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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 three main findings. First, counter to the evidence elsewhere, trade increases strongly in anticipation of uncertain future increases in tariffs. Second, even though the trade response can be quite large, the probability of a tariff increase was perceived to be relatively small, with an average annual probability of non-renewal of about 5.5 percent. And 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. The model is also consistent with a sizeable fraction of the cross-industry variation in annual trade flows documented elsewhere. Our results explain why trade may hold up well in advance of a prospective policy change such as Brexit or the US 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 three main findings. First, counter to the evidence elsewhere (Pierce and Schott (2016), Handley and Limao (2017), Graziano et al. (2018)), we find that trade increases strongly in anticipation of uncertain future increases in tariffs. Second, even though the trade response can be quite large, the probability of a tariff increase is viewed as relatively small, with an annual probability of non-renewal of about 5.5 percent and annual probabilities that ranged from 0 to 10 percent. And third, the expected future tariff is the primary driver of trade dynamics instead of the pure uncertainty. The "wait-and-see" real option forces from uncertainty only slightly weaken the incentives to anticipate the future tariff increase.

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 increase in tariffs firms shift the timing of their purchases so they have relative 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 high inventory levels 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 figuring out 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, armed with a model that captures the dynamics of trade flows in 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 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, having established the reduced form effects of uncertainty, we test the direct mechanism of inventory holding costs through which uncertainty worsens annual imports. Firms advance their purchases in anticipation of revocation of China's MFN status which leads to lumpier imports. We quantify the effect of uncertainty through lumpiness using a two-stage least squares approach and find significant negative effects operating through the lumpiness of trade. Further, we are able to generate 50% of the effects on annual import flows using the inventory model. We conclude that large sunk trade costs are not the necessary to explain the dampening effects of trade policy uncertainty on trade as long as there is some mechanism making trade a dynamic decision.

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 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 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

[1] An exception to the recent literature using sunk costs of exporting to assess the role of TPU is Caldara et al. (2019), that considers 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.

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 explains 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) it captures implosions of trade and 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

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

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

2.1 Environment

We consider a partial equilibrium model[5] of an industry in which goods are storable and a continuum of monopolistically competitive retailers decide whether to import or not every period. 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

[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).

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

producers run down their stocks 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 $p_{j,s,t}$ denote the retail prices charged by importer j industry s and $\nu_{j,s,t}$ the demand shock in period t. Importers face a CES demand function with the elasticity of substitution denoted by σ:

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

The variable cost of importing is $\omega_{s,t} = \omega(1+\tau_{s,t})$ where $\tau_{s,t}$ belongs to a finite set of possible tariffs, T. The cost of importing is the same for each firm in a 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, $s_{j,s,t}$ and their demand shock, $\nu_{j,s,t} \sim^{iid} N(0,\sigma_{\nu}^2)$, 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 need to pay a fixed cost f [8]. We assume that imported goods cannot be returned, $m_{j,s,t} \geq 0$. Because of demand uncertainty, importers will never run down their inventories to zero i.e. $\underline{s}_s > 0$, and because of the delivery lag, sales can never exceed current inventory holdings:

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

Assuming the goods in transit ($m_{j,s,t}$) depreciate at the same rate, δ_s[9], as in the warehouse,

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

[7]The iid demand shock is necessary to obtain variation in the anticipation to a tariff reduction. Without demand shocks the distribution over imports would degenerate and simulations would be irrelevant. 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.

[9]Industries vary in their depreciation rate.

the law of motion for the inventories is:

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

For the following discussion, considering the partial equilibrium nature of our environment, we will characterize the optimal policies and tariff process for an industry by dropping the industry subscript. Denote firm's value of adjusting 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:

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

are subject to (3) and (2). Solving for the optimal policies generates an ($\underline{s}$,$\overline{s}$) policy of ordering 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 expediting imports and buying cheaper today at the expense of paying the fixed cost today and assuming higher inventory holding costs. In what follows we describe how under different shock processes 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 light of the empirical application in the next section, we fix the period in which uncertainty is resolved[10]. Let m_{res} be the last period before the possible tariff change, so that in period $m_{res}+1$ the uncertainty is resolved.

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

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 shipments 3 per year. We calibrate the model at the monthly frequency by setting the discount rate equal to $\sqrt[12]{0.97}$. The monthly depreciation rate is set at 2.5%, yielding an annual rate of around 30%. We set the elasticity of substitution equal to 4[11]. Finally the delivery lag is set to be a month and the dispersion of taste shock is set at 0.8.

We now show that, conditional on a tariff increase, the magnitude of the anticipatory stockpiling is increasing in the probability of the tariff increase taking place. 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 provide importers with 12 months

[10] In general, there can be a lot of 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 4.

[11] The elasticity of substitution does not affect anticipatory behavior.

to anticipate this event.

Figure 1 plots the aggregate industry response of imports. In all cases, the expected tariff increase is not realized. Imports spike before the shock reaching its peak the month in m_{res} and then falling 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[12]. The size of these changes in import flows in anticipation of the uncertainty resolution are clearly increasing in the probability of the tariff rise. However, qualitatively the responses are very similar. In Figure 2 we observe that the rise in trade flows in the three months before the resolution 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 high level of inventory-sales ratio. From the figure, it is clear that beginning of the period inventory holdings over sales reach their peak in the months of uncertainty resolution. In the case of a 50% change of the tariff increase occurring the the inventory-sales ratio is around 35% above its equilibrium level. Again, how strong these effects are depend on the probability importers assign to the tariff increase taking place. 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. Uncertainty 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 anticipitory dynamics.[13]. In the next section we show that high frequency anticipatory dynamics of the US imports from China were similar to the one predicted by this model.

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

[13]In Figure A.1 of the Appendix we show that the value functions at m_{res} for the case of only one episode of TPU exactly overlaps with the case of two episodes of TPU with 12 months in between them.

