimated in other studies such as Handley and Limao (2017).

Moreover, equipped with a model that captures the dynamics of trade flows in the presence of uncertainty, we more generally quantify the role of pure uncertainty in the presence of inventory holdings and fixed costs of ordering. In particular, we compare the trade-dampening wait-and-see effect of uncertainty with the trade-boosting effect of an expected tariff hike. We simulate multiple spreads around the same expected tariff increase and decompose the anticipatory growth into the contribution of the first moment and the second moment. The results indicate that the standardized effect of an expected tariff change is 3.5 times the effect of pure uncertainty and almost all the variation in anticipatory import growth is explained by just the expected tariff change.

Next, we show that the frictions giving rise to within-year anticipatory stockpiling contribute to the negative effect of uncertainty on annual trade flows in the literature. Anticipatory stockpiling entails additional inventory holding costs that increase overall costs and reduce trade flows. Using a difference-in-difference technique, we confirm the finding of significant negative effects of uncertainty on annual US imports from China. We further find that the year-specific effects of uncertainty were highest in the early years of 1990s which is in line with high non-renewal probability for the same period.

Finally, we quantify the negative effect of the stockpiling costs on annual trade volume. Anticipatory stockpiling entails additional ordering and inventory holding costs. Firms advance their purchases in anticipation of revocation of China's MFN status which leads to lumpier imports. After replicating the trade-dampening effects of TPU from Handley and Limao (2017), we show that lumpiness of imports is significantly linked to increased tariff risk. Controlling for this increased lumpiness reveals that 30% of the total negative effect on trade is driven by costs linked to anticipatory behavior documented in this paper.

This paper is most related to early work evaluating the impact of uncertainty on international trade. Starting with Baldwin (1986), Baldwin and Krugman (1989) and

Dixit (1989), models with sunk costs of exporting have been employed to argue that uncertainty depresses trade, since entering firms prefer to wait and see how uncertainty resolves. While entry decisions have been shown to be important in international trade (Roberts and Tybout (1997), Alessandria and Choi (2007)), we focus on the behavior of incumbent firms in the short window before the resolution of uncertainty.

More recent work has focused on the impact of Trade Policy Uncertainty (TPU) by considering exporter market participation decisions in the presence of a possible tariff increases.[1] In particular, in our model firms stockpile in the months before uncertainty is resolved thereby leading to a rise in trade. We use the rise in trade to study the underlying uncertainty surrounding these events.[2]

Recent papers have used the structure of models with sunk costs of exporting and found large effects of uncertainty on trade in various episodes of TPU (Crowley et al. (2018), Feng et al. (2017), Handley and Limao (2014)). One of the most studied episode is the one studied in this paper, namely the renewal of China's MFN status during the 1990s. Although applied tariffs on US imports from China did not change after its accession to the WTO, Pierce and Schott (2016) find that US industries most exposed to the threat of protectionist tariffs experienced large declines in employment and increased imports from China after the threat was eliminated. Handley and Limao (2017), using the structure of a sunk cost models, find that reduced uncertainty accounted for one third of China's export growth. By comparing trade patterns between 2000 and 2005, their model-implied probability of MFN access reversal is 13%, or more than twice as large as the one found in this paper. Our approach is complementary to their approach and instead focuses on high frequency trade patterns, overcoming concerns of confounding long run factors. Our probabilities can be used as inputs to models with an export entry decision. In contrast with this literature, in our framework, pure uncertainty has little impact on trade patterns as anticipation is mostly driven by expected trade cost changes. In this sense, our results are more in line with Steinberg (2019), who finds a minimal impact of trade policy uncertainty on UK's aggregate trade due to Brexit. Our framework provides an alternative mechanism to explain why the UK's trade has not experienced any declines despite the looming threat of Brexit.

There is a growing literature that applies inventory models to explain high frequency dynamics of international trade at the producer level or in the propagation of shocks. In Alessandria et al. (2010a), stronger inventory management considerations in international trade are shown to have contributed to the sudden drop in trade during the Great Recession, while in Alessandria et al. (2010b) inventory adjustments explain import and

[1]Caldara et al. (2019) develop a model with sunk export costs but find that any TPU induced trade declines are due to investment adjustments costs and sticky prices.

[2]Ruhl (2011) uses a similar framework to determine the expected duration of a worldwide temporary export ban of Canadian beef following the discovery of a cow infected with Bovine Spongiform Encephalopathy.

pricing dynamics of retail goods following large devaluations in emerging economies. In Bekes et al. (2017) demand volatility raises the motive for precautionary inventory holdings and explains variation in trade lumpiness across French exporter markets. These papers as well as ours build on the non-convexities from fixed ordering or shipment costs, that have been widely documented.[3]

Our paper is also related to some recent papers that study anticipation to policy changes. Baker et al. (2018) show that households increase their stocks in anticipation of a future sales tax rate increase. Khan and Khederlarian (2019) find de-stocking by US imports from Mexico to upcoming tariff reductions from NAFTA substantially biases estimates of the trade elasticity. Unlike these papers, we study the effects of an uncertain policy change that did not materialize.

The rest of the paper is organized as follows. Section 2 lays out a model in which stockpiling in anticipation of a possible tariff rise increases trade before the resolution of uncertainty. We show that the trade boost increases in the probability of the tariff hike. In Section 3 we show that exports from China to the US rose in anticipation of the resolution of China's MFN status renewal. In Section 4 we simulate the model matching the anticipatory growth of Chinese exports to the US during this episode to determine the probability of MFN status being revoked. In Section 5 we separate the contribution to the anticipatory increase in trade of pure uncertainty (second moment) versus the expected tariff change (first moment). In Section 6 we show that the frictions giving rise to inventories explain a sizeable fraction of the cross-industry variation in trade flows emphasized elsewhere. In the final section, we conclude.

2 Model: Anticipation to TPU through Inventories

While previous work on trade policy uncertainty has focused on firms' export entry decisions (Handley and Limao (2017), Crowley et al. (2018), Steinberg (2019)), we study how it affects the shipment decisions of incumbent firms. Lumpiness in trade flows is pervasive and there is strong evidence that exporters ship their goods infrequently to economize on the fixed costs of shipments (Alessandria et al. (2010b), Kropf and Saure (2014), Hummels and Schaur (2013), Bekes et al. (2017)). When facing a possible tariff increase, a firm deciding on when to export (import) has strong incentives to expedite their shipments before tariffs might be raised. In this section we describe a model in which imports rise in anticipation of TPU resolution, leading to short-run reversals in trade flows. In particular, we introduce TPU into a standard $(\underline{s},\overline{s})$ inventory model[4] as

[3]See Alessandria et al. (2010b), Kropf and Saure (2014), Blum et al. (2019).

[4]Other models with durable goods, such as capital or durable consumer goods, display similar anticipation effects. We chose an inventory model because inventory dynamics have been proven to be very successful in accounting for the short run dynamics of international trade flows (See Alessandria et al. (2010b), Alessandria et al. (2010a), Charnavoki (2017).

in Alessandria et al. (2010b), in which firms stockpile before a possible tariff increase.

2.1 Environment

We consider a partial equilibrium model of an industry in which goods are storable and a continuum of monopolistically competitive retailers decide whether to import or not every period.[5] Ordering entails a fixed shipment cost, causing firms to order infrequent but large shipments. On top of the fixed cost, retailers face demand uncertainty and a one period delivery lag, leading to precautionary inventory holdings. These frictions give rise to a ($\underline{s}$,$\overline{s}$) policy, where producers run down their inventories to a level $\underline{s}$ and then replenish it up to $\overline{s}$. Retailers are identical except for their history of demand shocks, that determines their current inventory holdings.

Let $p_{j,z,t}$ denote the retail prices charged by importer j in industry z and $\nu_{j,z,t}$ the demand shock in period t. Importers face a CES demand function with the elasticity of substitution σ:

$$c_{j,z,t} = e^{\nu_{j,z,t}} p_{j,z,t}^{-\sigma} \tag{1}$$

The variable cost of importing is $\omega_{z,t} = \omega(1 + \tau_{z,t})$ where $\tau_{z,t}$ belongs to a finite set of possible tariffs, T. The cost of importing is the same for each firm in an industry and suppliers are assumed to be perfectly competitive, so that the pass-through of the tariff reduction is complete.[6] TPU is reflected in the markov process of τ_t, which has a transition matrix denoted by Π^τ. At the beginning of each period retailers observe their inventory holdings, $s_{j,z,t}$ and their demand shock, $\nu_{j,z,t} \sim^{iid} N(0, \sigma_\nu^2)$, assumed to be i.i.d. across firms and time[7], and then price their good and decide to import or not. To import, retailers incur a fixed cost f [8]. We assume that imported goods cannot be returned, $m_{j,z,t} \geq 0$. Because of demand uncertainty, importers will never run down their inventories to zero i.e. $\underline{s}_z > 0$, and because of the delivery lag, sales can never exceed current inventory holdings:

$$q_{j,z,t} = \min[e^{\nu_{j,z,t}} p_{j,z,t}^{-\sigma}, s_{j,z,t}] \tag{2}$$

Assuming the goods in transit ($m_{j,z,t}$) depreciate at the same rate, δ_z, as in the

[5]We abstract from general equilibrium considerations since we focus on high frequency dynamics of trade policy.

[6]Perfectly competitive suppliers allow us to rule out changes in prices charged by exporters. We test this in the empirical section.

[7]The iid demand shock generates variation in the anticipation to a tariff reduction. Without demand shocks the distribution of inventories would be degenerate and the effects would be bigger and lead to permanent oscillations. With perfectly correlated demand shocks all firms would respond equally to the incentives of anticipating the demand shock.

[8]We assume that the fixed cost of importing is the same across industries.

warehouse, the law of motion for the inventories is:

$$s_{j,z,t+1} = (1-\delta_z)[s_{j,z,t} + m_{j,z,t} - q_{j,z,t}] \tag{3}$$

Next, we characterize the optimal policies and the tariff process. To simplify the notation we drop the industry subscript. The firm's value of adjusting is denoted by $V^a(s,\nu,\tau)$ and not adjusting by $V^n(s,\nu,\tau)$. Every period retailers optimize by choosing $V(s,\nu,\tau) = \max[V^a(s,\nu,\tau), V^n(s,\nu,\tau)]$, where:

$$\begin{aligned} V^a(s,\nu,\tau) &= \max_{p,m>0} q(p,s,\nu)p - (1+\tau)\omega m - f + (1+r)^{-1}EV[s',\nu',\tau'|s,\tau] \\ V^n(s,\nu,\tau) &= \max_{p} q(p,s,\nu)p + (1+r)^{-1}EV[s',\nu',\tau'|s,\tau] \end{aligned} \tag{4}$$

are subject to (3) and (2). Solving for the optimal policies generates an ($\underline{s}$,$\overline{s}$) ordering policy that depends on current inventory holdings and the demand shock, $m = m(s,\nu,\tau)$. Similarly, the pricing schedule is characterized by a constant markup over the discounted marginal value of an additional unit of inventory next period, $p = \frac{\sigma}{\sigma-1}(1+r)^{-1}(1-\delta)V_{s'}(s',\nu',\tau')$. When facing an expected increase in τ', importers trade off importing sooner at the expense of paying the fixed cost today and incurring higher inventory holding costs. In what follows we describe how under different shock processes for tariffs this trade-off leads to different anticipatory dynamics.

2.2 Trade Policy Uncertainty and Stockpiling

We introduce TPU into this environment by formulating a non-stationary markov process in the form of a time-dependent transition matrix, denoted by Π_t^τ. Allowing importers to anticipate possible tariff changes leads them to stockpile before the resolution of the uncertainty. In line with the empirical application in the next section, we fix the period in which uncertainty is resolved.[9] Let m_{res} be the last period before the possible tariff change, so that in period $m_{res}+1$ the uncertainty is resolved.

$$\Pi_t^\tau = \begin{cases} I_{|T|} & \text{if } t \neq m_{res} \\ \tilde{\Pi}^\tau & \text{if } t = m_{res} \end{cases}, \qquad \tilde{\Pi}^\tau = \begin{bmatrix} (1-\pi) & \pi \\ 0 & 1 \end{bmatrix}$$

Conditional on (π,τ'), the key parameters determining anticipation are the fixed cost of ordering and the cost of inventory holding, that is, the interest rate and the depreciation rate. For now, we calibrate the model with the sole purpose of illustrating its qualitative response to TPU. In Table 1 we describe the parameter values of the model. We set the fixed cost per order to match the Herfindahl-Hirschman (HH) index of 0.32, that is, an average of 3 shipments per year. We calibrate the model at the monthly frequency by

[9] In general, there can be uncertainty about the timing of a possible policy change. However, US Congress voting on the renewal of China's MFN status took place every year by July and August. For more see section 3.1.

setting the discount rate equal to $\sqrt[12]{0.97}$. The monthly depreciation rate is set at 2.5% or an annual rate of around 30%. We set the elasticity of substitution equal to 4. Finally the delivery lag is set to be a month and the variance of the taste shock is set at 0.8. These parameters determine a median inventory-sales ratio of 3.64 months.

We now show that, conditional on a tariff increase, the magnitude of the anticipatory stockpiling is increasing in the probability of the tariff hike materializing. Initially, trade is tariff-free, i.e. $\tau_1 = 0$. In period $m_{res}+1$, importers face the possibility of either remaining at 0 or facing a tariff of 10%. Hence, the set of possible set of tariffs is $T = \{0, 0.10\}$. Afterwards, the new state is absorbing in the sense that $\tau_t = \tau_{m_{res}+1} \; \forall \; t > m_{res} + 1$ i.e. the tariff level will remain unchanged. To study how trade responds to different probabilities of the same tariff increase taking place, we vary transition probabilities in $\tilde{\Pi}^{\tau}_{m_{res}}$. In particular, importers face either a 20%, 50% or 100% chance of tariffs being raised to 10%. We assume importers have 12 months to anticipate this event.

Figure 1 plots the aggregate industry response of imports. In all cases, the expected tariff increase does not materialize. Imports rise in anticipation of the uncertainty resolution and then drop sharply afterwards. This reversal in trade flows is short-lived. Imports start rising only in the two to three months before the resolution of uncertainty.[10] The magnitude of the trade reversals around the time of the uncertainty resolution are clearly increasing in the probability of the tariff rise. However, qualitatively the responses are very similar. Figure 2 illustrates that the anticipatory rise is paralleled by a similarly strong increase in the aggregate inventory-sales ratio. Since importers want to avoid paying possibly higher tariffs, they stockpile so that they begin the possibly high tariff period with a high level of inventory-sales ratio. The inventory sales ratio reaches its peak in the month of uncertainty resolution. With a 50% chance of renewal, the inventory-sales ratio is around 35% above its equilibrium level. Again, the strength of these effects depend on the probability importers assign to the tariff increase. Once, uncertainty is resolved, trade drops temporarily as importers have amassed enough inventories to satisfy their demand.

Finally, note that these dynamics take place in a window of 5 months before and 5 months after the resolution of uncertainty. Figure 3 shows the time-varying $(\underline{s},\overline{s})$ bands where the firms in the top-left region orders positive quantities. The initial ordering policy is the same as the ordering policy 12 months ahead of the anticipated change. However, there are two notable changes in the ordering policy one month before the anticipated change. First, the $\underline{s}$ increases indicating an increase in the mass of ordering firms. Secondly, the gap between $\overline{s}$ and $\underline{s}$ increases, indicating larger orders.[11] Uncertainty

[10] Before imports start rising, echo-effects lead to temporary drops in imports in month 8. These are due to importers timing their purchases similarly to have enough inventories before the possible increase in tariffs while saving on the fixed ordering cost

[11] Ordering policy three months ahead of the change shows that firms economize on the fixed ordering costs by delaying the orders to right one month before the expected increase in tariffs.

over renewal of China's MFN status was resolved annually for a period of more than 10 years. In this framework, the dynamics driven by anticipation in one year settle before the beginning of next year's anticipatory dynamics.[12] In the next section we show that the high frequency anticipatory dynamics of the US imports from China were similar to those predicted by this model.

3 Seasonal Effects of China's TPU Episode

In this section we show that the annual possibility of tariff hikes during the 1990s induced strong seasonal patterns in China's exports to the US. Between 1991 and 2000, every year around September, US Congress voted on revoking China's MFN status. Although ex post China's access to MFN rates was never reversed, especially in the early years, the revocation vote came close to being successful. While previous studies have focused on the long run effects of this episode's TPU, we exploit the within year variation of this episode's tariff risk. Once Congress had voted, MFN rates were secured at least for another 12 months. We find that in the months prior to the voting, exports of products that faced the largest risk spiked. Once the voting had taken place exports plummeted. In section 4 we replicate this seasonal pattern using the model described in section 2 to estimate the probability importers assigned to the event of MFN revocation.