3 Anticipation during Annual Renewals of China's MFN Status

In this section we study anticipatory dynamics during the single most studied episode of TPU. During the 1990s US imports from China were only temporarily granted MFN status. Every year, China's MFN status had to be renewed by the President and the possibility of revoking was voted in Congress. Uncertainty ultimately resolved when China joined the World Trade Organization (WTO) in December 2001 and the US Congress granted China Permanent Normal Trade Relation (PNTR) status. Even though applied tariffs to China's imports to the US were unchanged during this period, previous literature has found large implications of China's access to PNTR on posterior China's export growth (Handley and Limao (2017)) and US manufacturing employment (Pierce and Schott (2016)), attributing those to the elimination of TPU. We abstract from the post uncertainty period and focus on the period between 1990 to 2001 to study how high frequency imports anticipated the annual renewal of China's MFN status. This episode of TPU is particularly suitable to this purpose because the implied trade cost change and the timing of the possible policy change are well established. According to the framework of the previous section, anticipation will only depend on the probability importers assign to the event of MFN status revoking. But before we calculate this probability in the next section, we examine the existence of anticipatory dynamics during this episode. First some background to this particular episode is provided. Then the empirical strategy built on a generalized triple difference approach is described. The results indicate that US imports from China responded significantly to the threat of reverting to NNTR rates and that imports peaked in the immediacy of uncertainty resolution. However, economically the elasticities are only modest.

3.1 Background

In the 1990s and until China's accession to the WTO in December 2001, US-China trade relations were subject to substantial policy uncertainty (See Handley and Limao (2017), Pierce and Schott (2016), Crowley et al. (2018)). With the eruption of the Cold War, the US applied protectionist non-NTR tariff rates[14] established by the Smoot-Hawley Tariff Act of 1930 to non-market economies. With the Trade Act of 1974, the US would grant 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. A bilateral commercial agreement in 1980 gave MFN status to China's exports to the US. During the 1980s the waiver was renewed annually without any sign of objection in the Congress. But after the events of the Tiananmen Square in 1989, concerns about human rights violations led the US House of Representative to introduce and vote on the disapproval of the President's waiver authority and legislation to revoke China's temporary NTR status. Indeed, the House voted on this issue every year from 1990 until 2001. 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.

The President's waiver renewal expired annually every 3rd of July. During the entire period, all presidents waived China's requirement to meet the freedom-of-emigration principle. Before being elected, President Bill Clinton announced he would link China's MFN status to human rights progress beginning in 1993, but went along with the waiver during his presidency. If renewed, Congress would have had 60 calendar days to consider a disapproval vote on the President's waiver authority. As can be seen in Figure 3 voting would generally take place between the end of July and beginning of August. Since in all years except 1992 legislation to revoke the President's waiver authority and legislate revoking of China's MFN status failed to

[14] Normal Trade Relations (NTR) is the term used by the United States for the MFN principle.

be passed by the Senate, uncertainty resolved by August. In 1992 such legislation passed both chambers of Congress. However, because legislation was vetoed by the President, uncertainty only resolved by the end of September, when the Senate failed to override the President's veto and China's MFN status remained in place. The annual nature of the waiver authority and the timing of the voting allows us to fix the period of uncertainty resolution between the months of July and September, included.

3.2 Identification of Anticipation to Annual Renewals

In this section we describe our empirical strategy to identify anticipatory behavior in the face of TPU. We follow a generalized triple difference approach, focusing on high frequency trade flows before the resolution of TPU. Following the literature, we measure uncertainty as the gap between the prevailing MFN rate and the threat tariff rate defined by Non-NTR (NNTR) rates, also known as column 2 tariff rates[15]. We obtain the NNTR gap at HS-8 product level from Pierce and Schott (2016). Our analysis is at the industry level[16], and in particular we consider 6-digit NAICS industries, which provides us with a panel of 446 industries over a 12 year period of TPU. Every year between 1990 and 2001 China's exporters to the US were facing the threat of tariff rates being reverted to NNTR rates. We exploit variation in industries and time across NNTR gaps to study how imports prior to the TPU resolution responded to this threat. We denote the independent variable and our first difference as $X_{s,t} \equiv (\tau_{s,t}^{NNTR} - \tau_{s,t}^{MFN})$, where s indexes industries. As you can see in Figure 4, the NNTR gaps were sizeable throughout the entire period, with the median gap being around 30 percentage points. Revoking the MFN status would have meant facing four times larger tariffs for the median industry. There was little time variation within industry gaps. Only between 1996 and 1997, due to lower MFN rates from the

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

[16]Because we are interested in high frequency trade flows, lumpiness in trade flows becomes pervasive at HS-6 product level. Although most results hold at HS-6 level they are smaller in magnitude.

Uruguay Round, the gap increased. As you can see in Figure 5 there is substantial variation in NNTR gaps across industries[17].

We consider growth rates of trade flows at high frequencies in order to capture short run dynamics of trade in the immediacy of TPU resolution. In our baseline, we fix the uncertainty to be resolved by the beginning of October. We calculate the growth as the monthly average of trade flows between July and September relative to a reference level of monthly trade flows, which we define to be the average between February and April. Hence, our dependent variable is defined as the log growth rate of exports from country j to country i of industry s in year t, considering the monthly average between the month m_1 and m_{res} (September and July respectively) relative to the reference average between the months m_2 and m_3 (Feburary and April respectively). We denote the dependent variable as $\ln(v^{i,j,s,t}_{m_1:m_{res}}/v^{i,j,s,t}_{m_3:m_2})$. In section 3.4, we perform robustness tests on the choice of combinations of m_1, m_2, m_3 and m_{res}. Trade flows are in CIF value of imports for consumption.

One of the main concerns when considering high frequency growth rates are within year changes in aggregate variables, such changes in aggregate price indexes or demand (e.g. China's New Year, Christmas, etc.). To address these we implement a second and third difference, controlling for importer and exporter fixed effects. As a reference importer we consider a group of 12 EU member countries[18] (EU). China's exports to the EU were granted unconditional MFN status in the 1980. As a reference exporter we consider a group of 135 countries that were granted unconditional MFN status and no preferential rates[19] by both the US and the EU. Hence, our sample considers 4 different directions of trade flows, $j \in \{CHN, RoW\}$ to $i \in \{US, EU\}$.

[17]Within industries, HS-8 NNTR gaps were highly correlated at industry level.

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

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

Our baseline estimation equation is the following:

$$\ln(v^{i,j,s,t}_{Jul:Sep}/v^{i,j,s,t}_{Feb:Apr}) = \sum_{i'}\sum_{j'}\beta_{i',j'}\mathbb{1}_{\{i=i'\}}\mathbb{1}_{\{j=j'\}}X_{s,t} + \gamma_s + \gamma_{i,j,t} + \varepsilon_{i,j,s,t} \quad (5)$$

We introduce destination-source-year fixed effects for each direction of aggregate trade flows, $\gamma_{i,j,t}$, to control for the aforementioned concerns of confounding changes in aggregate variables. Industry specific fixed effects at 2-digit NAICS, γ_s, are introduced to control for seasonal effects specific to industries. Our coefficient of interest is $\beta_{i',j'}$ with $i' = US, j' = CHN$, that is the sensitivity of anticipatory import growth to NNTR spreads for the specific US imports from China. If imports rise in anticipation of TPU resolution, as predicted by the model in section 2, then $\beta_{i',j'} > 0$ for $i' = US, j' = CHN$. Moreover, since the other three trade flows were not subject to the threat of reverting to NNTR rates, we expect $\beta_{i',j'} \approx 0$ for $i' \neq US$ or $j' \neq CHN$. Note that we set the NNTR gap, $X_{s,t}$, to be the same for all directions of trade flows. Since only China's exports to the US were subject to the threat of non-renewal of its MFN status, coefficients of $\beta_{i',j'}$ on non-US-China trade flows should be interpreted as placebo tests[20].

3.3 Baseline Results

In Table 2 we present our baseline results. In all specifications the anticipatory response of US imports from China (row 1) to the resolution of uncertainty is positive and significant as expected. However, its magnitude is rather small[21]. In column one we don't control for changes in aggregate variables nor industry specific seasonal effects. Results indicate that the response of US imports from China responded significantly at the 5% significance level. In column two we incorporate changes in aggregate variables and the coefficient of interest drops but is more

[20] We could have set $X_{s,t} = 0$ for all non-US-China trade flows. This would not significantly affect the coefficient on US-China trade flows. The importance of introducing non-US-China trade flows relies in the inclusion of relevant fixed effects.

[21] To provide a comparison, Khan and Khederlarian (2019) estimates the counterpart to this anticipatory elasticity during the NAFTA phaseouts (when the tariff change was certain to take place) to be around 4 to 6, or two thirds of their long run trade elasticities

precise. Column three is the result of estimating equation (5) and our baseline estimate. The anticipatory elasticity during the entire period of TPU is 0.40. An industry that faced the median NNTR threat of 30pp on average responded to the threat by increasing its imports before the resolution of uncertainty by 12% with respect to the baseline level of imports. Importantly, we find that for the other 3 directions of trade there is no significant response of trade flows to the NNTR gap, consistent with these trade flows not being subject to the uncertainty. The coefficients are insignificant and their magnitude is well below that of US imports from China. In column four we group non-US-China trade flows into one group.

In Figure 6 we report the results of estimating equation 5 with different values of m_{res} i.e. running 12 regressions with equating m_{res} to each month of the year, that is we estimate

$$\ln(v^{i,j,s,t}_{m_{res}-2:m_{res}}/v^{i,j,s,t}_{m_{res}-7:m_{res}-5}) = \sum_{m'}\sum_{i'}\sum_{j'}\beta_{m',i',j'}\mathbb{1}_{\{m_{res}=m'\}}\mathbb{1}_{\{i=i'\}}\mathbb{1}_{\{j=j'\}}X_{s,t} + \gamma_s + \gamma_{i,j,t} + \varepsilon_{i,j,s,t} \tag{6}$$

for $m_{res} = 1, 2, .., 12$. As you can see, the peak response in the growth rate of imports for US imports from China is in September[22] and is significantly above zero between July and October. After the uncertainty resolution, imports drop significantly, reaching their trough in March and April. In the model described above, the drop in imports is explained by the fact that importers have amassed sufficient inventories in the run up tp the uncertainty resolution. It is notorious that almost throughout the entire year imports from China to the US responded significantly to the threat of facing the NNTR gap after September. The growth rate of non-US-China trade flows is never significantly different from zero, as one would expect to be the case if those trade flows are unresponsive to the NNTR threat faced by China.

[22] This is why we establish September as our baseline month of uncertainty resolution.

3.4 Robustness

The baseline results are robust to several potential issues which we discuss below.

Different Time Horizons. - In columns two to four of Table 3 we vary the time horizons considered in the calculation of the short run growth rates of imports. In column two we consider the import peak before the uncertainty resolution to be between June and August and fix the baseline period between January and March. In column three we consider the import peak before the uncertainty resolution to be between June and September and include all 4 months before June in the calculation of the reference import level, i.e. the average between February and May. In column four we consider the peak to be between June and September again but use the average between January and April. The main result is unchanged. Only US imports from China respond significantly to the NNTR gap. The size of the coefficients is slightly smaller than our baseline. This suggests that, as predicted by the model, import growth was more concentrated in a few months.

Different Industry Fixed Effects. - In the first column of Table 3 we apply industry fixed effects at the 4-digit NAICS level to allow for more control over seasonal effects at the cost of variation in the identification of the effect of the NNTR gap on import growth. The magnitude of the coefficient on US imports from China falls slightly from to 0.4 to 0.3 and not surprisingly falls in its estimation precision. All other coefficients remain insignificant.

Quantities and Unit Values. - In column five and six of Table 3 we measure the short run response of quantities and unit values to the tariff threat. On the one hand, the quantity response is positive and significant and its size exceeds the value response, although it is less precisely estimated. In turn, there is no significant response in unit values. This suggests that anticipation was taking place in terms of goods and not because of pricing dynamics.

More Placebos: Post-WTO & Taiwan - In column seven of Table 3 we extend the sample period from 1990 to 2009 and set the NNTR Gap after 2001 to be the same as in 2001. On top of the source-destination interactions, we interact the NNTR gap with a dummy variable for whether the period corresponds to pre- or post-WTO accession year. We expect the short run import growth not to persist after China's WTO accession, given that it granted China permanent NTR status. In effect, in row 5 we report that after China's accession is insignificant and negligible in size. Finally, in column eight we perform another placebo test and check whether Taiwan's exports to the US displayed a similar response to the NNTR gap. Taiwan was not subject to the annual renewal of their MFN status and hence its exports to the US are not expected to respond to the NNTR gap. We estimate our baseline estimation equation but instead china define the source dummy on Taiwan. We find that indeed Taiwan's exports to the US did not respond significantly to the tariff threat.

Others. - We also exclude those industries with more than 50% of their HS-8 goods affected by the Multifiber Arrangement and winsorize the import growth rates at at their 5% (95%) percentile level. Results are unchanged.