3.1 Background

During the 1990s, US imports from China were subject to substantial policy uncertainty since China's MFN status had to be renewed annually (see Handley and Limao (2017), Pierce and Schott (2016), Crowley et al. (2018)).[13] In the 1980s the annual renewal of China's MFN status was carried out without any political considerations. But after the events of the Tiananmen Square in 1989, revocation of China's MFN status gained central attention as a measure of potential sanction. Every year after 1990 and until 2000, the US Congress voted on the disapproval of the President's renewal of China's NTR status. Although China's MFN status was never actually revoked it came close in 1990, 1991 and 1992 when the House passed legislation to revoke it but the Senate failed to sustain the vote. Revocation would have lead to the imposition of non-Normal Trade Relations (NNTR) tariff rates, also known as column 2 tariff rates, that on average were

[12] In Figure 3 we show that the steady state policy functions exactly overlap with the ones 12 months before the anticipated policy change

[13] With the advent of the Cold War, the US applied protectionist non-Normal Trade Relations (NNTR) tariff rates established by the Smoot-Hawley Tariff Act of 1930 to non-market economies. Under the Trade Act of 1974, the US granted MFN access to non-market economies in the presence of (1) a bilateral commercial agreement and (2) the compliance of freedom-of-emigration requirement. The US President was given authority to waive the second requirement on annual renewable basis, subject to approval by the US Congress. The US and China signed a bilateral commercial agreement in 1980.

ten times larger than MFN rates.

The political process that determined the annual renewal of China's MFN status was characterized by a relatively fixed calendar. The President renewed China's status before its expiration on the 3rd of July.[14] After the renewal, the Congress had 60 days to consider a disapproval vote on the Presidential renewal. As can be seen in Figure 4 voting would generally take place between the end of July and beginning of August. If such legislation was passed in both the chambers, the President had the right to veto it. In fact, in 1992 President Bush executed this right and the Senate failed to override the veto. Uncertainty resolved only by the end of September and China's MFN status remained in place. Under the described political process, in any year, uncertainty regarding the renewal of China's MFN status would be resolved between the months of August and September.

3.2 Empirical Strategy

Our identification of the seasonal effects of the uncertainty regarding China's annual MFN status renewal is based on (1) product specific variation in the tariff risk, and (2) within year variation of the risk. First, we follow the literature and measure the tariff risk as the gap between the prevailing MFN rate and the NNTR rates.[15] We define the tariff risk of a HS-6 product z in year t to be $X_{z,t} \equiv \ln((1+\tau_{z,t}^{NNTR})/(1+\tau_{z,t}^{MFN}))$. Figure 5 illustrates that the tariff risk was sizeable throughout the entire period. The median deviation from the prevailing MFN rate was above 25 percentage points. However there was little variation over time. Only between between 1996 and 1997, when MFN rates fell after the agreements of the Uruguay Round, the gap between NNTR and MFN rates increased. However, Figure 6 illustrates that there was substantial variation in the tariff risk faced across different products. While for a product in the 10th percentile the gap between the MFN and NNTR rate was less than 5pp, applied tariffs of a product in the 90th percentile could have increased by more than 60pp.

Second, the fact that the political stages required to revoke China's MFN status had a fixed calendar presumably allowed importers to anticipate the resolution of uncertainty. Once the process had concluded by latest October, importers were certain that rates would remain the same at least until the end of August of the following year. Hence, if importers assigned a non-zero probability to the likelihood of revocation, expected tariffs would deviate from the MFN rate only in the months between August and October. In the model of section 2, the possibility of a tariff hike leads importers to anticipate TPU by increasing their imports in the immediacy of the uncertainty resolution. The fixed

[14]Only in 1993 there was uncertainty around the execution of the President's renewal authority. Before being elected, President Bill Clinton announced he would link China's MFN status to human rights progress, but then went along with the waiver during his presidency.

[15]Because NNTR rates were defined in 1930 by the Smoot-Hawley Trade Act, it is argued that product variation in NNTR rates is exogenous to political economy motives in 1990.

timing of the uncertainty resolution during this episode provides an excellent laboratory to test the empirical relevance of this effect of TPU.

Our empirical strategy follows a difference-in-difference specification that nets out US and China specific seasonalities unrelated to the tariff risk by including a reference importer and exporter.[16] As the reference importer we consider a group of 12 EU member countries (EU).[17] China's exports to the EU were granted unconditional MFN status in 1980. As the reference exporter we consider a group of 135 countries that were granted unconditional MFN status and no preferential rates[18] by both the US and the EU. The effect of TPU is measured as the treatment effect of a HS-6 product being traded by the US and China relative to the base effect of $X_{z,t}$ on the other trade flows not affected by the TPU.

Our baseline estimation equation is the following:

$$\begin{aligned}\ln(v^{i,j,z,t}_{m-2:m}/v^{i,j,z,t}_{m-7:m-5}) = &\sum_{m'} \beta^{TPU}_{m} \mathbb{1}_{\{i=US,j=China\}} \mathbb{1}_{\{m=m'\}} X_{z,t} \\ &+ \sum_{m'} \beta_m \mathbb{1}_{\{m=m'\}} X_{z,t} + \gamma_{i,t,m} + \gamma_{j,t,m} + \gamma_{z,m} + \varepsilon_{i,j,z,t,m} \end{aligned} \tag{5}$$

The left hand side of (5) is our baseline dependent variable that captures within year fluctuations in trade flows. We construct a log growth rate of trade for every month m by taking the average of imports of that month and the previous two relative to the monthly average of a previous period, in particular, the average between $m-7$ and $m-5$.[19] The first term on the right hand side of (5) is our coefficient of interest, $\beta^{TPU}_{m'}$, namely the treatment effect of TPU on movements in monthly exports from China to the US. The second term of (5) is the base effect of $X_{z,t}$ on trade flows that were not subject to the TPU. If imports rose in anticipation of TPU resolution, as predicted by the model in section 2, then $\beta^{TPU}_{m'} > 0$ for the month before Congress voted. We introduce destination-month-year and source-month-year fixed effects, $\gamma_{i,t,m}$ and $\gamma_{j,t,m}$, to control for source and destination specific seasonalities, such as Chinese New Years, that we allow to vary every year. To address concerns of product specific seasonalities, such as demand peaks for toys during Christmas, we introduce monthly sector specific fixed effects, $\gamma_{z,m}$, using the 21 sectors of the HS sections. Notice that any confounding factor that varies at annual frequency will be eliminated by taking time differences.

[16] In the robustness section we extend this approach to a triple difference in which we consider China's exports to the US during the uncertainty period relative to those after uncertainty resolved.

[17] These are Austria, Belgium, France, Finland, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Spain, and Portugal.

[18] See the list of countries in Table A.1 of the Appendix

[19] We take monthly averages because of the lumpiness in trade flows at HS-6 level of aggregation. In section 3.5 we show that the seasonal pattern we document is robust to other choices of dependent variables.

3.3 Data

We use monthly trade flows at the 6-digit level of the Harmonized System (HS) product classification. [20] US import data is obtained from the Census Bureau and EU import data from Eurostat. Imports are in CIF value of imports for consumption. MFN and NNTR rates at HS-8 product level are from Pierce and Schott (2016) and computed their means at HS-6 level. Our baseline sample period includes the years 1991 to 2000, when China's MFN status was subject to the possibility of revocation and importers had sufficient time to anticipate the resolution of uncertainty. The baseline sample is restricted to those products that were traded at least once every year in all four directions of trade, that is from the RoW and China to the US and the EU. We do this because (1) the model used to obtain the likelihood of MFN status reversal abstracts from the entry decision; and (2) because it allows for comparison of sectoral seasonalities common in the four directions of trade. The balanced sample includes 1,812 HS-6 products. In the case of US-China trade, these 1,812 HS-6 products account for 88% of the total value of trade during the baseline sample period.[21] Similarly, when we extend the sample period until 2005 to study the TPU induced seasonality relative to the period after China joined the WTO, we restrict the sample to be those HS-6 products that were traded at least once a year in all four directions. This leaves 1,750 HS-6 products.

3.4 Baseline Results

In Figure 7 we present the estimates of $\hat{\beta}^{TPU}$ for $m \in \{1, 2, ..., 12\}$.[22] There is a distinct pattern in the growth rates of trade flows in response to the tariff risk. By June imports start growing significantly with the tariff risk. The effect peaks around August and September. Growth rates then decline and become significantly negative in January, reaching its trough in March. At its peak (trough), for the median tariff risk, imports are on average 10% higher (7% lower) than compared to the reference period.

In Table 2 we report the coefficients of $\hat{\beta}^{TPU}$ for $m \in \{1, 2, ..., 12\}$. In column 1 we estimate (5) under the full unbalanced sample and without fixed effects. The seasonal pattern is the same but coefficients are larger. In column 2 we introduce source- and destination-month-year fixed effects and the coefficients decline. Column 3 reports the

[20] Results are similar when considered at 6-digit level of the NAICS industry classification.

[21] For China EU trade, the balanced sample accounts for 89% of the value of trade. Naturally, the sample selection is more relevant in the case of exports from the RoW. In the case of exports from the RoW to the US, the balanced sample accounts for 47%. The inclusion of these goods would affect the measurement of sectoral industry effects. Nonetheless, results below are not sensitive to the sample selection.

[22] Figure A.1 includes the estimates of $\hat{\beta}_m$, i.e. the effect of $X_{z,t}$ on non-US-China trade flows. These results can be interpreted as placebo tests since thos trade flows were not subject to TPU. However, there could also be some substitution between those trade flows and US-Chinese. We find that the response of non-US-China trade flows is inversely related to that of the US-China response (substitution), but is much smaller in magnitude and almost never statistically significant throughout the year.

estimates from (5) with controls for industry-specific seasonalities under the full sample of HS-6 goods. Column 4 corresponds to the described estimates of our baseline specification, plotted in Figure 7. In comparing column three with column four we ascertain that the seasonal pattern of our baseline is very similar to the one obtained under the full unbalanced sample.

These results show that throughout the entire year imports from China to the US responded significantly to the threat of facing a tariff hike. US importers anticipated the possibility of a tariff hike by increasing their purchases before the resolution of uncertainty. When the tariff hike didn't materialize, imports dropped in the beginning of the year. This TPU induced seasonal pattern of US-China trade flows signals that importers indeed assigned a non-zero probability to the non-renewal of China's MFN status. However, the magnitude of the anticipatory response was rather small.[23] Next we show that these results are robust to various choices made.

3.5 Robustness

The baseline results presented above are robust to several alternative fixed effects specifications, the time horizon of the short run import growth rate and alternative dependent variables. Additionally, the documented seasonal effect of TPU is driven by quantities, rather than unit values. Results are presented in Table 3 and discussed below. Moreover, in subsection 3.7 we show that results also hold under a triple difference approach that incorporates a pre- and post-WTO accession difference.

Alternative Seasonality Controls. - In column 2 of Table 3 we introduce a more demanding structure of source- and destination-sector-month-year fixed effects. This allows the Christmas peak in demand for toys to be specific to the direction of trade, but also undermines some of the potential variation in the response to the tariff risk, since NNTR gaps are positively correlated within HS sections. In column 3 we introduce product-month fixed effects instead of sector-month fixed effects. In the first case, the estimates drops slightly with respect to our baseline estimates (column 1), but the same seasonal pattern remains. In the second case the estimates are almost unchanged.

Different Time Horizons of Trade Growth. - In columns 4 and 5 we vary the time horizons considered in the calculation of the short run growth rates of imports. In column 4 we consider the rolling growth rate of the last four month relative to the previous four months, i.e. $\ln(v^{i,j,t,z}_{m-3:m}/v^{i,j,t,z}_{m-7:m-4})$. In column 5 we introduce a one month gap between the two periods, i.e. $\ln(v^{i,j,t,z}_{m-3:m}/v^{i,j,t,z}_{m-8:m-5})$. The seasonal pattern is unchanged, although the size of the coefficients is slightly smaller than our baseline. This suggests that, import growth was more concentrated in a few months before the expected change.

[23] To provide a comparison, Khan and Khederlarian (2019) estimate short run anticipatory elasticities during the NAFTA phaseouts to be around 4 to 6. Importantly, in the episode studied here tariff changes are uncertain and observed anticipation is the result of underlying expectations.

Missing Values. - To overcome concerns of missing values in the log growth measure, in column 6 we estimate (5) using the mid-point growth rate of the same trade flows, i.e. $\frac{2(v^{i,j,t,z}_{m-2:m}-v^{i,j,t,z}_{m-7:m-5})}{v^{i,j,t,z}_{m-2:m}+v^{i,j,t,z}_{m-7:m-5}}$. Results are similar to the baseline, indicating that missing value do not drive our baseline results.

Timing of the Peak. - The baseline dependent variable defines monthly import growth with respect to a reference period that varies for each month and considers contemporaneous imports and that of the previous two months. This might cloud the actual timing of the peak response. We address these concerns by fixing the reference period to average imports between February and April for every month of the year, i.e. $\ln(v^{i,j,t,z}_{m-2:m}/v^{i,j,t,z}_{Feb:Apr})$. Although the magnitude coefficients drop slightly, the timing of the peak and trough response remains the same, that is September and March. We also considered the annual share of imports at each month, i.e. $v^{i,j,t,z}_{m}/\sum_{m=1}^{12} v^{i,j,t,z}_{m}$. The timing and significance of the seasonal response is the same.

Quantities and Unit Values. - In column 8 and 9 we estimate (5) using quantities and unit vales instead of value of trade as the dependent variable, respectively. Estimates in column 8 are almost identical to those of the baseline, while the estimates in column 9 are mostly insignificant and small.[24] These results indicate that the TPU induced seasonal pattern is driven entirely by changes in quantities traded and that pricing dynamics did not play any role.

3.6 TPU Effects and Product Storability

Next we investigate product heterogeneity in the response to the tariff risk and provide evidence for the mechanism that drives anticipation to a possible tariff hike in the model of section 2. In particular, we study the interaction between the TPU-induced seasonality and the degree of storability of a product. Similar to the approach in Khan and Khederlarian (2019), storability is proxied by the observed lumpiness of trade.[25] A product specific measure of storability is obtained by predicting the annual inverse HH index of all HS-6 goods the US imported from the 135 RoW countries between 1991 and 2000 net of source-time fixed effects such as distance and source-specific shocks.[26] The inverse HH index is the effective number of months in a year with positive orders. More storable products are ordered less frequently and therefore will have fewer months with import flows.[27] Through the lens of the model in section 2, more storable products are

[24] Only in the month of December do unit values display a significant response.

[25] Lumpiness in trade flows can be rationalized by lumpy demand or inventory holdings. As documented by Alessandria et al. (2010b) and Bekes et al. (2017) among others, trade is intensive in inventories and we take the second view.

[26] The HH index of annual imports of z from i in year t is $HH_{j,z,t} = \sum_{m=1}^{12}(v_{j,z,t,m}/\sum v_{j,z,t,m})^2 \in [1/12, 1]$. Once calculated for all z, t and countries listed in Table A.1, we estimate $1/HH_{j,t,z} = \delta_0 + \delta_z + \delta_{j,t} + u_{j,t,z}$ and then define the degree of storability as $1/\hat{HH}_z = \hat{\delta}_0 + \hat{\delta}_z$. The source-year fixed effects net out determinants of lumpiness that are unrelated to the product storability.

[27] In Figure A.3 we report the distribution of our measure of storability over HS-6 products.

expected to display stronger responses to TPU.

We test this estimating the following equation:

$$
\begin{aligned}
\ln(v^{i,j,z,t}_{m-2:m}/v^{i,j,z,t}_{m-7:m-5}) = &\sum_{m'} \beta^{HH}_m \mathbb{1}_{\{i=US,j=China\}} \mathbb{1}_{\{m=m'\}} [1/HH_z] \times X_{z,t} \\
&+ \sum_{m'} \beta^{TPU}_m \mathbb{1}_{\{i=US,j=China\}} \mathbb{1}_{\{m=m'\}} X_{z,t} \\
&+ \sum_{m'} \beta_m \mathbb{1}_{\{m=m'\}} X_{z,t} + \gamma_{i,m} + \gamma_{j,m} + \gamma_{s,m} + \varepsilon_{i,j,z,t,m} \qquad (6)
\end{aligned}
$$

Table 5 reports the responses to the tariff risk for the months we identified as the peak and trough response in our baseline estimation. In column three the interaction term is negative in the peak month and positive in the trough, as predicted by the inventory mechanism.[28] Figure 9 further confirms the heterogeneous response throughout the entire year. A product in the 20th percentile of the inverse HH distribution displays a strong response to $X_{z,t}$ throughout the entire year, larger than the average response from our baseline estimation. For a product in the 80th percentile of the inverse HH distribution the response is small. In the model described in section 2, products that are characterized by monthly inventory-sales ratios close to one display relatively less anticipation to a possible tariff hike. The documented evidence of stronger TPU-induced seasonal dynamics of more storable products is suggestive of the proposed mechanism.