3.5 Anticipation and Storability

Before we estimate the model implied probability of MFN access withdrawal, we investigate the relationship between storability of a good and anticipation dynamics. Although we do not observe inventory holdings at the desired level of disaggregation, we can infer from the lumpiness with which a good is traded how storable it is. As in Khan and Khederlarian (2019) we use the HH index of concentration of annual imports to proxy storability. In that sense, and consistent with the model of 2 goods that are more storable will display more infrequent orders and hence an HH index close to unity. To calculate the HH index, we consider goods, indexed by g, at HS-6 level exported from China to the US during the second year they enter our sample and calculate their HH index[23], that is $HH_g = \sum_{m=1}^{12}(v_{g,m}/\sum v_g)^2 \in [1/12, 1]$. We then take the

[23] We consider RoW trade flows instead of China's trade flows to preclude contamination of the HH index with the endogenous lumpiness stemming from the TPU studied. We consider the second year of their appearence in the sample to rule out any partial-year effects.

mean over HH_g to calculate the HH index at 6-digit NAICS level. To elicit whether anticipatory dynamics are stronger for industries characterized by more storable (lumpier) goods we interact our independent variable with an indicator variable that is one if the industries' HH index is above the median. Results are presented in Table 4. Indeed, for goods above the median HH index the coefficient of interest is around 50% larger than in for goods with below median lumpiness. Moreover, these industries are driving the aggregate anticipatory response. We consider this an evidence of more storable goods driving our baseline results which is in line with the model in Section 2.

4 TPU Estimation: Likelihood of MFN Revocation

After having identified anticipatory import growth in the months before China's MFN status was under the risk of being revoked, we use the structure of the model described in section 2 to estimate the likelihood with which importers expected the 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 size of the tariff threat, namely the NNTR gap. By matching the import growth driven by anticipatory dynamics, and imposing (1) and (2) we can obtain the probability importers were assigning to the MFN access being revoked. For an incumbent firm, once the Congress had voted over the MFN status renewal, the risk of revoking MFN status was eliminated for the next 12 months. In contrast with other measures of the probability of this event, our methodology exploits within-year variation of the risk of revocation. This is appealing because it overcomes concerns of confounding long run factors driving trade patterns. It generates a time-varying path of the probability of non-renewal that can then be used as inputs to the models with export decision. We first show that the probability of revocation was relatively small. We then provide an estimate of the probability of this event for each year between 1990 and 2002. Finally, we disentangle the role of uncertainty from the expected downside risk in the anticipatory response.

4.1 Model Calibration

The magnitude of the anticipatory import growth displayed in the model in section 2 depends on the trade-off between (1) saving on the future variable cost of goods $\tau_{m_{res}+1}/\tau_{m_{res}}$ in case revocation occurs and (2) the cost incurred while expediting the purchase order, namely f, δ_s, r. The details of the calibration are displayed in Table A.5. We calibrate the model to the monthly frequency by setting $(1+r)^{-1} = 0.97^{(1/12)}$, yielding a mean annual interest rate of 3%. We set the fixed ordering cost, f, at the value of 0.095 borrowed from AKM. We calibrate industry-specific deprecation rates, δ_s, to match each industry's concentration of annual US imports from the rest of the world during the 1990s[24]. Higher fixed cost and lower depreciation rates are associated with more infrequent purchases and hence with higher HH indexes. In that sense, goods with lower rates of depreciation are more storable, providing stronger incentives to stockpile in anticipation of a possible tariff increase. We set the elasticity of substitution equal to 4. The elasticity of substitution does not significantly impact the results, since the dynamics before the uncertainty resolution are determined the trade-off between possible tariff increase and the ordering costs.

4.2 Baseline Result

To obtain the probability with which importers expected the China's MFN status to be revoked we simulate the model described in section 2. In particular, we simulate it separately[25] for each industry, s, considered in the empirical analysis of section 3. We assume all industries assigned a common probability π to China's MFN status revocation. In each simulation, all firms face a tariff increase of the size of the industry's mean NNTR gap between 1990 and 2001, $\hat{X}_s$,

[24]We first calculate the HH index for each HS10 product in the second year it appears in our sample. Then we take the mean for each NAICS industry. We use imports from the rest of the world for HH indexes to capture the nature of the good while ruling out any confounding effects of TPU on our lumpiness measure.

[25]Effectively we assume 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.

that occurs after 12 months with probability π. From the simulations, we generate a dataset with the within-year industry-level import growth rates before the uncertainty resolution and estimate the anticipatory import response to the tariff threat as in the empirical section. We measure import growth as in our baseline estimation equation, that is, $\ln(v^s_{m_{res}-2:m_{res}}/v^s_{m_{res}-5:m_{res}-7})$, where $m_{res}+1$ is the period in which uncertainty is resolved. We estimate the model analog of β[26] from estimation equation 5 in the empirical section using the following equation[27]:

$$\ln(v^s_{m_{res}-2:m_{res}}/v^s_{m_{res}-5:m_{res}-7}) = \beta_1^{sim} X_s + \beta_2^{sim}\gamma_s + \varepsilon_s \tag{7}$$

We repeat this procedure while varying π until we match β_1^{sim} to $\hat{\beta}$ estimated in the empirical analysis of section 3. In particular we target $\hat{\beta} = 0.4$ from our baseline estimation equation, reported in column 3 of Table 2. β_2^{sim} is the simulation counterpart to the industry fixed effects in our empirical exercise and prevents the joint distribution of γ_s and X_s from clouding the probability estimate. The estimated probability $\hat{\pi}$ that matches the coefficient on spread from the model to the one from the empirical analysis is 5.5%. This implies an expected probability of China's MFN status revocation that is significantly lower than the one obtained by Handley and Limao (2017). In the next subsection we estimate a probability of revocation for each year between 1990 and 2001.

4.3 Annual Probabilities

The implied probability above reflects the average probability assigned to the MFN status withdrawal over the entire period. However, uncertainty varied across the years, with the early 1990's presumably being the most uncertain. Our empirical strategy allows us to study anticipatory behavior in every single year of this period. We do so by interacting the NNTR gap with an indicator variable for every year and then applying the estimation approach from above

[26] For this section, let us simplify the notation by using $\hat{\beta} = \hat{\beta}_{i',j'}$ where $i' = US, j' = CHN$

[27] We don't need to control for seasonalities nor aggregate fixed effects since these are absent in the model.