3.7 Post-WTO Triple Difference

In this robustness check the baseline difference-in-difference approach is extended with a third difference: The period before and after China joined the WTO. We set the post WTO period to be between 2003 and 2005 and estimate the following equation:[29]

$$
\begin{aligned}
\ln(v^{i,j,z,t}_{m-2:m}/v^{i,j,z,t}_{m-7:m-5}) = &\sum_{m'} \beta^{TPU}_m \mathbb{1}_{\{i=US,j=China\}} \mathbb{1}_{\{t\in Pre\}} \mathbb{1}_{\{m=m'\}} X_{z,t} \\
&+ \sum_{m'} \beta^{Post}_m \mathbb{1}_{\{i=US,j=China\}} \mathbb{1}_{\{m=m'\}} X_{z,t} \\
&+ \sum_{m'} \beta_m \mathbb{1}_{\{m=m'\}} X_{s,t} + \gamma_{i,m} + \gamma_{j,m} + \gamma_{s,m} + \varepsilon_{i,j,z,t,m} \qquad (7)
\end{aligned}
$$

As in our baseline estimation, β^{TPU}_m reflects the effect of the tariff risk on monthly changes in imports from China to the US, but now the treatment is also relative to the base effect of $X_{z,t}$ on US-China trade flows after the year 2001. Figure 8 shows the

[28]Similarly, Figure A.4 shows the growth of imports during September in response to the median tariff risk. Products that are ordered in the lower percentile of the inverse HH distribution respond with import rises of up to 20%, while for upper percentiles the rise is much smaller.

[29]In Table A.2 we report the results for the post-WTO period being between 2001 and 2005. The seasonal pattern remains the same but the coefficient drop. This is because in 2001 and 2002 the TPU-induced seasonal pattern remained partially in place, hence depressing the difference of the Pre WTO accession treatment.

estimates of β_m^{TPU} for $m \in \{1, 2, ..., 12\}$. The same pattern as in our baseline remains, although the coefficient estimates are slightly smaller, suggesting that some of the TPU-induced seasonalities persisted even after China joined the WTO.

4 Estimation of the Likelihood of MFN Revocation

Thus far, we have identified the TPU-induced seasonality in US imports from China during the decade before China's accession to the WTO. We now use the structure of the model described in section 2 to estimate the likelihood with which importers expected the MFN revocation to take place. In this particular episode, two of the three uncertainty components are observed: (1) the timing of the resolution, and (2) the tariff risk. The probability of revocation is obtained by matching the anticipatory rise in trade flows before the uncertainty resolution while fixing (1) and (2). In contrast with other approaches in the literature, our methodology exploits the within-year variation of the policy risk. This is appealing because it overcomes concerns of confounding long run factors driving trade patterns. In this section we show that (1) the probability of revocation was relatively small; (2) it is largest in the early years of the 1990s and drops in the end; and (3) uncertainty played a minor in driving the anticipatory response relative to the expected downside risk.

4.1 Model Calibration

In the model described in section 2, the magnitude of the anticipatory import rise depends on the trade-off between two factors. On the one hand, firms want to avoid paying high tariffs in case the MFN status is revoked. On the other hand, firms want to avoid the ordering and holding costs incurred while expediting the purchase order. Higher fixed costs and lower depreciation rates are associated with more infrequent purchases and hence with lower inverse HH indexes. We calibrate the model to the monthly frequency by setting $(1 + r)^{-1} = 0.97^{(1/12)}$, to generate mean annual interest rate of 3%. The value of the fixed ordering cost is borrowed from AKM and set at the value of 0.095, implying average fixed costs are equal to 7% of average monthly revenues at steady state.

We calibrate the depreciation rate to match the inverse HH index of different HS-6 products. More storable goods allow for more stockpiling in anticipation of a possible tariff increase, as documented in section 3.6. Precisely, we classify the 1,812 HS-6 products of our baseline sample into 453 bins of 4 products grouping them according to their mean tariff risk between 1991 and 2000. The depreciation rate of each bin is calibrated to match the median inverse HH index of the 4 HS-6 products in the bin.[30] The elasticity

[30]In section 3.6 we described the calculation of the inverse HH index. Because in each simulation all firms import the same product and face the same tariff risk, we intend the 4 HS-6 products of each bin

of substitution is set to equal 4, but does not influence our results.

4.2 Baseline Result

The probability of non-renewal of China's MFN status is obtained by simulating the model described in section 2 to match the peak import rise in response to the tariff risk estimated in section 3.4. We then simulate the model for each of the 453 product bins described above. Hence each simulation is characterized by a pair of $(\tilde{X}_b, \delta_b)$, where b indicates a bin and $\tilde{X}_b$ is the mean tariff risk the bin of HS-6 products faced between 1991 and 2000.[31] For each b, we simulate the transition from the steady state without tariffs to an increase in tariffs of X_b that occurs with probability π, common to all bins. This change occurs 12 months from the initial steady state with probability π. After simulating the transition for each bin we generate a dataset with the monthly aggregate trade flows and compute the analog of our baseline dependent variable of section 3, i.e. $\ln(\tilde{v}_{b,m-2:m}/\tilde{v}_{b,m-5:m-7})$.[32,33] We then estimate the model analog of β_m^{TPU} from our baseline estimation equation (5) using the following equation:[34]

$$\ln(\tilde{v}_{b,m-2:m}/\tilde{v}_{bm-5:m-7}) = \sum_{m=m'} \beta_m^{sim} \mathbb{1}_{\{m=m'\}} \tilde{X}_b + \epsilon_{b,m} \tag{8}$$

We repeat this procedure varying π until we match the peak response to the tariff risk, i.e. equalizing $\max_m\{\hat{\beta}_m^{sim}\}$ to $\max_m\{\hat{\beta}_m^{TPU}\}$ estimated in the empirical analysis of section 3. In particular, we target $\hat{\beta}_{m=9}^{TPU} = 0.35$ from our baseline estimation equation, reported in column 3 of Table 2.[35] The estimated probability $\hat{\pi}$ that matches the coefficient on the tariff risk from the model to the one from the empirical analysis is 6%. This probability is lower than the one obtained by Handley and Limao (2017) in a framework that exploits the sensitivity of firms' market entry decision to TPU. In the next subsection we estimate a probability of revocation for each year between 1991 and 2000.

4.3 Annual Probabilities

The probability above reflects the average probability assigned to the non-renewal of China's MFN over the entire period. However, uncertainty varied across the years, with

to be as similar as possible in terms these two variables.

[31] In what follows, tildes on top of variables indicate that they are used or from model simulations.

[32] This implies that there are no general equilibrium effects through movements of aggregate price indexes and substitution across industries. We believe that at relatively high frequency this assumption is a reasonable simplification.

[33] We simulate 24 months, but only keep months 6 to 17 to construct the dataset. As can be seen in Figure 1 the trade dynamics generated by a possible tariff hike are sufficiently short lived not to affect the dynamics in successive year of TPU shocks.

[34] Its not necessary to control for seasonality since these are absent in the model.

[35] Equivalently we could have matched the trough-to-peak response or any other salient moment of the observed response to China's MFN status renewal. Results are not sensitive to our choice of matched moment.

the early 1990's presumably being the most uncertain. We estimate annual probabilities by estimating the annual response to the tariff risk and then applying the estimation approach from above to the year-specific estimates of $\max_m\{\hat{\beta}_m^{TPU}\}$. Precisely, we estimate the following equation:

$$\ln(v_{m-2:m}^{i,j,z,t}/v_{m-7:m-5}^{i,j,z,t}) = \sum_{m'}\sum_{t}\beta_{m,t}^{TPU}\mathbb{1}_{\{i=US,j=China\}}\mathbb{1}_{\{m=m'\}}\mathbb{1}_{\{t=t'\}}X_{z,t}$$
$$+\sum_{m'}\sum_{t'}\beta_{m,t}\mathbb{1}_{\{m=m'\}}\mathbb{1}_{\{t=t'\}}X_{z,t}+\gamma_{i,t,m}+\gamma_{j,t,m}+\gamma_{s,m}+\varepsilon_{i,j,z,t,m} \quad (9)$$

Column 1 of Table 6 reports the estimates of annual $\max_m\{\hat{\beta}_m^{TPU}\}$ and column 2 the model implied probabilities.[36] There is a large annual variation in both estimates. Three major takeaways emerge. First, in all years we find a non-zero probability of non-renewal. Second, the probability rises in the beginning of the decade, remains relatively high in the middle and declines in the end of the period of uncertainty. Third, the annual probabilities of non-renewal are line with the contemporaneous political developments. The probability jumps up to around 10% in 1991, when US Congress came closest to reverse the President's renewal vote. The probability rises again in 1994 to its maximum value of 11% when President Clinton was first authorized to revoke China's MFN status. During his Presidential campaign Clinton had announced he would link China's MFN status to its human rights record. However after being installed he opted to renew the waiver. The probability of non-renewal spikes again in 1997, and drops significantly thereafter. As reflected in Figure 10, our measure of TPU based on trade patterns is qualitatively similar to the newspaper article counts by Pierce and Schott (2016), since the two measures coincide in their first three spikes. However, our measure does not suggest a rise in the probability in 2000, when the US President signed into law China's permanent MFN status conditional on joining the WTO.

Further, we use our estimated annual probabilities to infer the time-varying likelihood of China maintaining MFN status for the years until 2001 when the process of annual renewal ended with China's WTO accession. We can infer this likelihood by compounding our estimated annual probability of not revoking China's MFN status in the years prior to 2001. Figure 11 contains the result of this calculation. We see that, because of the overall relatively low $\hat{\pi}$, the probability in 1991 of China enjoying MFN benefits during the uncertain period was considerably high at around 50%. This probability grows as China MFN status is renewed annually until its WTO accession. However, because of the

[36]Note that because in the estimation of the annual probabilities we use $\max_m\{\hat{\beta}_m^{TPU}\}$ of every year, the average probability over all years is larger (7.45%) than our baseline estimate (6%), which chooses the $\max_m\{\hat{\beta}_m^{TPU}\}$ in the pooled sample. This is the result of September not being the peak response in every year. However, column 4 of Table 6 informs that in 9/10 year the peak response is between August and October, in line with timing of the resolution process described in section 3.1. Moreover, the response in September (column 3) in those years it wasn't the peak is generally close to the peak response.

low estimates in the final years of the TPU period, the probability of continued access 3 years before China obtained the PNTR was already around 90%.

4.4 Role of Pure Uncertainty

In this section we separate the effects of a change in expected tariffs from the effects of uncertainty about the change. Theoretically, the real options literature suggests that uncertainty about future states of the world acts as a deterrent to irreversible investments[37]. Irreversibility of investments in such models necessitates a large gap between expected benefits and costs to incentivize entry which creates action and inaction regions within the state space. However, the importance of pure uncertainty depends on the sensitivity of these cutoffs and the distribution of firms around it. Both of these factors make the role of pure uncertainty dependent on the calibration and the nature of the uncertainty shock.

Since the real options models have a similar stopping time formulation as our inventory model, we investigate the role of pure uncertainty by simulating the certainty equivalent of the expected tariff change. Specifically, we give each bin b a change in tariffs equal to $\hat{\pi}\tilde{X}_b$ with certainty and estimate equation (8) with the simulated data. For a certain change of $\hat{\pi}\tilde{X}_b$, the coefficient $\hat{\beta}^{sim}_{m_{res}}$ is 0.46. This is higher than the estimate of 0.35 when the tariffs are expected to increase by $\tilde{X}_b$ with a probability of $\hat{\pi}$. Therefore, when we keep the expected increase in tariffs the same, we find that the uncertainty depresses the anticipatory growth coefficient by 24% on average. The negative effect of uncertainty is in line with the wait-and-see effect widely reported in the literature. It arises because the chance of the tariff rate remaining unchanged makes an advanced payment of the fixed ordering cost sub-optimal.

To illustrate the mechanism, consider the ordering cutoffs in the uncertain and certain case in Figure 12.[38] The top-left region is the ordering region i.e. firms order if they have fewer goods in inventories or higher demand shock. The ordering region in the uncertain case is smaller than the inaction region with the same expected but certain tariff change. The region between the two curves is the inaction region due to pure uncertainty. In this example, the expected tariff change is much larger than the ones face by imports from China during 1990's where the maximum expected tariff increase was around 8%.[39] This explains the minor difference in the coefficient of $\hat{\beta}$ of the certainty equivalent. In the next section we study how pure uncertainty affects the response to tariff risk more generally in this setting.

[37] See Bernanke (1983), Dixit (1989), Pindyck (1991) and more recently Kellogg (2014)

[38] For demonstration purpose, Figure 12 plots the ordering cutoffs when the tariff change is 40% in expectation. The solid blue line shows cutoffs when tariffs are scheduled to rise by 40% with certainty. Dashed red line plots the case when with equal chance tariffs stay the same or increase by 80%.

[39] $\hat{\pi} \times \max_z\{\tilde{X}_b\} = 10\% \times 80$.

5 Pure Uncertainty in Inventory Models

In this section we simulate the model described in section 2 to explore the role of pure uncertainty in a more general setting. By considering multiple spreads around the same expected tariff changes, two features of the anticipatory response to possible tariff hikes are illustrated. In the first place, the anticipatory trade surge is decreasing over the expected tariffs, that is, for larger expected tariff increases, the anticipatory increase in imports is smaller. Secondly, the variance or uncertainty component becomes relatively more important in dampening the anticipatory trade surge for larger expected tariff hikes. Because the implied probabilities (expected tariff hikes) we found in 4.4 were low, the findings in this section explain why uncertainty contributed relatively little in driving the anticipatory rise to the NNTR threat.

In all simulations, the parameter values are held constant and the same as in Table 1, with exception of the expected tariff change. For the rest of the section, the combination of future tariff and its probability is indexed by n and tilde denotes the simulation counterpart of the data variables in Section 3. We consider multiple expected tariff increases ranging from 1pp to 20pp by varying the probabilities, $\tilde{\pi}_n$ and the tariff changes, $\tilde{X}_n$, in order to have multiple spreads around the same expected change. For example, an expected tariff increase of 10pp can occur through a 25% chance of a 40pp increase or through a 50% chance of 20pp increase. We then analyze the anticipatory response through different estimation specifications. The anticipatory growth for each simulation is plotted in Figure 13. As expected, the response is non-linear and decreasing over $\tilde{\pi}_n\tilde{X}_n$. Moreover, conditional on an expected tariff change, the anticipatory rise in imports is increasing in the probability of the change. This is the trade dampening effect of uncertainty.

We formalize these findings[40] through different estimation specification that disentangle the role of the first, $\mathbb{E}(\tilde{X}_n) = \tilde{\pi}_n\tilde{X}_n$, and second moment[41], $Var(\tilde{X}_n) = \tilde{\pi}_n(1-\tilde{\pi}_n)\tilde{X}_n^2$, of the tariff hike. Results are presented in Table 7. In all regression the left hand side variable is the anticipatory import growth before the resolution of uncertainty, measured as $\tilde{v}^n_{m_{res}-2:m_{res}}/\tilde{v}^n_{m_{res}-7:m_{res}-5}$, as above. In the first and third column, we estimate the linear relationship between the anticipation and the expected tariff change. As expected the relationship is positive. This is the trade boosting effect of anticipation. Moreover, it explains the majority of the variation as can be seen in the R^2. In column 4 we include the square of the expected tariff change. The negative coefficient on the square term indicates that the trade boom is decreasing in the expected tariff change. Further, the

[40]We focus on simulations of a quantitative version of the model rather than on a simplified analytical model to enhance the understanding of the main results of the paper, namely the probability of non-renewal of China's NTR status.

[41]The formula for variance is determined by considering the tariff change as a bernouli process where the only two outcomes are a tariff staying zero with probability $(1 - \tilde{\pi}_i)$ or increasing to X_z with probability $\tilde{\pi}_z$.

R^2 increases and explains 93% of the variation, highlighting the importance of the first moment in explaining the anticipatory response.

In column two and five we introduce the pure uncertainty or variance term into the estimation. In both cases the coefficient on the variance is negative. This is the trade dampening effect. In column 2, we standardize all variables for ease of interpretation. The effect of the first moment is 3.5 times larger than that of the second moment. In column 5, including the first moment, the non-linear term and the variance, all the variation in the anticipatory trade response is captured. Finally, in column six we interact the expected tariff change with the variance to show that as the tariff change increases the variance strongly dampens the anticipatory rise in trade. In fact, the coefficient on the variance term itself is now insignificant and variance only matters through its interaction with the expected tariff change. The coefficient is negative indicating that conditional on a variance, the trade dampening effect is stronger for higher expected tariff changes.

Through the lens of an ($\underline{s}$,$\overline{s}$) inventory model, in section 4 we found that US importers assigned a relatively low probability to the non-renewal of China's MFN status. In this section, we demonstrated that in this model and for the relevant expected tariff change uncertainty played a minor role in importers' behavior and that anticipation was close to linear. However, when expected tariff changes become large stockpiling effects flatten out and uncertainty strongly depresses anticipatory rises in trade.

6 Stockpiling Effect on Annual Trade Flows

This section studies the effect of the within-year anticipatory stockpiling on annual trade flows. In the model described in section 2, the seasonality induced by the TPU implies increased inventory holding cost that depresses trade. There exists a tight link between uncertainty, lumpiness and reduced annual trade flows in the model. During the period of uncertainty around China's MFN status, trade in products that faced larger tariff risk was indeed lumpier, in line with the findings of section 3. We relate these findings to those in Handley and Limao (2017) and show that controlling for the lumpiness of imports explains around 30% of the total trade dampening effect of uncertainty.

6.1 Trade Dampening Effect of TPU in Inventory Model

In the model, the anticipated nature of the possibility of an upcoming tariff hike generates strong fluctuations of trade around the period of uncertainty resolution. These fluctuations come at the cost of deviating from the efficient stationary distribution over inventory holdings. Forward looking firms trade-off the use of inventories as a hedge of the tariff risk and increased inventory holding costs. Although trade rises with the tariff risk in the months before the TPU resolution, over the span of a full year increases in the tariff risk are associated with more concentrated trade flows. Overall, the increased inventory costs linked to more concentrated purchases are passed onto the consumers. As a result of this, annual trade decreases. This trade dampening effect of TPU-induced seasonality is complementary to the entry channel emphasized by Handley and Limao (2017).

The mechanism that drives the trade dampening effect in the inventory model is reflected in the concentration of annual purchases. To illustrate the link between concentration, risk and annual trade we study the annual pattern of trade flows in the cross-section of HS-6 bins from the simulated dataset used in section 4. The following equations are estimated:

$$\ln(\widetilde{HH}_b) = \beta \ \widetilde{X}_b^{HL} + \alpha \ \tilde{\delta}_b + \epsilon_b \tag{10}$$

$$\ln \tilde{v}_b = \beta_1 \ \widetilde{X}_b^{HL} + \alpha \ \tilde{\delta}_b + \epsilon_b \tag{11}$$

$$\ln \tilde{v}_b = \beta \ \widetilde{X}_b^{HL} + \beta^{HH} \ \ln(\widetilde{HH}_b) + \alpha \ \tilde{\delta}_b + \epsilon_b \tag{12}$$

where $\widetilde{HH}_b$ is the corresponding HH index of annual concentration of the monthly trade flows, $\tilde{v}_b$ is the log annual trade, $\widetilde{X}_b^{HL} \equiv \left(\frac{1+\tau_b^{NNTR}}{1+\tau_b^{MFN}}\right)^{-3}$ is the profit loss under non-renewal used in Handley and Limao (2017), δ_b controls for the depreciation rate and ϵ_b captures the model's non-linear ordering behavior. Note that the measures of tariff risk X^{HL} used in this section and X used in section 3 are negatively related (See Figure A.5 in the Appendix). Results are reported in Table 8. Column 1 shows the tight negative relation between spreads and concentration. Column 2 is the trade dampening effect of spreads present in the inventory model. Column 3 illustrates that almost all of the trade dampening effect can be accounted for by the increased concentration of trade flows. In the next subsection we evaluate the relevance of the inventory mechanism in explaining the trade dampening during the TPU episode studied here.

6.2 Evaluating the Mechanism

We evaluate the effect of TPU-induced stockpiling during China's annual MFN status renewal building on the approach of Handley and Limao (2017). At annual frequency, recent literature has shown that products facing larger tariff risk during the 1990s displayed strong growth in the aftermath of China's WTO accession (see Handley and Limao (2017), Pierce and Schott (2016), Crowley et al. (2018)). First, we confirm the trade dampening effects of the tariff risk. Secondly we show that indeed the annual concentration of monthly trade flows responded negatively to the tariff risk. In third place, we establish that the TPU-induced lumpiness explains around one third of the reduction in trade.

A generalized triple difference approach similar to that of Pierce and Schott (2016) is implemented to consider the role of the trade dampening effect of the profit loss risk, $X_{z,t}^{HL}$. In line with our approach in section 3, we consider trade flows between US and

China before 2001 relative to (1) those after 2001, (2) those from China to the EU and (3) those from the RoW to the US. Precisely, the following equation is estimated:

$$\ln(v_{i,j,z,t}) = \beta \ \mathbb{1}_{\{(i,j)=(US,China)\}} \mathbb{1}_{\{t \in Pre\}} X^{HL}_{z,t} + \delta_{i,z,t} + \delta_{j,z,t} + \delta_{i,j,t} + \varepsilon_{i,j,z,t} \qquad (13)$$

The coefficient of interest β should be interpreted as the response of annual trade flows to the potential profit losses in case of the revocation of China's MFN status. A positive coefficient indicates that products with larger tariff risks experienced relatively lower trade volumes. In our baseline we consider aggregate bilateral fixed effects ($\delta_{i,j,t}$); destination-sector-year ($\delta_{i,z,t}$) fixed effects that account for demand shocks[42]; and source-product-year ($\delta_{j,z,t}$) fixed effects that account for export supply shocks. Results are reported in Panel A of Table 9. Column 1 reports the results of the baseline specification. The coefficient is positive and significant. The estimate is very similar to an analogous specification in Handley and Limao (2017).[43] In columns 2-4 the result is similar under different choices of fixed effects. Figure 14 shows the point estimate of β_t from estimating (13) including an indicator variable for each $t \in \{1991, 1992, ..., 2001\}$. Notably, the annual effect of potential profit loss falls as the plausibility of the MFN revocation falls in Figure 10.

Before evaluating the role of TPU-induced lumpiness in the trade dampening effect of the profit loss risk, the link between lumpiness and the tariff risk is established estimating the following equation:

$$\ln(HH_{i,j,z,t}) = \beta_1 \ \mathbb{1}_{(i,j)=(US,China)} \mathbb{1}_{\{t \in Pre\}} X^{HL}_{z,t} + \delta_{i,z,t} + \delta_{j,z,t} + \delta_{i,j,t} + \varepsilon_{i,j,z,t} \qquad (14)$$

This specification is the same as (13) but changes the dependent variable to the observed trade lumpiness of annual trade flows from i to j of product z. Results are reported in Panel B of Table 9. Under all choices of fixed effects, the US-China lumpiness before 2001 increases for those goods that faced larger profit losses in the event of non-renewal. This results validates the relevance of the proposed mechanism, since under the structure of the model increased tariff risk causes stockpiling that is associated with increased lumpiness. Stockpiling in turn increases the inventory holding costs which has negative effects on annual imports as shown in Table 8.

Finally, we study how much of the trade dampening effect can be accounted for by the TPU-induced lumpiness in US-China trade flows by including both, the profit loss risk, $X^{HL}_{z,t}$, and the measured lumpiness, $HH_{i,j,z,t}$, in estimation equation of the trade dampening effect. The idea here is that, by controlling for the lumpiness we shut down the effect of tariff that goes through higher inventory holding costs. Therefore, any change in the coefficient of tariff risk would help isolate the contribution of stockpiling to reduced

[42]This also eliminates the need to control for changes in MFN rates as in the baseline specification of Pierce and Schott (2016) and Handley and Limao (2017), since all countries in our group of reference exporters faced the same MFN rates as China.

[43]See Table A5 column 4 in the online Appendix of Handley and Limao (2017).

trade. We estimate:

$$\ln(v_{i,j,z,t}) = \beta \ \mathbb{1}_{(i,j)=(US,China)}\mathbb{1}_{\{t\in Pre\}}X_{z,t}^{HL} + \beta^{HH} \ \ln(HH_{i,j,z,t}) + \delta_{i,z,t} + \delta_{j,z,t} + \delta_{i,j,t} + \varepsilon_{i,j,z,t} \tag{15}$$

Results are reported in Panel C of Table 9. We are interested in the coefficient β on $X_{z,t}^{HL}$ relative to the estimate reported in Panel A. In our baseline choice of fixed effects (column 1), the effect of the profit loss is reduced by 26%, that is, lumpiness accounts for 26% of the effect of the risk of profit loss. When relaxing the fixed effects in columns 2-4, the reduction in β increases. The evidence provided in this section suggests that TPU-induced lumpiness can account for a non-negligble share of the trade dampening effect of the tariff risk.

7 Conclusion

The aim of this paper is threefold. First, we show that uncertain future changes in tariffs have sizeable effects on trade flows in the interval before and after these proposed policy changes even when no change in tariff is realized. Second, we show how to use these trade dynamics through the lens of a standard ($\underline{s}$,$\overline{s}$) inventory model to identify the probability distribution of future trade policy. Third, we demonstrate that these frictions give rise to more costly inventory holdings that can account for a sizeable portion of the cross-sectional dampening of trade flows.

China's annual US NTR renewal provides the ideal setting to achieve these aims. In models with storable goods and fixed ordering costs, incumbent importers anticipate uncertain future trade policy changes by increasing their purchases before a possible policy change. Given two possible policy outcomes, the magnitude of anticipatory dynamics depend on three components of uncertainty, (1) the size of the policy change, (2) its probability, and (3) the amount of time until the uncertainty resolution. The features of China NTR fixes the timing and size of the policy change good-by-good and and allows us to use the model to estimate the probability of the policy change. We find a lower mean probability of non-renewal than elsewhere but year-to-year variations that match up well with some other qualitative measures.

We also use the model to distinguish between the role of pure uncertainty and the level-effect of the expected tariff change. Even though the "wait-and-see" effect due to pure risk is present in the ($\underline{s}$,$\overline{s}$) model, its relative contribution is shown to be quite small relative to the first moment of the policy change.

A benefit and limitation of our approach to identify the path of future trade policy is that it hinges on a relatively short-run dynamic decision on the timing of purchases. As the frictions from trade and inventory costs lead importers to hold 3-4 months of imported inventories, future trade policy outside this window has almost no effect on ordering behaviour. Thus our approach can be applied to numerous other episodes to estimate the near term path of policy. For instance import decisions soon after the Trump election can help identify the expected tariff in 2017.

To learn about the longer-run path of trade policy it will be useful to consider more durable investments such as exporting or FDI as in Alessandria and Mix (2018). Ruhl and Willis (2017) find that the expected duration of exporting of a new exporter is only about three years compared to 9 years for a continuing exporter and so perhaps by leveraging these different horizons we can recover a longer path of future trade policy. Of course, these alternative approaches must remain consistent with the information recovered using the approach here. Indeed, our estimates can be used as inputs into models with alternative margins that could be affected by TPU.

Finally, our results provide a mechanism to explain why trade has held up fine in advance of a future policy change such as Brexit. Likewise, trade may not fall in the presence of an increase in tariffs provided they are expected to escalate further as in the case of US-China trade war of 2018-19. Our results suggest that trade could fall off sharply following a possible increase in tariffs that is unrealized owing to an inventory overhang, although general equilibrium considerations could mitigate this effect. Indeed, revisiting these findings in a general equilibrium framework would be useful to explore the effects on trade policy uncertainty on the aggregate economy.

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Table 1: Moments and Parameters for Section 2

Parameter		Value	Source
$(1+r)^{-1}$	Annual Discounting factor	0.97	St. Louis Fed
σ	Elasticity of Substitution	4	Literature
f	Fixed Cost Ordering	0.095	Match HH index
μ	Delivery lag	1 pd	AKM
σ_ν	Std Dev of Taste Shocks	0.8	AKM
δ	Annual Depreciation Rate	30%	AKM
Moments			
	HH Index	0.32	75^{th} pctile - Imports from China
	Median Inventory-Sales	3.64 months	
	Mean(Fixed Cost/Revenue)	6.9%	

Table 2: Seasonal Effects of Tariff Risk

Dep. Var:$\ln(v^{i,j,t,z}_{m-2:m}/v^{i,j,t,z}_{m-7:m})$ Sample	(1) Full	(2) Full	(3) Full	(4) Balanced
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=1\}}X_{z,t}$	0.02	-0.10**	-0.10**	-0.16***
	(0.04)	(0.05)	(0.05)	(0.05)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=2\}}X_{z,t}$	-0.04	-0.20***	-0.20***	-0.22***
	(0.04)	(0.04)	(0.04)	(0.04)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=3\}}X_{z,t}$	-0.19***	-0.23***	-0.23***	-0.23***
	(0.04)	(0.04)	(0.04)	(0.04)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=4\}}X_{z,t}$	-0.11***	-0.24***	-0.23***	-0.19***
	(0.03)	(0.04)	(0.04)	(0.04)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=5\}}X_{z,t}$	0.08**	-0.05	-0.06	0.04
	(0.03)	(0.05)	(0.05)	(0.05)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=6\}}X_{z,t}$	0.32***	0.15***	0.15***	0.19***
	(0.03)	(0.04)	(0.04)	(0.04)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=7\}}X_{z,t}$	0.47***	0.22***	0.22***	0.24***
	(0.03)	(0.04)	(0.04)	(0.04)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=8\}}X_{z,t}$	0.83***	0.30***	0.30***	0.35***
	(0.04)	(0.04)	(0.04)	(0.04)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=9\}}X_{z,t}$	0.96***	0.33***	0.33***	0.35***
	(0.04)	(0.04)	(0.04)	(0.04)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=10\}}X_{z,t}$	0.85***	0.25***	0.25***	0.26***
	(0.03)	(0.04)	(0.04)	(0.04)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=11\}}X_{z,t}$	0.41***	0.16***	0.16***	0.11**
	(0.03)	(0.04)	(0.04)	(0.04)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=12\}}X_{z,t}$	0.25***	0.03	0.03	-0.02
	(0.03)	(0.04)	(0.04)	(0.05)
HS Section - Month FE			✓	✓
Destination - Month - Year FE		✓	✓	✓
Source - Month - Year FE		✓	✓	✓
Observations	1437298	1437298	1437298	764374
Adjusted R^2	0.008	0.013	0.017	0.032

Note: The independent variable $X_{z,t}$ is defined as $\ln((1+\tau^{NNTR}_{z,t})/(1+\tau^{MFN}_{z,t}))$. Column 4 is the results of estimating equation (5), our baseline. Column 3 is the result of estimating (5) for the full sample. Columns one and two include different fixed effects. In this table we only report estimates of coefficients of β^{TPU}_m for $m = [1, 12]$. Sample period is from 1990 until 2000. Standard errors, in parentheses, are clustered at HS-6- product level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Post-WTO Accession - Triple Difference

Dep. Var: $\ln(v^{i,j,t,z}_{m-2:m}/v^{i,j,t,z}_{m-7:m})$	(1)	(2)
Post-WTO Years	2001-05	2003-05
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=1\}} \times X_{z,t}$	-0.15***	-0.16***
	(0.05)	(0.06)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=2\}} \times X_{z,t}$	-0.13***	-0.17***
	(0.05)	(0.06)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=3\}} \times X_{z,t}$	-0.12**	-0.14***
	(0.05)	(0.06)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=4\}} \times X_{z,t}$	-0.070	-0.088
	(0.05)	(0.05)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=5\}} \times X_{z,t}$	0.03	0.06
	(0.06)	(0.07)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=6\}} \times X_{z,t}$	0.13***	0.18***
	(0.05)	(0.05)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=7\}} \times X_{z,t}$	0.13***	0.22***
	(0.05)	(0.05)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=8\}} \times X_{z,t}$	0.17***	0.28***
	(0.05)	(0.06)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=9\}} \times X_{z,t}$	0.18***	0.29***
	(0.05)	(0.06)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=10\}} \times X_{z,t}$	0.11**	0.21***
	(0.05)	(0.06)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=11\}} \times X_{z,t}$	0.02	0.07
	(0.05)	(0.05)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=12\}} \times X_{z,t}$	-0.10*	-0.10*
	(0.05)	(0.06)
HS Section-Month-PreWTO FE	✓	✓
Destination-Month-Year FE	✓	✓
Source-Month-Year FE	✓	✓
Observations	1167996	1003593
Adjusted R^2	0.031	0.030