to the year-specific estimates of $\hat{\beta}$ to back out the year-specific $\hat{\pi}$. The underlying assumption here is that the distribution over industries with respect to storability does not change over this decade which allows us to use the same calibration of δ_s for each year. More specifically, we run

$$\ln(v^{i,j,s,t}_{Jul:Sep}/v^{i,j,s,t}_{Feb:Apr}) = \sum_{year=1990}^{2009} \sum_{i'} \sum_{j'} \beta_{year,i',j'} \mathbb{1}_{\{t=year\}} \mathbb{1}_{\{i=i'\}} \mathbb{1}_{\{j=j'\}} X_{s,t} \tag{8}$$

$$+ \gamma_s + \gamma_{i,j} + \varepsilon_{i,j,s,t}$$

The estimates from (8) show variation in the annual probability of non-renewal over the decade of 1990's. Table 5 contains the annual implied probabilities. The annual coefficients for $\beta_{year,i',j'}$ are taken from Table A.3. There are three major takeaways that emerge from the table. First, in ten out of twelve years we find that there was a statistically significant estimate of the probability of China losing its MFN status. Second, the spikes in the probability estimates are in line with the contemporaneous political developments. For instance, the probability estimates are significantly high in 1991 and 1992, which were the only years in which the House passed bills (later vetoed by the President) that would have revoked China's MFN status. Moreover, President Clinton announced to link China's MFN status to human rights conditions in 1994, which is the year in which we obtain the highest probability of non-renewal of around 10%. Also, as reflected in Figure 7, our measure of TPU is not at odds with the measure of newspaper article counts by Pierce and Schott (2016) although we do find a more stable probability than suggested by their measure. Third, there is some variation in the estimated $\hat{\pi}$ over the years. Among the years with statistically significant probability, the chances of revoking China's MFN access ranges from 1.5% to 10%. Therefore, since our approach is based on within-year movements in imports, it is able to capture the time varying feature of uncertainty.

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 8 contains the result of this calculation. We see that, because of the low estimated $\hat{\pi}$ during this period, the probability in 1990 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. Next, we turn to the effect of pure uncertainty by looking at the certainty equivalent of the uncertain tariff increase.

4.4 Role of Pure Uncertainty

In this section we separate the effects of change in expected tariffs from the effects of uncertainty about the change. Theoretically, the real options literature has suggested that uncertainty about future states of the world acts as a deterrent to irreversible investments[28]. 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 which make the role of pure uncertainty dependent on the calibration and the nature of the experiment.

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 industry s a change in tariffs equal to $\hat{\pi}X_{st}$ with certainty and estimate equation (5) with the simulated data. For a certain change of $\hat{\pi}X_{st}$, $\hat{\beta}$ is 0.53. This is higher than the estimate of 0.4 when the tariffs are expected to increase by X_{st} with a probability of $\hat{\pi}$. Therefore, when we keep the expected increase in tariffs the same, we find that the uncertainty depresses anticipatory import growth by 13pp on average. The negative effect of uncertainty is in line with the wait-and-see effect widely reported in the literature. It

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

arises because there is a chance of tariffs staying at the same level, in which case paying fixed ordering costs in anticipation will not be worthwhile.

To illustrate the mechanism, consider the ordering cutoffs in the uncertain and certain case in Figure 9[29]. 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%[30]. This explains the minor difference in the coefficient of $\hat{\beta}$ of the certainty equivalent. Nevertheless, in the next section we use model simulations to study the role of pure uncertainty in this setup and its effect on the response to expected tariff change.

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 different expected tariff changes, two features of the anticipatory response to possible tariff hikes are illustrated. In first place, the anticipatory trade surge is decreasing over the expected tariffs, that is, for larger expected tariff increases, anticipatory rises in imports flatten out. 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. Moreover, they illustrate

[29]For demonstration purpose, Figure 9 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%.

[30]$\hat{\pi} \times \max_s\{X_{s,t}\} = 10\% \times 80$.

that uncertainty becomes more operative when tariff threats are large.

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 10. 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[31] 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[32], $Var(\tilde{X}_n) = \tilde{\pi}_n(1-\tilde{\pi}_n)\tilde{X}_n^2$, of the tariff hike. Results are presented in Table 5. 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 R^2 increases and explains 93% of the variation, highlighting the importance

[31] 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.

[32] 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_s with probability $\tilde{\pi}_s$.

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 stockpiling.

6 Effect on Annual Trade Flows

In this section, we explore the effect of within-year anticipatory stockpiling on annual trade flows. The stockpiling in anticipation of a possible rise in trade barriers implies extra holding and depreciation costs that depress trade. We find significantly negative effects of uncertainty on imports across industries. These effects are larger during the early years of 1990s when the probability of revoking MFN status was higher. We then explore the mechanism of these negative effects by specifically looking at the effect of uncertainty operating through the lumpiness of trade. Comparison with the effects found in the simulations from Section 4 shows that the inventory model matches the effect of spreads operating through this channel in the data. Moreover, the results suggest that the costs associated with anticipatory stockpiling account for around 50% of the cross-sectional trade reduction caused by the NNTR threat during the pre-WTO period.

6.1 Reduced-Form Effect

Since the resolution of uncertainty occurs in the middle of the year, annual trade flows include the anticipatory rise as well as the ensuing fall after the resolution. In this section we consider the impact of uncertainty on the annual level of trade. The dampening effects of the NNTR threat have been widely studied previously (Pierce and Schott (2016), Handley and Limao (2017), Crowley et al. (2018)). We follow a standard approach but focus on the negative impact in the pre-WTO period.

We implement a generalized difference-in-difference approach to isolate the effect of spreads on the level of annual imports during the period preceeding China's accession to the WTO. This approach is similar to the one used by Pierce and Schott (2016). In contrast with Pierce and Schott (2016) we incorporate a reference importer to overcome US specific fixed effects and aggregate at 6-digit NAICS level[33]. Our choices of the reference importer and exporter group are the same as in section 3. Again, the identification strategy is based on the cross-sectional effect of NNTR spreads. Since we are interested in the treatment effect of spreads on US-China trade, the NNTR spreads, $S_{i,j,s,t}$, take a value of zero for the non-US-China trade flows. We run the following specification,

$$\ln(v^{i,j,s,t}) = \beta_0 S_{i,j,s,t} + \beta_1 \mathbb{1}_{\{wto=0\}} S_{i,j,s,t} + \gamma_{i,s,t} + \gamma_{j,s} + \gamma_{i,j,t} + \varepsilon_{i,j,s,t} \tag{9}$$

[33] Appendix A contains the comparison of our approach to the one used by Pierce and Schott (2016).

where $v^{i,j,s,t}$ is i's annual imports from j of industry s in year t where $i \in \{US, EU\}$ and $j \in \{China, RoW\}$. $\gamma_{i,s,t}$ and $\gamma_{j,s}$ denote the destination-industry-year and source-industry fixed effects to capture the demand and supply determinants of imports[34]. In addition to these, source-destination-year fixed effects, given by $\gamma_{i,j,t}$, are added to prevent contamination from the pair-specific (pre-)trends as shown in Figure A.2. We set $S_{US,CHN,j,t} = S_{US,CHN,j,2001}$ $\forall t \geq 2002$ and interact the NNTR spreads with an indicator variable for the period before China's accession to WTO. β_0 is the effect of spreads after China joined the WTO. Our object of interest is β_1 which is the difference-in-difference effect of uncertainty on annual trade flows during the treatment period.