Note: Estimates in this Table are the result of estimating (7). In column 1 the sample period is 1991-2005. In column 2 we exclude 2001 and 2002, when some of the seasonal effects of TPU persisted. Standard errors, in parentheses, are clustered at HS-6- product level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Robustness - Fixed Effects, Time Horizon, Dependent Variables & Quantities

Dep. Var: $\ln(v^{i,j,t,z}_{m-2:m}/v^{i,j,t,z}_{m-7:m-5})$	Baseline	FEs	FEs	$\ln(v^{i,j,t,z}_{m-3:m})-\ln(v^{i,j,t,z}_{m-7:m-4})$	$\ln(v^{i,j,t,z}_{m-3:m})-\ln(v^{i,j,t,z}_{m-8:m-5})$	Mid-Point Growth	$\ln(v^{i,j,t,z}_{m-3:m})-\ln(v^{i,j,t,z}_{Feb:Apr})$	Quantities	Unit Values
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=1\}} \times X_{z,t}$	-0.16***	-0.00	-0.16***	-0.12***	-0.09**	-0.05	-0.04	-0.15**	-0.03
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=2\}} \times X_{z,t}$	-0.22***	-0.09**	-0.22***	-0.18***	-0.19***	-0.13***	-0.10***	-0.18***	-0.03
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=3\}} \times X_{z,t}$	-0.22***	-0.12***	-0.22***	-0.23***	-0.23***	-0.14***	-0.12***	-0.12**	-0.04
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=4\}} \times X_{z,t}$	-0.19***	-0.15***	-0.17***	-0.12***	-0.19***	-0.10***	-0.09***	-0.09	-0.05
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=5\}} \times X_{z,t}$	0.02	-0.02	0.04	-0.02	-0.09**	0.05	-0.02	0.11*	-0.05
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=6\}} \times X_{z,t}$	0.19***	0.08*	0.20***	0.14***	0.09**	0.20***	0.10***	0.27***	-0.03
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=7\}} \times X_{z,t}$	0.24***	0.13***	0.24***	0.31***	0.22***	0.24***	0.15***	0.27***	0.01
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=8\}} \times X_{z,t}$	0.35***	0.24***	0.33***	0.28***	0.33***	0.31***	0.17***	0.30***	0.03
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=9\}} \times X_{z,t}$	0.35***	0.27***	0.32***	0.30***	0.33***	0.31***	0.19***	0.28***	0.04
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=10\}} \times X_{z,t}$	0.27***	0.22***	0.24***	0.19***	0.30***	0.25***	0.17***	0.19***	0.06*
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=11\}} \times X_{z,t}$	0.12***	0.17***	0.11**	0.11***	0.21***	0.15***	0.17***	-0.02	0.09***
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=12\}} \times X_{z,t}$	-0.02	0.07*	-0.03	0.02	0.04	0.04	0.06	-0.10*	0.03
HS Section-Month FE	✓			✓	✓	✓	✓	✓	✓
6-Digit HS-Month FE			✓						
Destination-Month-Year FE	✓		✓	✓	✓	✓	✓	✓	✓
Source-Month-Year FE	✓		✓	✓	✓	✓	✓	✓	✓
Destination-HS Section-Month-Year FE		✓							
Source-HS Section-Month FE-Year		✓							
Observations	764374	764374	764374	766576	766107	769245	778659	696434	696431
Adjusted R^2	0.033	0.040	0.230	0.031	0.033	0.040	0.044	0.019	0.003

Note: The independent variable $X_{z,t}$ is defined as $\ln((1+\tau^{NNTR}_{z,t})/(1+\tau^{MFN}_{z,t}))$. Again, we only report estimates of coefficients of β^{TPU}_m for $m=[1,12]$. Column one shows the result of the estimating equation (**??**). Column two includes tighter product-specific seasonal effects (HS6-month). Column three includes even tighter controls for seasonalities unrelated to the tariff risk by including $\gamma_{i,z,m}$ and $\gamma_{j,z,m}$. Columns four and five vary the time horizon of the growth rate. Column six and seven use the growth rate of quantities and unit values as the dependent variable of estimation equation (**??**). Column 8 considers the mid-point growth rate $(\frac{2(x'-x)}{x'+z})$ of within year trade flows to overcome concerns related to missing values. Standard errors, in parentheses, are clustered at HS-6 product level, but are omitted from the table to save space * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 5: Effect of TPU & Product Storability

Dep. Var: $\ln(v^{i,j,t,z}_{m-2:m}/v^{i,j,t,z}_{m-7:m})$	(1) Baseline	(2) Dif-in-Dif	(3) Interaction
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=3\}} \times X_{z,t}$	-0.22***	-0.18***	-0.68***
	(0.04)	(0.06)	(0.21)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=9\}} \times X_{z,t}$	0.35***	0.24***	1.14***
	(0.04)	(0.06)	(0.22)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=3\}}\mathbb{1}_{\{HH_z<Median(HH_z)\}} \times X_{z,t}$		-0.14	
		(0.12)	
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=9\}}\mathbb{1}_{\{HH_z<Median(HH_z)\}} \times X_{z,t}$		0.34**	
		(0.13)	
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=3\}} \times [1/HH_z] \times X_{z,t}$			0.10**
			(0.04)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{m=9\}} \times [1/HH_z] \times X_{z,t}$			-0.18***
			(0.05)
HS Section-Month-PreWTO FE	✓	✓	✓
Destination-Month-Year FE	✓	✓	✓
Source-Month-Year FE	✓	✓	✓
Observations	764374	764374	764374
Adjusted R^2	0.033	0.033	0.033

Note: In this Table only coefficients for the months of March (trough in baseline) and September (peak in baseline). The inverse HH index proxies for storability of a HS-6 product and its calculation is described in the text. Lower inverse HH products are presumably more storable. Column 1 is the baseline. Column 2 introduces an indicator variable that is 1 if the products inverse HH index is below the median. In column 3 displays the results of (6) that introduces the interaction between storability and the response to the tariff risk. Standard errors, in parentheses, are clustered at HS-6- product level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Annual Probabilities

Year	$\max_m\{\hat{\beta}^{TPU}_m\}$	$\hat{\pi}$	$\hat{\beta}^{TPU}_{m=9}$	m_{max}	Peak-to-Trough
1991	0.61***	10.4%	0.52***	October	1.02***
1992	0.41***	7.0%	0.41***	September	0.57***
1993	0.51**	8.7%	0.47***	August	0.89***
1994	0.65***	11%	0.45***	October	0.88***
1995	0.46***	7.9%	0.46***	September	0.82***
1996	0.50***	8.6%	0.47***	August	0.99***
1997	0.58***	9.9%	0.43***	August	0.83***
1998	0.26**	5.0%	0.23**	June	0.64***
1999	0.21***	3.6%	0.12	August	0.33***
2000	0.14*	2.4%	0.12	October	0.44***
Average					
1991 - 2000	0.43***	7.45%	0.37***	8.6	0.74***
Pooled Sample (Baseline)					
1991 - 2000	0.35***	6%	0.35***	September	0.58***

Note: Results from column 1 to 3 are estimating (9). Column 1 is the peak response of each year, i.e. $\max_m\{\hat{\beta}^{TPU}_m\}$. The regression table with standard errors is in Table A.3. Column 2 are the annual $\hat{\pi}$'s estimated from the model using the simulated method of moments described in the main text. Column 3 is the estimate of $\hat{\beta}^{TPU}_{m=9}$, that is the response of US-China trade flows to $X_{z,t}$ in September, the month with the strongest response over the pooled sample. Column 4 is the month of the peak response. Column 5 is the difference between the largest and smallest coefficient of each year, that is, the trough-to-peak response to the tariff risk and can be viewed as alternative moment to estimate the probability of non-renewal. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Decomposing Level Effect from Pure Uncertainty

$\tilde{v}^n_{m_{res}-2:m_{res}}/\tilde{v}^n_{m_{res}-7:m_{res}-5}$:	Standardized (1)	Standardized (2)	Level (3)	Level (4)	level (5)	Level (6)
Standardized $\mathbb{E}(\tilde{\pi}_n\tilde{X}_n)$	0.94***	1.1***				
Standardized $Var(X_n)$		-0.32***				
$\mathbb{E}(\tilde{\pi}_n\tilde{X}_n)$			8.85***	17.1***	17.1***	10.5***
$[\mathbb{E}(\tilde{\pi}_n\tilde{X}_n)]^2$				-39.29***	-32.73***	
$Var(X_n)$					-6.06***	0.56
$\mathbb{E}(\tilde{\pi}_n\tilde{X}_n) \times Var(X_n)$						-41.7***
Oberservations	80	80	80	80	80	80
R^2	0.89	0.96	0.89	0.93	1	0.97

Note: This table contains the results from the regression on the simulated data from Section 5. The data is simulated by changing the expected tariff change in the interval [0.01,0.2] by varying probabilities and the level of tariff change. The dependent variable is the standardized and level anticipatory import growth and the independent variables are the mean and variance terms of the tariff change. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Effect of Uncertainty on Annual Trade

	$\ln(\widetilde{HH}_b)$	$\ln(\tilde{v}_b)$	$\ln(\tilde{v}_b)$
$\widetilde{X}^{HL}_b$	-0.78***	3.03***	0.23***
	(0.04)	(0.05)	(0.05)
$\ln(\widetilde{HH}_b)$			-3.57***
			(0.08)
Reduction in Effect			92%
Observations	453	453	453

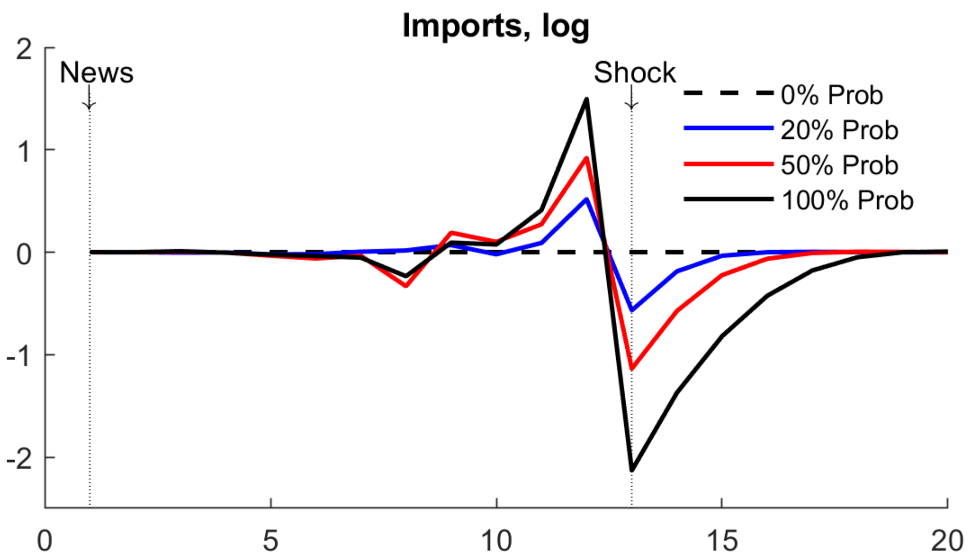
Note: This table presents results from the estimation of (10)-(12) on the simulated data. It uses calibration described in 4.1. The dependent variable in the first column is the log HH index of lumpiness of imports. The dependent variable in the last two columns is the log annual imports by industry. The explanatory variable in the first row is -HS-6 specific potential profit loss. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Effect of Uncertainty on Annual Trade

Panel A: Dep Variable $\ln(v_{i,j,z,t})$	(1)	(2)	(3)	(4)
$1_{\{(i,j)=(US,China)\}}1_{\{t\in Pre\}} \times X_{z,t}^{HL}$	0.41***	0.72***	0.20***	0.23***
	(0.13)	(0.06)	(0.07)	(0.07)
Adj R^2	0.76	0.76	0.76	0.49
Panel B: Dep Variable $\ln(HH_{i,j,z,t})$				
$1_{\{(i,j)=(US,China)\}}1_{\{t\in Pre\}} \times X_{z,t}^{HL}$	-0.05***	-0.12***	-0.03***	-0.05***
	(0.02)	(0.01)	(0.01)	(0.01)
Adj R^2	0.81	0.81	0.81	0.50
Panel C: Dep Variable $\ln(v_{i,j,z,t})$				
$1_{\{(i,j)=(US,China)\}}1_{\{t\in Pre\}} \times X_{z,t}^{HL}$	0.31***	0.48***	0.16***	0.13***
	(0.05)	(0.02)	(0.03)	(0.03)
$\ln(HH_{i,j,z,t})$	-1.94***	-1.95***	-1.94**	-2.65***
	(0.01)	(0.01)	(0.01)	(0.01)
Adj R^2	0.86	0.86	0.86	0.75
Reduction	24%	33%	20%	43%
Dest-HS2-Year	✓	✓	✓	
Source-HS6-Year	✓	✓	✓	
Dest-Source-Year	✓			
Dest-Source			✓	✓
Dest-Sector-Year				✓
Source-HS4-Year				✓
Observations	234294	234294	234294	252582

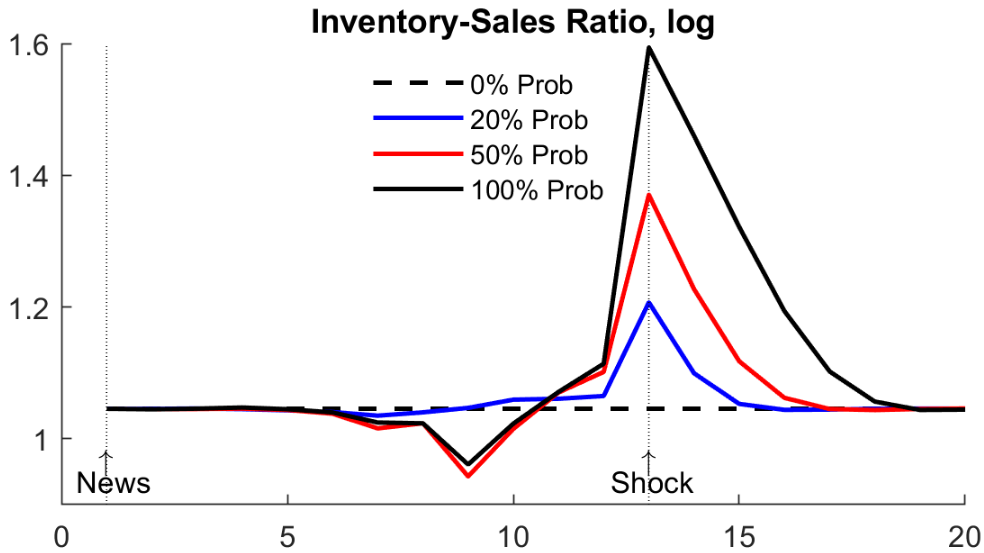
Note: Panel A,B and C contain results from (13), (14) and (15), respectively. The dependent variable in panel A and C is the log annual imports by country i from country j of product z in year t. The dependent variable in panel B is the log HH index of lumpiness by country i from country j of product z in year t. The first independent variable in all the panels is the measure of potential profit loss. Panel C adds HH index as a control to the regression specifications in panel A to quantify the effect of uncertainty coming through HH index. Robust standard errors are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Import Response to Different Probabilities of a Tariff Hike



Note: This plot illustrates the anticipatory response of Imports to an uncertain change in tariff. We assign different probabilities to the event of 10% increase in tariffs 12 months ahead. The vertical dotted line denotes the time of the uncertainty resolution. In all cases, the uncertain shock does not realize.

Figure 2: Inventory Response to Different Probabilities of Tariff Hike



Note: This plot illustrates the anticipatory response of aggregate Inventory-Sales ratio to an uncertain change in tariff. We assign different probabilities to the event of 10% increase in tariffs 12 months ahead. The vertical dotted line denotes the time of the uncertainty resolution. In all cases, the uncertain shock does not realize.