We find negative significant effects of uncertainty on annual trade flows. Results from (9) are presented in Table 7. First column contains result without any fixed effects and shows a high negative estimate of β_1. We control for time-invariant demand factors in the second column and find a negative significant coefficient of -0.56 on annual imports. Our baseline specification is reported in the third column where we control for time-varying industry-specific demand term. We find a negative significant coefficient of -0.82[35]. Also the estimate for β_0 falls significantly after the inclusion of the fixed effects. This estimate of β_1 translates into 18% lower annual US imports from China as we move from 25$^{\text{th}}$ percentile (16pp) industry to a 75$^{\text{th}}$ percentile (38pp) industry.

We next assess how the negative uncertainty effect evolved as China neared its accession to the WTO. By augmenting the previous specification with year indicator variables instead of the post-WTO indicator, year specific coefficients on the difference-in-difference term are obtained

[34] These high-dimensional fixed effects capture the importer- and exporter-specific aggregate terms from a standard armington setup. More precisely, the destination-industry-year fixed effects capture the time-varying industry demand effect and the source-industry fixed effects account for a supplier's comparative advantage in a sector.

[35] In accordance with the difference-in-difference approach, when we replace the pre-WTO indicator variable with post-WTO variable, we get the same coefficient with a positive sign.

from estimating,

$$\ln(v^{i,j,s,t}) = \beta_0 S_{i,j,s,t} + \sum_{t=1990}^{2006} \beta_t \mathbb{1}_{\{y=t\}} S_{i,j,s,t} + \gamma_{i,s,t} + \gamma_{j,s} + \gamma_{i,j,t} + \varepsilon_{i,j,s,t} \tag{10}$$

The resulting estimates of $\{\beta_t\}$ are plotted with 1 standard error bands in Figure 11 where the dashed red line denotes the first year after China joined the WTO. Table A.4 contains the point estimates from (10). The strongest response of β_t is obtained during the early years of 1990's when the probability of revocation of China's MFN status found Section 4.3 was the highest. Moreover, $\{\beta_t\}$ declines as China came closer to its WTO accession, after which the point estimate becomes insignificant.

6.2 Trade Dampening Effect of Stockpiling

Having found robust negative effect of uncertainty on the cross-sectional level of trade flows, we now examine the mechanism behind it. In particular, we test whether anticipatory stockpiling and de-stocking due to the within year changes in uncertainty lead trade flows to decline. In the model described in section 2, uncertainty lead firms to concentrate their purchases in the months before was uncertainty resolved, thereby deviating from the optimal inventory holding path. We show that in the model the resulting lumpiness leads to a dampening of annual purchases[36]. We find that in the data, increased lumpiness due to the NNTR threat lead to similar effects on annual trade flows.

Empirically annual imports and trade lumpiness are jointly determined creating a simultaneity bias in a simple OLS specification. To overcome this, we use a two stage least squares (TSLS) method to quantify the causal effect of spread that operates only through the HH index. Following the specification in (9), we replace the NNTR spreads with the HH index. Further,

[36]This is because holding costs go up and ultimately this leads to higher relative prices of goods affected by the NNTR threat.

the HH index is instrumented using the NNTR spreads. We use the following specification,

$$\ln(v^{i,j,s,t}) = \beta_0^{HH} \ln(\widehat{HH_{i,j}}_{,s,t}) + \beta_1^{HH} \mathbb{1}_{\{wto=0\}} \ln(\widehat{HH_{i,j}}_{,s,t}) \tag{11}$$

$$+ \gamma_{i,s,t} + \gamma_{j,s} + \gamma_{i,j,t} + \varepsilon_{i,j,s,t}$$

$$\ln(\widehat{HH_{i,j}}_{,s,t}) = \theta_0^{HH} S_{i,j,s,t} + \theta_1^{HH} \mathbb{1}_{\{wto=0\}} S_{i,j,s,t} + \gamma_s + \gamma_t \tag{12}$$

where $HH_{i,j,s,t}$ is the source-destination-industry-year specific lumpiness of imports. We use (12) as the first stage regression which captures the period-specific effects of spreads on the lumpiness of trade after controling for the industry determinants and time trends. Next, we apply the predicted HH index to (11) and consider how it affects the volume of trade. Therefore β_1^{HH} is the effect of spreads on annual imports that operates through our proposed mechanism.

The results indicate a strong negative effect of NNTR spread on imports through its effect on the lumpiness of trade. Table 8 reports the result of TSLS regression. The result of the first stage is reported in the third column. As predicted by the model, the NNTR threat caused a strong rise in lumpiness of annual imports some of which also holds in the post-WTO period. The first column contains the result of a simple OLS regression of (11) where the effect of HH index in the pre-WTO period is positive. However, using the TSLS approach in the second column, we find significant negative effect of lumpiness on annual imports during the uncertain period.

Next, we compare the effect in the data to the model simulations from Section 4. We run the TSLS regression from (11) on the simulated data. Since the steady state HH index was calibrated using the depreciation rate, we also control for the depreciation rate of the industry in our regressions. Results, presented in Table 9, indicate a similar effect of spreads on the import flows through the lumpiness of trade. The coefficient from the model is not significantly different from the coefficient found in the data.

Using the results from our TSLS estimates, we can quantify the contribution of increased inventory holding costs to the aggregate dampening effect of the NNTR threat. We use the point estimates from Tables 7 and 8 and look at the effect of moving to an industry with a 1pp higher NNTR spread. Plugging this increase into the third and then second column of Table 8 suggests a reduction of imports of around 0.41%[37]. This back-of-the-envelope calculation suggests that the negative effect of spreads operating through increased lumpiness of trade flows is around 50% of the total cross-sectional negative effect.

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

[37]Given by 0.28×-1.49.