Figure 3: Time-Varying Ordering Cutoffs: $(\underline{s}, \overline{s})$ bands

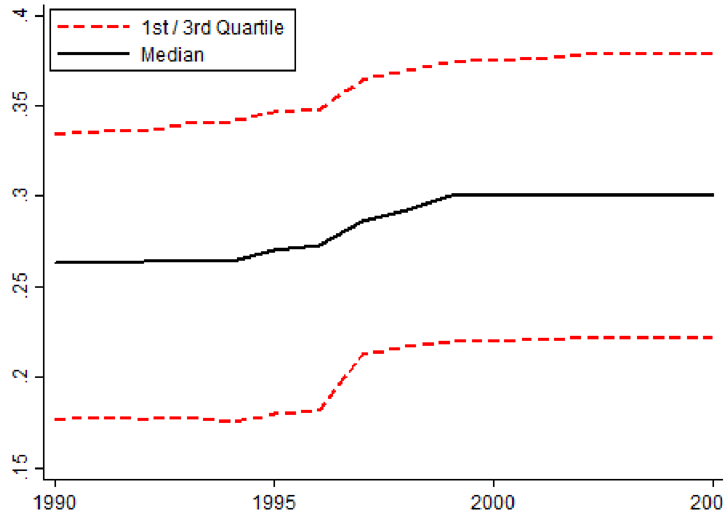
Note: This plot illustrates the anticipatory response of aggregate Inventory-Sales ratio to an uncertain change in tariff. We assign different probabilities to the event of 10% increase in tariffs 12 months ahead. The vertical dotted line denotes the time of the uncertainty resolution. In all cases, the uncertain shock does not realize.

Figure 4: Congressional Consideration of MFN for China: 1989-2000

Year	Disapproval Res.	Final Status	Alternate bills	Final Status	
1989	None	—	None	—	
1990	H.J.Res. 647	Passed House 10/18 (247-174)	H.R. 4939	Passed House 10/28 (384-30)	
1991	H.J.Res. 263	Passed House 7/10 (223-204) Senate Postponed 7/18, Unanimous Consent	H.R. 2212	Passed House 7/10 (313-112)	Conference Report H.Rept. 102-392 passed House 11/27 (409-21)
	S.J.Res. 153	Senate Postponed 7/18, Unanimous Consent	S. 1367	Passed H.R. 2212 in lieu 7/18 (55-44)	
1992	H.J.Res. 502	Passed House 7/21 (258-135)	H.R. 2212	Conference Report H.Rept. 102-392 passed Senate 2/25 (59-39) Vetoed by President 3/2 House override vote 3/11 (357-61) Senate override vote 3/18 (60-38) - veto sustained	
			H.R. 5318	Passed House 7/21 (339-62) Senate amended with text of S. 2808, passed by voice vote, 9/14 House passed Senate version 9/22, voice vote	H.R. 5318 vetoed by President, 9/28 House override vote 9/30 (345-74) Senate override vote 10/1 (59-40) - veto sustained
			S. 2808		
1993	H.J.Res. 208	House rejected 6/8 (105-318)	H.R. 1835 S. 806	No action	
1994	H.J.Res. 373	House rejected 8/9 (75-356)	H.R. 4590	Amended to impose no conditions, then passed House 6/8 (280-152)	
1995	H.J.Res. 96	House tabled 7/20 (321-107)	H.R. 2058	Passed House 7/20 (416-10)	
	S.J.Res. 37	—			
1996	H.J.Res. 182	House rejected 6/27 (141-286)	H.Res. 461	Passed House 6/27 (411-7)	
	S.J.Res. 56	—			
1997	H.J.Res. 79	House rejected 6/24 (173-259)	—	—	
	S.J.Res. 31 S.Amdt. 890*	— Senate rejected 7/16 (22-77)		*(S.Amdt. 890 expressed the sense of the Senate that China's MFN status should be revoked. It was offered as non-binding language to S. 955, the FY1998 Foreign Operations Appropriations bill.)	
1998	H.J.Res. 121	House rejected 7/22 (166-264)	—	—	
1999	H.J.Res. 57	House rejected 7/27 (170-260)	—	—	
	S.J.Res. 27	Senate rejected motion to discharge committee 7/20 (12-87)	—	—	
2000	H.J.Res. 103	House rejected 7/18 (147-281)	H.R. 4444	House passed 5/24 (237-197)	Signed by President on October 10, 2000, as P.L. 106-286, giving China Permanent NTR upon accession to WTO
	—	—	S. 2277	Senate passed H.R. 4444 on 9/19 (85-13)	

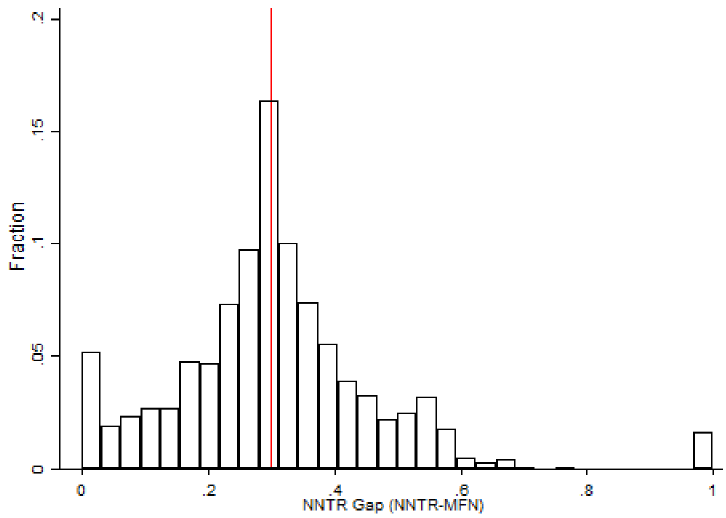
Source: Congressional Research Service, Report for Congress, "Voting on NTR for China Again in 2001, and Past Congressional Decisions".

Figure 5: Time Variation of Trade Policy Risk



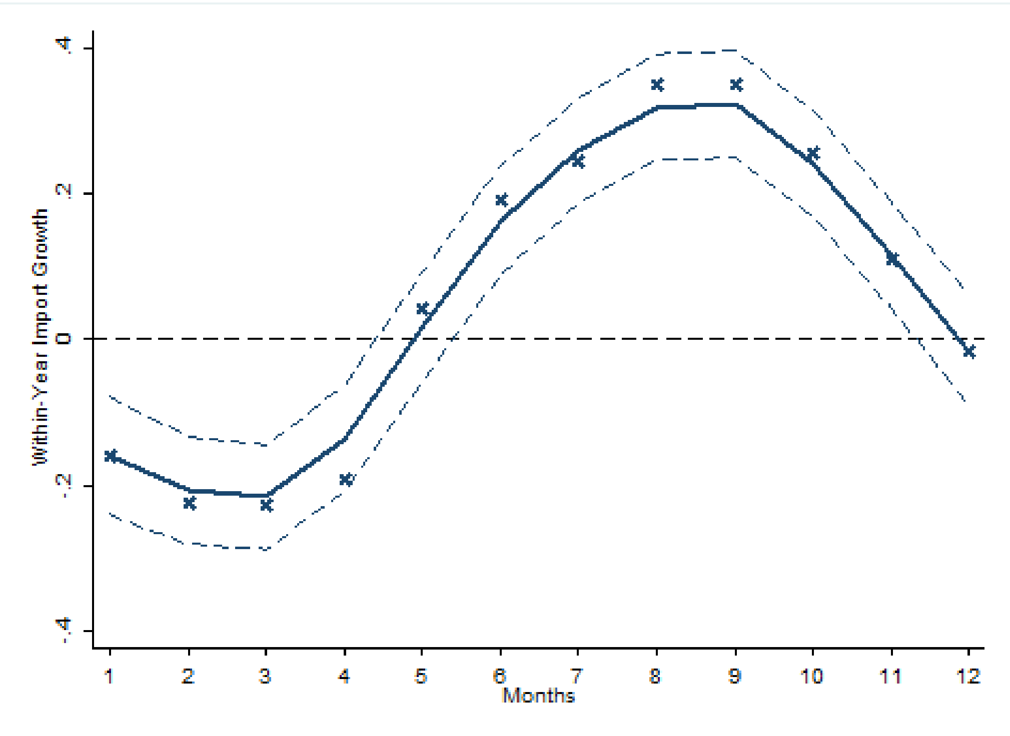
Note: This figure illustrates the time variation of our independent variable, $X_{z,t} \equiv \ln((1 + \tau_{z,t}^{NNTR})/(1 + \tau_{z,t}^{MFN}))$. NNTR and MFN rates are measured as means at HS-8 level from from Pierce & Schott (2016). HS-6 products included are those from our baseline sample of goods traded at least once a year in all four directions of trade.

Figure 6: HS-6 Product Variation of Trade Policy Risk in 2001



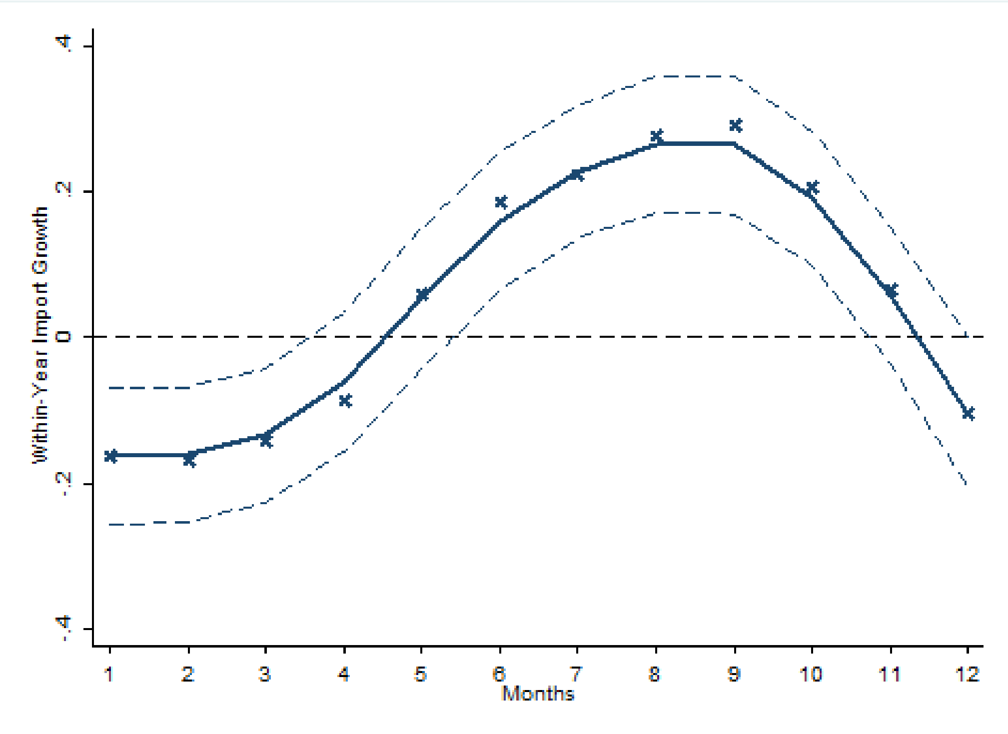
Note: This figure illustrates the cross-sectional variation of our independent variable, $X_{z,t} \equiv \ln((1+\tau_{z,t}^{NNTR})/(1+\tau_{z,t}^{MFN}))$. The NNTR and MFN rates are measured as means at HS-8 level from from Pierce & Schott (2016). For illustration purposes, in this figure we set $X_{z,2001} = 1$ if $X_{z,2001} > 1$. The red line is the median value, equal to 31pp. HS-6 products included are those from our baseline sample of goods traded at least once a year in all four directions of trade.

Figure 7: Seasonal Effect of TPU



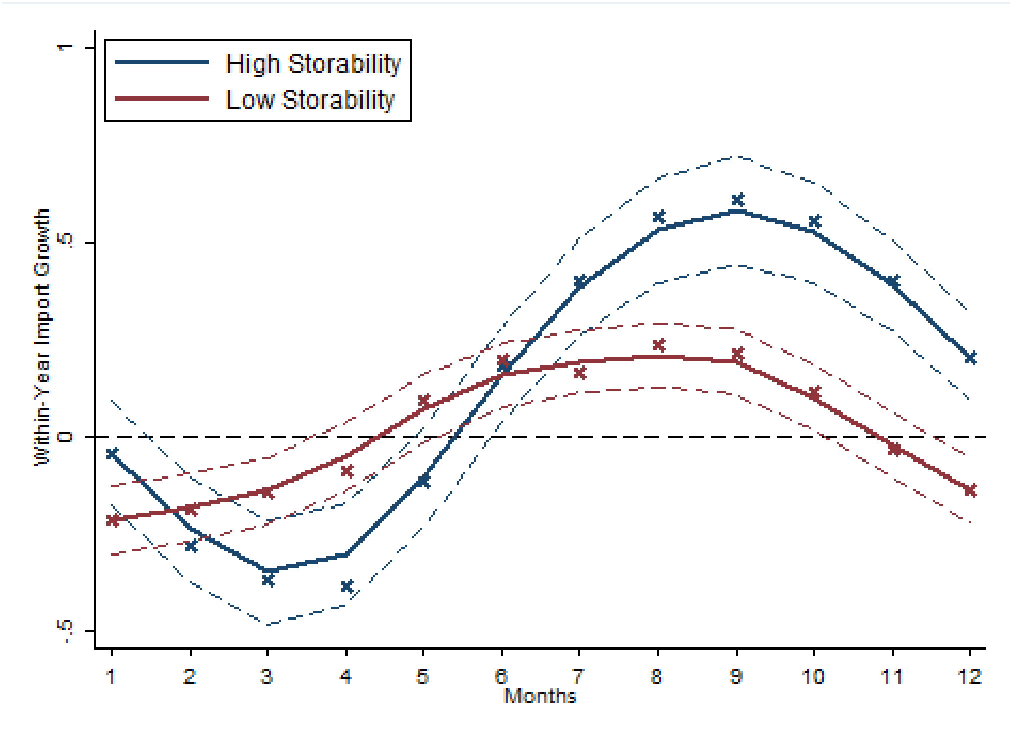
Note: Crosses are the estimates of $\hat{\beta}_m^{TPU}$ for each month $m = [1, 12]$ from estimating equation (5). Estimates of $\hat{\beta}_m$ are the treatment effect of $X_{z,t}$ for US-China trade flows. Results of coefficients of $\hat{\beta}_m^{TPU}$ are reported in Table 2. Results of the effect of $X_{z,t}$ for non-US-China trade flows can be seen in Figure A.1. The blue line is the applied locally weighted scatterplot smoother. Dashed lines are the 90% confidence interval. Standard errors are clustered at HS-6 product level.

Figure 8: Robustness - Post-WTO Accession



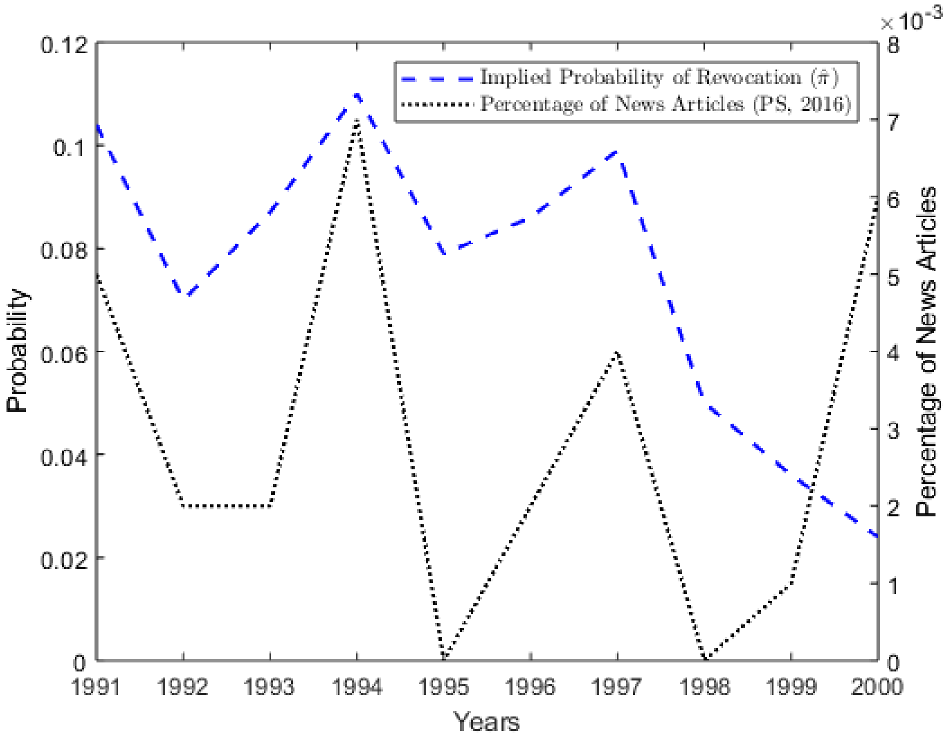
Note: Crosses are the estimates of $\hat{\beta}_m^{TPU}$ for each month $m = [1, 12]$ from estimating equation (7). Results of coefficients of $\hat{\beta}_m^{TPU}$ are reported in Table A.2. Results of of the effect of $X_{z,t}$ for post-WTO trade flows can be seen in Figure A.2. The blue line is the applied locally weighted scatterplot smoother. Dashed lines are the 90% confidence interval. Standard errors are clustered at HS-6 product level.