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)	26.34%	

Table 2: Baseline - Anticipation to Resolution of Uncertainty over China's MFN Status

$\ln(v^{i,j,t,s}_{Jul:Sep}/v^{i,j,t,s}_{Feb:Apr})$	(1)	(2)	(3)	(4)
$\mathbb{1}_{\{US\}} \times \mathbb{1}_{\{CHN\}} \times X_{t,s}$	0.83^{*}	0.56^{**}	0.40^{***}	
	(0.25)	(0.16)	(0.06)	
$\mathbb{1}_{\{EU\}} \times \mathbb{1}_{\{RoW\}} \times X_{t,s}$	0.04	0.29	0.11	
	(0.23)	(0.21)	(0.05)	
$\mathbb{1}_{\{US\}} \times \mathbb{1}_{\{RoW\}} \times X_{t,s}$	0.18	0.33	0.16	
	(0.21)	(0.31)	(0.12)	
$\mathbb{1}_{\{EU\}} \times \mathbb{1}_{\{CHN\}} \times X_{t,s}$	0.45	0.21	0.04	
	(0.24)	(0.23)	(0.09)	
$\mathbb{1}_{\{US,CHN\}} \times X_{t,s}$				0.37^{***}
				(0.06)
$\mathbb{1}_{\{\neq US \text{ or } \neq CHN\}} \times X_{t,s}$				0.10
				(0.06)
2-Digit NAICS FE	No	No	✓	✓
Destination-Source-Year FE	No	✓	✓	✓
Observations	18743	18743	18743	18743
Adjusted R^2	0.03	0.04	0.05	0.04

Note: The dependent variable is the log growth rate in monthly CIF value of imports before the resolution of uncertainty. In the baseline this is the growth rate from the average between September and July, with respect to the baseline period, set to be the monthly average between February and April. Sample period is from 1990 until 2001. Columns (3) to is the result of estimating our baseline estimation equation 5. Columns one and two don't include full controls and column 4 groups non-US-China trade flows into one group. Standard errors, in parentheses, are clustered at 2-digit NAICS industry level, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3: Robustness - Anticipation to Resolution of Uncertainty over China's MFN Status

Baseline: $\ln(v^{i,j,t,z}_{Jul:Sep}/v^{i,j,t,z}_{Feb:Apr})$	$\ln(v^{i,j,t,z}_{Jul:Sep})-$ $\ln(v^{i,j,t,z}_{Feb:Apr})$	$\ln(v^{i,j,t,z}_{Jun:Aug})-$ $\ln(v^{i,j,t,z}_{Jan:Mar})$	$\ln(v^{i,j,t,z}_{Jun:Sep})-$ $\ln(v^{i,j,t,z}_{Feb:May})$	$\ln(v^{i,j,t,z}_{Jun:Sep})-$ $\ln(v^{i,j,t,z}_{Jan:Apr})$	Quantities	Unit Values	Post WTO	Taiwan
$\mathbb{1}_{\{EU\}} \times \mathbb{1}_{\{RoW\}} \times X_{t,s}$	-0.01	-0.10	0.08*	0.00	0.12	0.00		
	(0.11)	(0.10)	(0.04)	(0.07)	(0.06)	(0.06)		
$\mathbb{1}_{\{US\}} \times \mathbb{1}_{\{RoW\}} \times X_{t,s}$	0.03	0.01	0.20	0.16	0.18	-0.06		
	(0.16)	(0.12)	(0.15)	(0.13)	(0.18)	(0.11)		
$\mathbb{1}_{\{EU\}} \times \mathbb{1}_{\{CHN\}} \times X_{t,s}$	-0.03	0.05	0.07*	0.02	0.07	0.03		
	(0.15)	(0.13)	(0.03)	(0.08)	(0.08)	(0.05)		
$\mathbb{1}_{\{US\}} \times \mathbb{1}_{\{CHN\}} \times X_{t,s}$	0.29**	0.40***	0.29***	0.38***	0.29**	-0.01		
	(0.14)	(0.11)	(0.06)	(0.08)	(0.12)	(0.18)		
$\mathbb{1}_{\{US\}} \times \mathbb{1}_{\{CHN\}} \times \mathbb{1}_{\{PreWTO\neq1\}} \times X_{t,s}$							0.33	
							(0.18)	
$\mathbb{1}_{\{US\}} \times \mathbb{1}_{\{CHN\}} \times \mathbb{1}_{\{PreWTO=1\}} \times X_{t,s}$							0.39***	
							(0.06)	
$\mathbb{1}_{\{US,TWN\}} \times X_{t,s}$								0.11
								(0.24)
4-Digit NAICS FE	✓	No	No	No	No	No	No	No
2-Digit NAICS FE	No	✓	✓	✓	✓	✓	✓	✓
Destination-Source-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	18743	18709	18894	18839	18330	18330	31915	18077
Adjusted R^2	0.08	0.03	0.04	0.04	0.03	0.01	0.05	0.02

Note: Column one includes industry FE at the 4-Digit level. Columns two to four vary the time horizon of the import growth rate. Column five takes quantities of imports of consumption instead of CIF value of imports for consumption. In column six we extend the sample until 2009 and include an interaction for the pre- and post-WTO period. We only report the two coefficients for US imports from China. In column seven we perform another placebo and consider Taiwan's exports to the US, which were not subject to the threat of MFN revoking. In the last column we exclude industries with more than a 50% of their HS8 goods affected by the Multifiber Arrangement. Standard errors, in parentheses, are clustered at 2-digit NAICS industry level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Anticipation & Storability

$\ln(v^{i,j,t,s}_{Jul:Sep}/v^{i,j,t,s}_{Feb:Apr})$	(1)	(2)
$\mathbb{1}_{\{\neq US\ or\ \neq CHN\}} \times \mathbb{1}_{\{HH_s<med(HH_s)\}} \times X_{t,s}$	-0.03	-0.03
	(0.10)	(0.11)
$\mathbb{1}_{\{\neq US\ or\ \neq CHN\}} \times \mathbb{1}_{\{HH_s\geq med(HH_s)\}} \times X_{t,s}$	0.11	0.11
	(0.08)	(0.09)
$\mathbb{1}_{\{US,CHN\}} \times \mathbb{1}_{\{HH_s<med(HH_s)\}} \times X_{t,s}$	0.23**	0.25**
	(0.07)	(0.08)
$\mathbb{1}_{\{US,CHN\}} \times \mathbb{1}_{\{HH_s\geq med(HH_s)\}} \times X_{t,s}$	0.41***	0.45***
	(0.08)	(0.09)
2-Digit NAICS FE	✓	✓
Destination-Source FE	✓	No
Destination-Source-Year FE	No	✓
Observations	18743	18743
Adjusted R^2	0.05	0.05

Note: The dependent variable is the log growth rate in monthly CIF value of imports before the resolution of uncertainty. In the baseline this is the growth rate from the average between September and July, with respect to the baseline period, set to be the monthly average between January and March. Sample period is from 1990 until 2001. The HH index is calculated as the mean over the HH index of HS-6 goods imported by the US from China in the second year they appear in our sample. Standard errors, in parentheses, are clustered at 2-digit NAICS industry level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Annual Simulation Result

Year	$\hat{\beta}$	$\hat{\pi}$
1990	0	0%
1991	0.62***	8.5%
1992	0.75***	10.3%
1993	0.35**	4.8%
1994	0.73***	10%
1995	0.5***	6.9%
1996	0.54***	7.4%
1997	0.7***	9.6%
1998	0.14**	1.9%
1999	0.38**	5.2%
2000	0.22*	3%
2001	0.1	1.4%
Pooled		
1990 - 2001	0.4***	5.5%

Note: The annual $\hat{\beta}$ coefficients used in this table are taken from Table A.3. Negative coefficients are replaced by zeros. Annual $\hat{\beta}$'s are estimated using the simulated method of moments described in the main text.