Figure 9: High vs. Low Storable Good



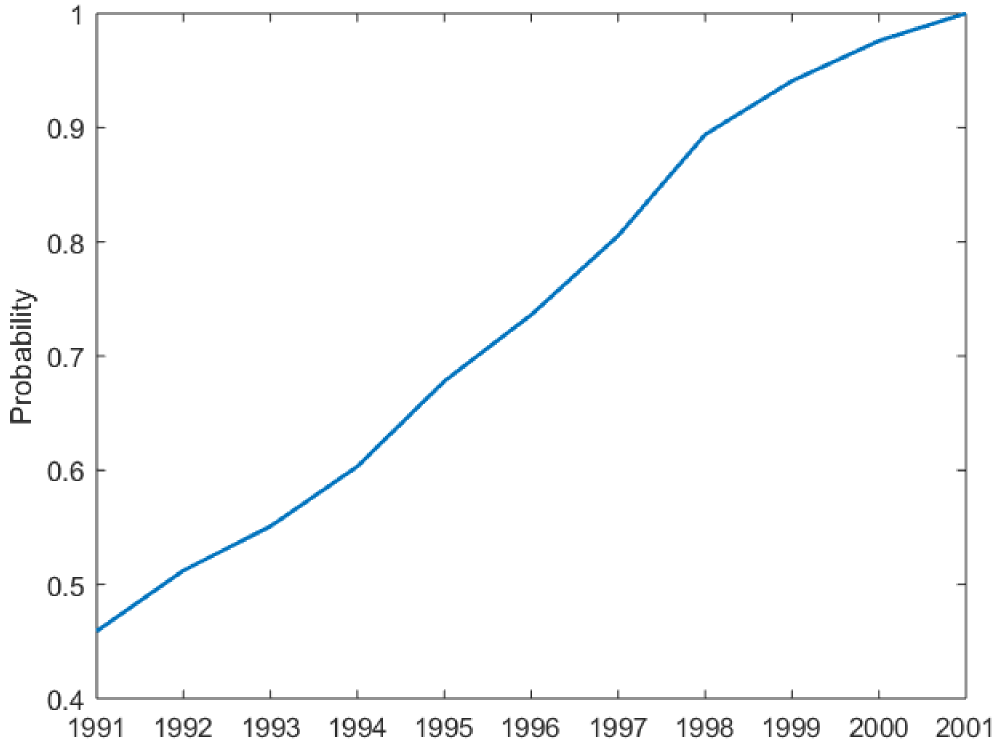
Note: Crosses are the marginal effect of $X_{z,t}$ for US-China trade flows from estimating equation (6), that is $\hat{\beta}_m^{TPU} + \hat{\beta}_m^{1/HH} \times [1/HH_z]$ for each month $m = [1, 12]$ for the 20th and 80th percentile of the inverse HH distribution. The red and blue lines are the applied locally weighted scatterplot smoothers. Dashed lines are the 90% confidence interval. Standard errors are clustered at HS-6 product level.

Figure 10: Estimated Annual Probabilities of Revoked Access to MFN Rates



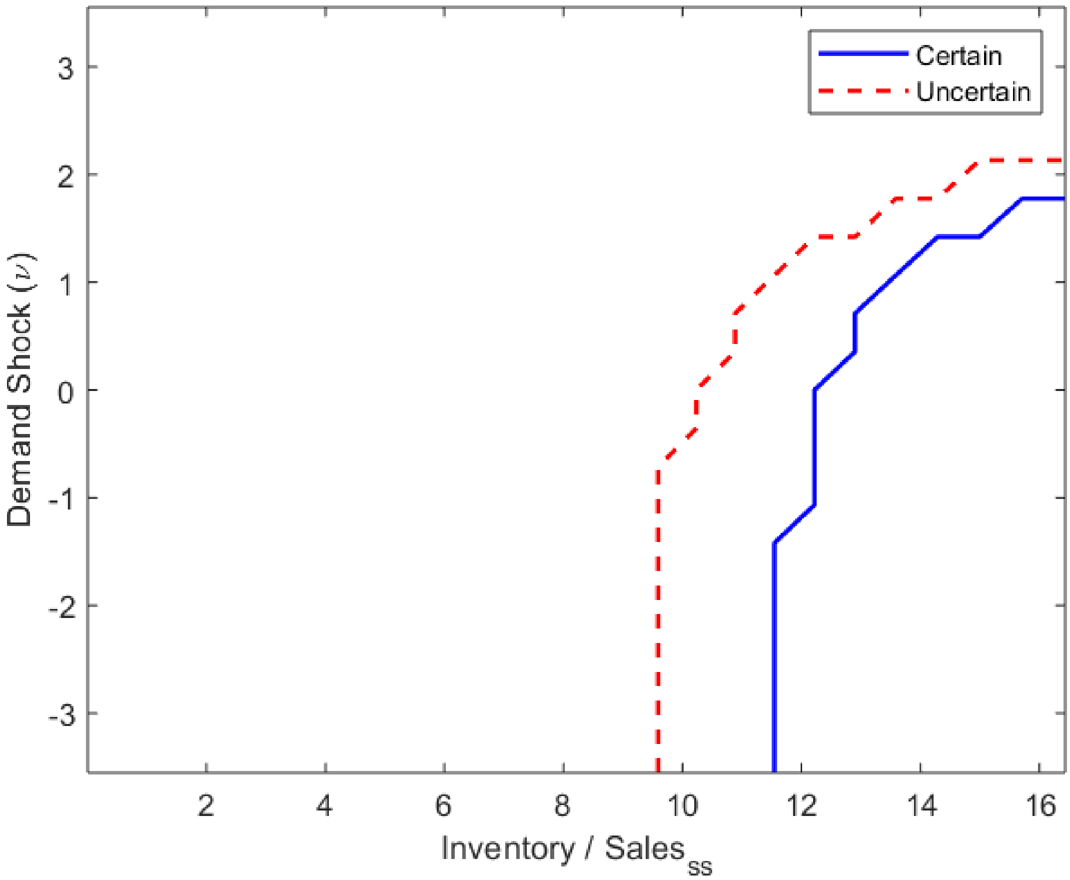
Note: On the left y-axis are our model implied probabilities from simulating the model for HS 6-digit products. Coefficients for β_t are reported in Table A.3 of the Appendix. On the right y-axis is the percent of news articles of the New York Times, Wall Street Journal, and the Washington Post discussing the uncertainty of China's NTR status.

Figure 11: Estimated Annual Probabilities of China maintaining MFN Access



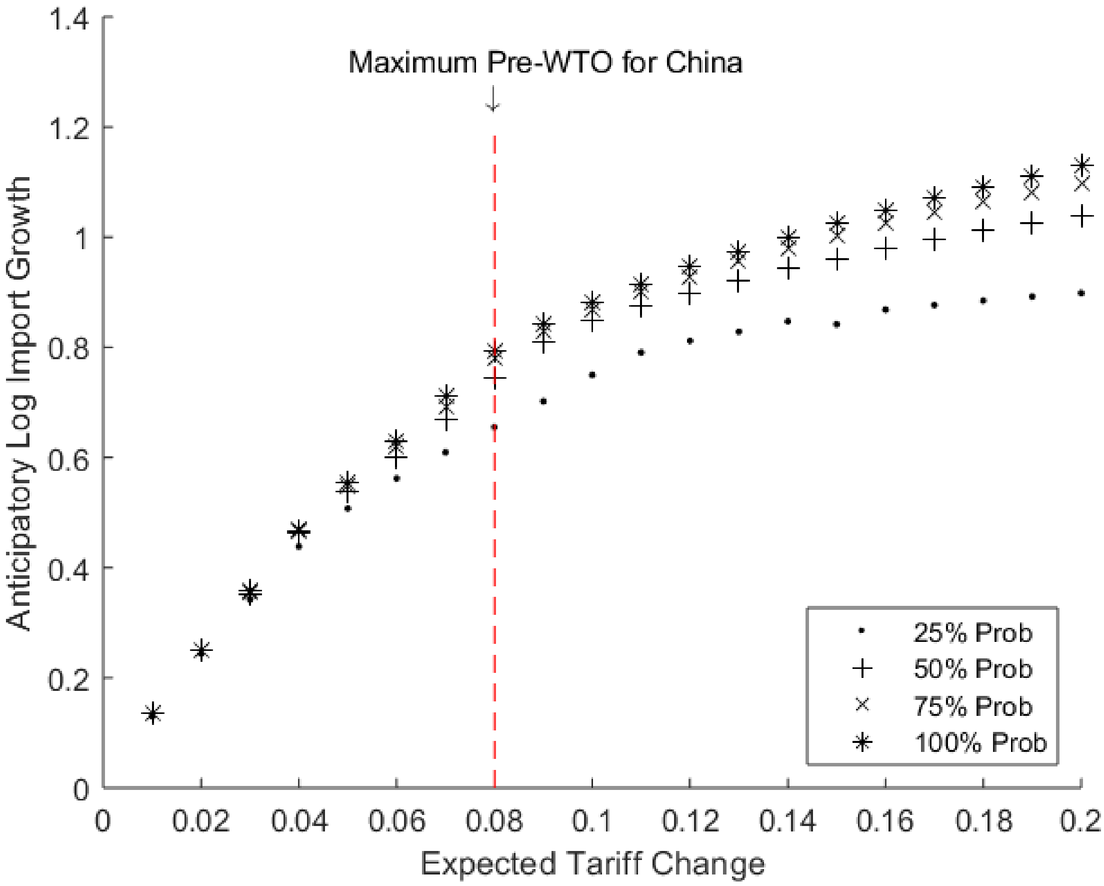
Note: On the y-axis are the model implied probabilities of China maintaining its MFN status till 2001 and years are on the x-axis. To obtain these we simulate the model for HS 6-digit products and match the $\hat{\beta}_9^{TPU}$ coefficient from (5) by changing probability input to the model. We then compound the probability of China maintaining its MFN status for the successive years until 2001.

Figure 12: Comparison of Ordering Cutoffs: The Wait-and-See Effect



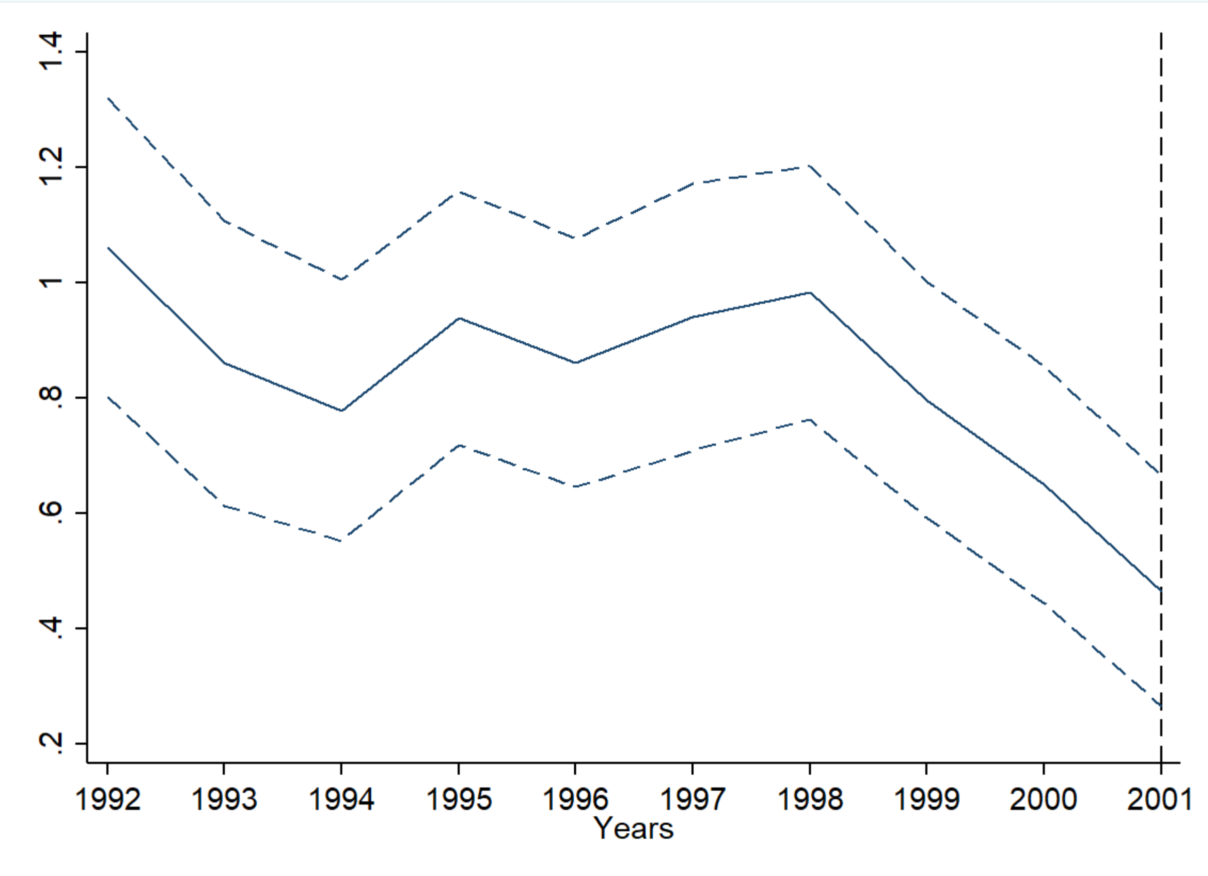
Note: On the y-axis is the level of demand shock and inventory holdings relative to steady-state average sales is on the x-axis. The area towards the top-left side of the curves is ordering region. Blue solid line shows the ordering cutoffs in the case of a 40% tariff change with certainty. Red dashed line shows the ordering cutoffs in the uncertain case of tariff staying the same or increasing by 80% with equal probabilities.

Figure 13: Simulation Result with Varying Expected Tariff Change



Note: On the y-axis plots the log of anticipatory import growth in the months prior to the expected tariff change. X-axis plots the expected tariff change. We have multiple observations for similar expected tariff change with different spreads around the same tariff change. For example, we can have a expected tariff increase of 10pp through either 100% probability of 10pp increase or 25% probability of 40pp increase. The dashed line shows the maximum expected tariff change faced by China which is obtained by using maximum annual probability of non-renewal (8%) and the maximum spread (80%).

Figure 14: Response of Annual Trade Flows to Risk of Profit Loss



Note: On the y-axis is the estimate of β_t for $t = [1992, 2001]$ from:

$$\ln(v_{i,j,z,t}) = \sum_t \beta_t \ \mathbb{1}_{\{(i,j)=(US,China)\}}\mathbb{1}_{\{t=t'\}}X^{HL}_{z,t} + \delta_{i,z,t} + \delta_{j,z,t} + \delta_{i,j,t} + \varepsilon_{i,j,z,t}$$

The blues dashed lines are its 90% confidence interval. Standard errors are robust.

A Appendix

Table A.1: Reference Exporter Countries

Afghanistan	Gabon	Norfolk Is	Angola	Gambia	North Korea
Antigua Barbuda	Ghana	Norway	Argentina	Greenland	Oman
Aruba	Grenada Is	Pakistan	Australia	Guatemala	Palau
Bahamas	Guinea	Panama	Bahrain	Guinea-Bissau	Papua New Guin
Bangladesh	Guyana	Paraguay	Barbados	Haiti	Peru
Belize	Honduras	Philippines	Benin	Hong Kong	Pitcairn Is
Bermuda	India	Qatar	Bhutan	Indonesia	Rwanda
Bolivia	Iran	Samoa	Botswana	Jamaica	Saudi Arabia
Brazil	Japan	Senegal	Brunei	Kenya	Seychelles
Burkina Faso	Kiribati	Sierra Leone	Burundi	Korea	Singapore
Cambodia	Laos	Solomon Is	Cameroon	Lesotho	Somalia
Cape verde	Liberia	Sri Lanka	Cayman Is	Libya	St Kitts-Nevis
Cen African Rep	Macao	St Lucia Is	Chad	Madagascar	St Vinc & Gren
Chile	Malawi	Sudan	Fiji	Malaysia	Suriname
Christmas Is	Maldive Is	Swaziland	Cocos Is	Mali	Switzerland
Colombia	Marshall Is	Niue	Comoros	Mauritania	Tanzania
Congo (DROC)	Mauritius	Thailand	Congo (ROC)	Mongolia	Togo
Cook Is	Montserrat Is	Tonga	Costa Rica	Mozambique	Trin & Tobago
Cote d'Ivoire	Namibia	Tuvalu	Cuba	Nauru	Uganda
Djibouti	Nepal	United Arab Em	Dominica Is	Netherlands Ant	Uruguay
Dominican Rep	New Caledonia	Venezuela	Ecuador	New Zealand	Vietnam
El Salvador	Nicaragua	Yemen	Eq Guinea	Niger	Zambia
Ethiopia	Nigeria	Zimbabwe			

Table A.2: Robustness - Post-WTO Accession

Dep. Var:$\ln(v_{m-2:m}^{i,j,t,z}/v_{m-7:m}^{i,j,t,z})$	(1)	(2)
Post-WTO Years	2001-05	2003-05
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=1\}} \times X_{z,t}$	-0.15***	-0.16***
	(0.05)	(0.06)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=2\}} \times X_{z,t}$	-0.13***	-0.17***
	(0.05)	(0.06)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=3\}} \times X_{z,t}$	-0.12**	-0.14***
	(0.05)	(0.06)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=4\}} \times X_{z,t}$	-0.070	-0.088
	(0.05)	(0.05)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=5\}} \times X_{z,t}$	0.03	0.06
	(0.06)	(0.07)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=6\}} \times X_{z,t}$	0.13***	0.18***
	(0.05)	(0.05)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=7\}} \times X_{z,t}$	0.13***	0.22***
	(0.05)	(0.05)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=8\}} \times X_{z,t}$	0.17***	0.28***
	(0.05)	(0.06)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=9\}} \times X_{z,t}$	0.18***	0.29***
	(0.05)	(0.06)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=10\}} \times X_{z,t}$	0.11**	0.21***
	(0.05)	(0.06)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=11\}} \times X_{z,t}$	0.02	0.07
	(0.05)	(0.05)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t<2001\}}\mathbb{1}_{\{m=12\}} \times X_{z,t}$	-0.10*	-0.10*
	(0.05)	(0.06)
HS Section-Month-PreWTO FE	✓	✓
Destination-Month-Year FE	✓	✓
Source-Month-Year FE	✓	✓
Observations	1167996	1003593
Adjusted R^2	0.031	0.030

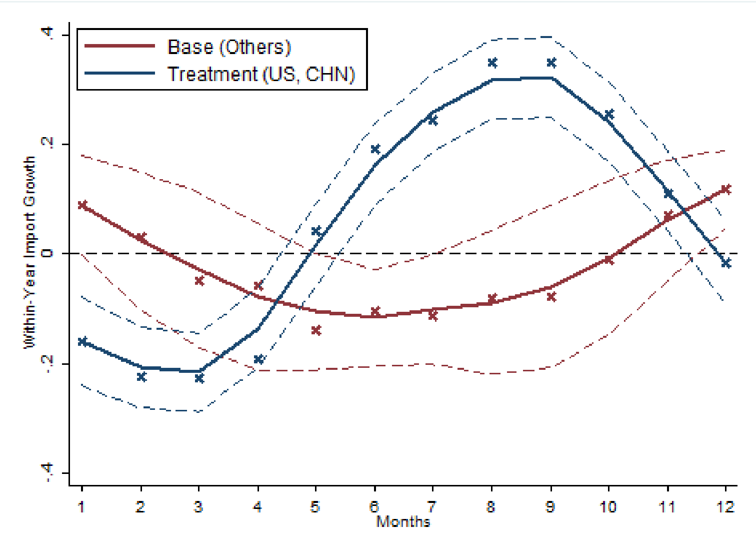
Note: This Table reports the estimates of the coefficient of interest $\hat{\beta}_m^{TPU}$ from estimating equation (7). On top of the baseline difference-in-difference, these are treatment effects relative to US-China trade flows after China's WTO accession in 2001. In column one the post-WTO sample period includes 2001-05. Column two excludes 2001 and 2002, when some of the uncertainty effects persisted. Standard errors, in parentheses, are clustered at HS-6- product level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Annual Peak Response to Tariff Risk, 1990-2000

	Dep. Var:$\ln(v^{i,j,t,z}_{m-2:m}/v^{i,j,t,z}_{m-7:m})$
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t=1991\}}\mathbb{1}_{\{m=10\}}X_{z,t}$	0.61^{***}
	(0.12)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t=1992\}}\mathbb{1}_{\{m=9\}}X_{z,t}$	0.41^{***}
	(0.12)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t=1993\}}\mathbb{1}_{\{m=8\}}X_{z,t}$	0.51^{***}
	(0.11)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t=1994\}}\mathbb{1}_{\{m=10\}}X_{z,t}$	0.65^{***}
	(0.13)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t=1995\}}\mathbb{1}_{\{m=9\}}X_{z,t}$	0.46^{***}
	(0.12)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t=1996\}}\mathbb{1}_{\{m=8\}}X_{z,t}$	0.50^{***}
	(0.10)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t=1997\}}\mathbb{1}_{\{m=8\}}X_{z,t}$	0.58^{***}
	(0.10)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t=1998\}}\mathbb{1}_{\{m=6\}}X_{z,t}$	0.26^{***}
	(0.09)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t=1999\}}\mathbb{1}_{\{m=8\}}X_{z,t}$	0.21^{***}
	(0.08)
$\mathbb{1}_{\{US,China\}}\mathbb{1}_{\{t=2000\}}\mathbb{1}_{\{m=10\}}X_{z,t}$	0.14^{*}
	(0.08)
HS Section - Month FE	✓
Destination - Month - Year FE	✓
Source - Month - Year FE	✓
Observations	1514754
Adjusted R^2	0.039

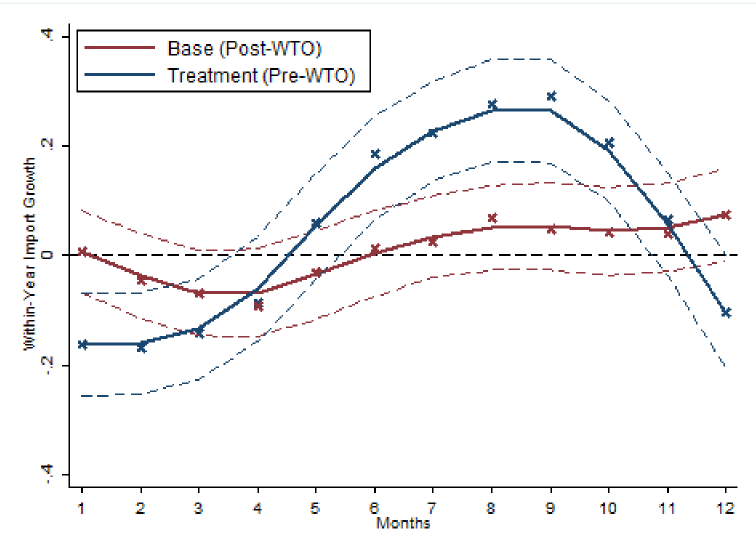
Note: This table contains the results of $\max_m\{\hat{\beta}^{TPU}_{m,t}\}$ for $t = [1990, 2000]$ from (9). Standard errors, in parentheses, are clustered at HS-6 product level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.1: Baseline Result



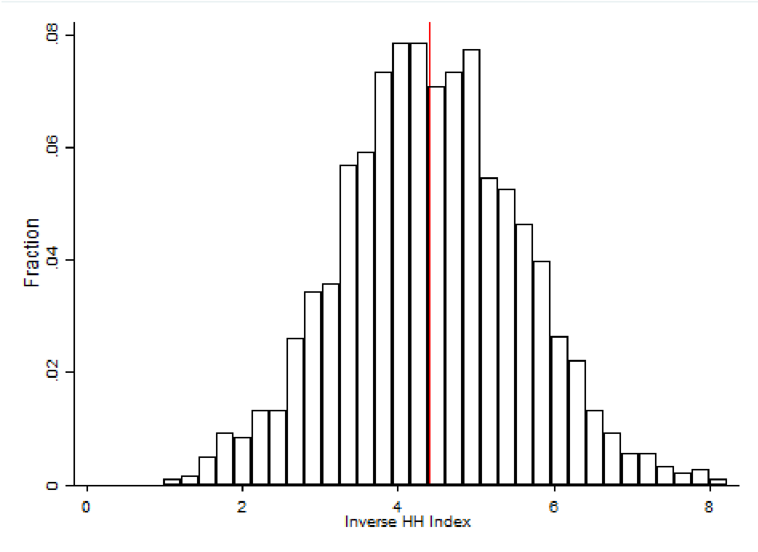
Note: Crosses are the estimates of $\hat{\beta}_m$ and $\hat{\beta}_m^{TPU}$ for each month $m = [1, 12]$ from estimating (5). The red and blue lines are the applied locally weighted scatterplot smoothers. Dashed lines are its 90% confidence interval. Standard errors are clustered at HS-6 product level.

Figure A.2: Triple Difference - Post-WTO Accession



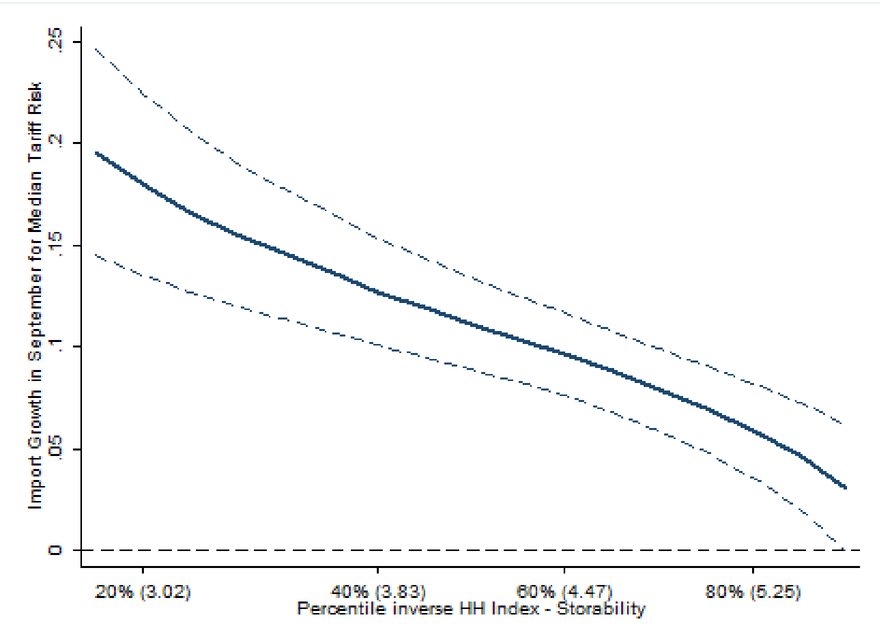
Note: Crosses are the estimates of $\hat{\beta}_m$ and $\hat{\beta}_m^{TPU}$ for each month $m = [1, 12]$ from estimating equation (7). The red and blue lines are the applied locally weighted scatterplot smoothers. Dashed lines are its 90% confidence interval. Standard errors are clustered at HS-6 product level.

Figure A.3: Distribution of Product Storability



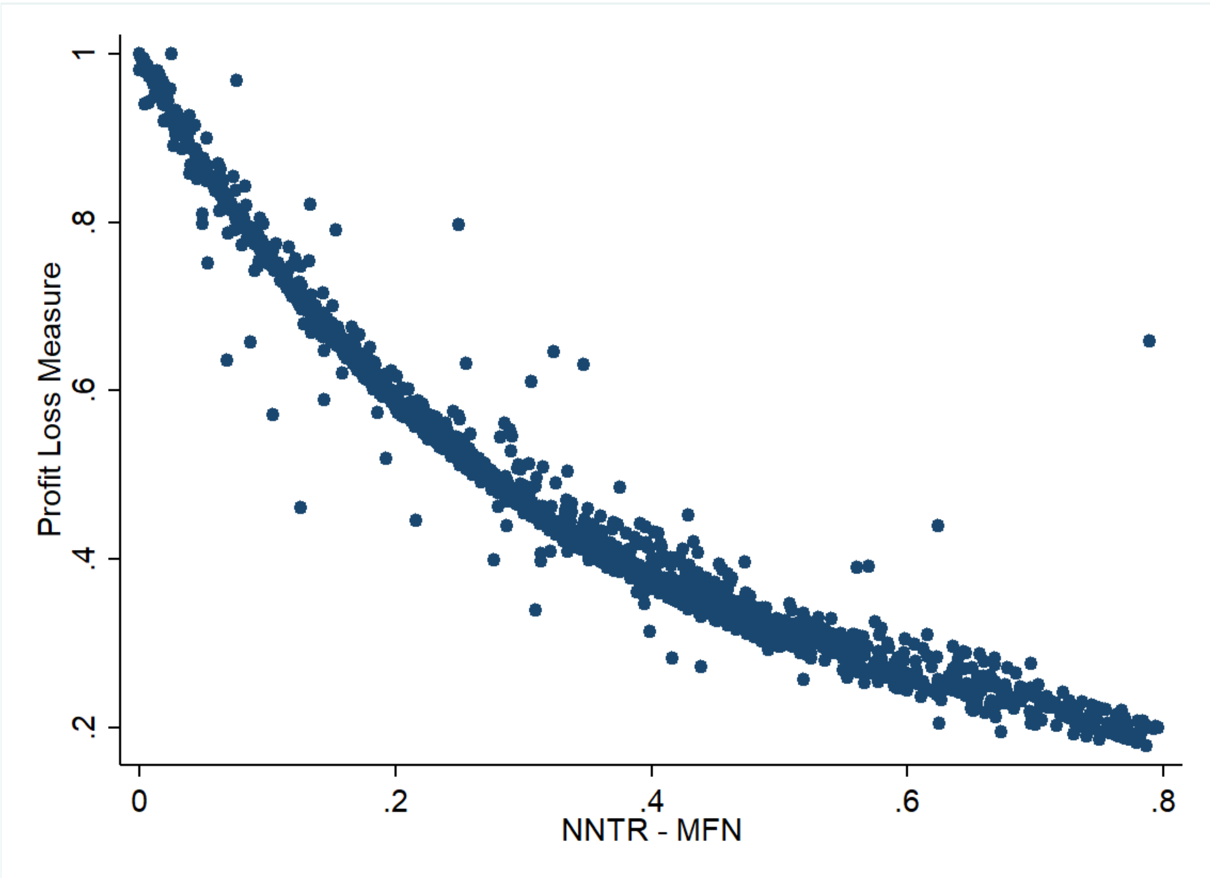
Note: This Figure plots the distribution of our measure of storability, namely the inverse HH index. Its value can be interpreted as number of months within a year that have shipments. The red line is the median. Goods that are ordered less frequently are presumably more storable. It is calculated as follows. The HH index of annual imports of z from i in year t is $HH_{j,z,t} = \sum_{m=1}^{12}(v_{j,z,t,m}/\sum v_{j,z,t,m})^2 \in [1/12, 1]$. Once calculated for all z, t and countries listed in Table A.1, we estimate $1/HH_{j,t,z} = \delta_0 + \delta_z + \delta_{j,t} + u_{j,t,z}$ and then define the degree of storability as $1/\hat{HH}_z = \hat{\delta}_0 + \hat{\delta}_z$. The source-year fixed effects net out determinants of lumpiness that are unrelated to the product storability, such as distance or country specific annual shocks.

Figure A.4: Anticipatory Rise in September & Storability



Note: This Figure plots the heterogeneous import growth in September in response to the median tariff risk (26pp) for the distribution of goods according to their inverse HH index. Goods that are ordered more infrequently and thus presumably more storable respond stronger than less storable goods. Estimates are obtained from equation (6), so that the point estimate for a particular value of the inverse HH index is $\hat{\beta}_m^{TPU} \times Median(X_{z,t}) + \hat{\beta}_m^{HH} \times Median(X_{z,t}) \times [1/HH_z]$. Dashed lines are its 90% confidence interval. Standard errors are clustered at HS-6 product level.

Figure A.5: Profit Loss Measure and Spreads



Note: On the y-axis is the potential profit loss measure from Handley and Limao (2017), $X^{HL}_{z,t} = 1 - \left(\frac{\tau^{MFN}_{z,t}{}_{z,t}}{\tau^{NNTR}_{z,t}}\right)^{-3}$, and the X-axis contains the spread between NNTR and MFN rates, $tau^{NNTR}_{z,t} - \tau^{MFN}_{z,t}$, for $t = 2001$.