Table 6: Decomposing Level Effect from Pure Uncertainty

	Standardized	Standardized	Level	Level	level	Level
$\tilde{v}^n_{m_{res}-2:m_{res}}/\tilde{v}^n_{m_{res}-7:m_{res}-5}$:	(1)	(2)	(3)	(4)	(5)	(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 7: Effect of Uncertainty on Annual Flows

$\ln(v^{i,j,s,t})$	(1)	(2)	(3)
$\mathbb{1}_{\{wto=0\}} \times S_{i,j,s,t}$	-5.50***	-0.56***	-0.82***
	(0.18)	(0.17)	(0.19)
$S_{i,j,s,t}$	2.45***	-0.18	-0.05**
	(0.12)	(0.18)	(0.16)
Dest-Source-Year FE		✓	✓
Source-NAICS FE		✓	✓
Dest-NAICS FE		✓	
Dest-NAICS-Year FE			✓
Observations	33887	33878	32776
Adjusted R^2	0.02	0.90	0.92

Note: This table contains results from estimation of (9). The dependent variable is the log annual imports from j to i of industry s in year t. The explanatory variables are NNTR spread and its interaction with the dummy for China's pre-WTO period. Interacted industry fixed effects are at 6-digit NAICS level. Robust standard errors are in in the parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Effect of Uncertainty on Annual Flows Through HH index

	OLS	2SLS	1st Stage
	$\ln(v_{i,j,s,t})$	$\ln(v_{i,j,s,t})$	$\ln(HH_{i,j,s,t})$
$\mathbb{1}_{\{wto=0\}} \times \ln(HH_{i,j,s,t})$	0.27***	-1.49***	
	(0.08)	(0.67)	
$\ln(HH_{i,j,s,t})$	-1.59***	-0.22	
	(0.08)	(0.71)	
$\mathbb{1}_{\{wto=0\}} \times S_{i,j,s,t}$			0.28***
			(0.02)
$S_{i,j,s,t}$			0.23***
			(0.01)
Dest-Source-Year FE	✓	✓	
Source-NAICS FE	✓	✓	
Dest-NAICS-Year FE	✓	✓	
NAICS FE			✓
Year FE			✓
Observations	32876	32776	33887
Adjusted R^2	0.93	0.92	0.44

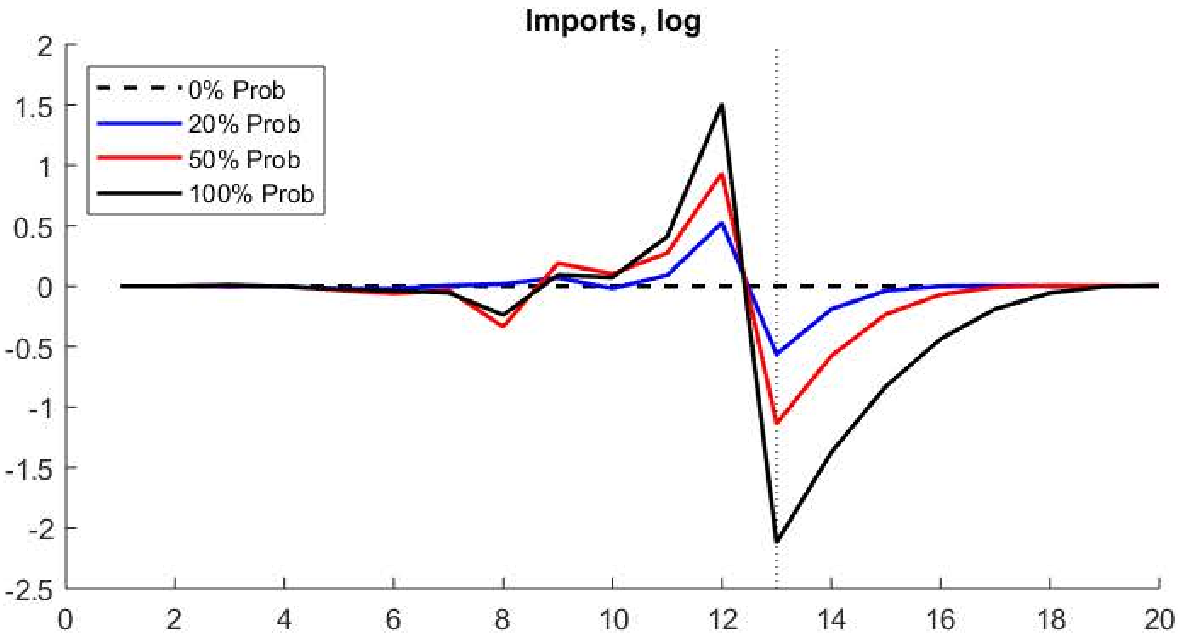
Note: This table contains results from estimation of (11). The dependent variable in the first and second columns is the logged annual imports from j to i of industry s in year t. The dependent variable in the third column is the logged annual HH index. The explanatory variables in the first two columns are logged HH index and its interaction with the dummy for China's pre-WTO period. Interacted industry fixed effects are at 6-digit NAICS level. Robust standard errors are in in the parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Effect of Uncertainty on Annual Flows in the Model Simulations

	OLS	2SLS	1^{st} Stage
	$\ln(\tilde{v}_s)$	$\ln(\tilde{v}_s)$	$\ln(\widetilde{HH}_s)$
$\ln(\widetilde{HH}_s)$	-1.20***	-1.19***	
δ_s	-1.04***	-1.18***	
$\widetilde{S}_s$			0.09***
			(0.01)
Observations	446	446	446

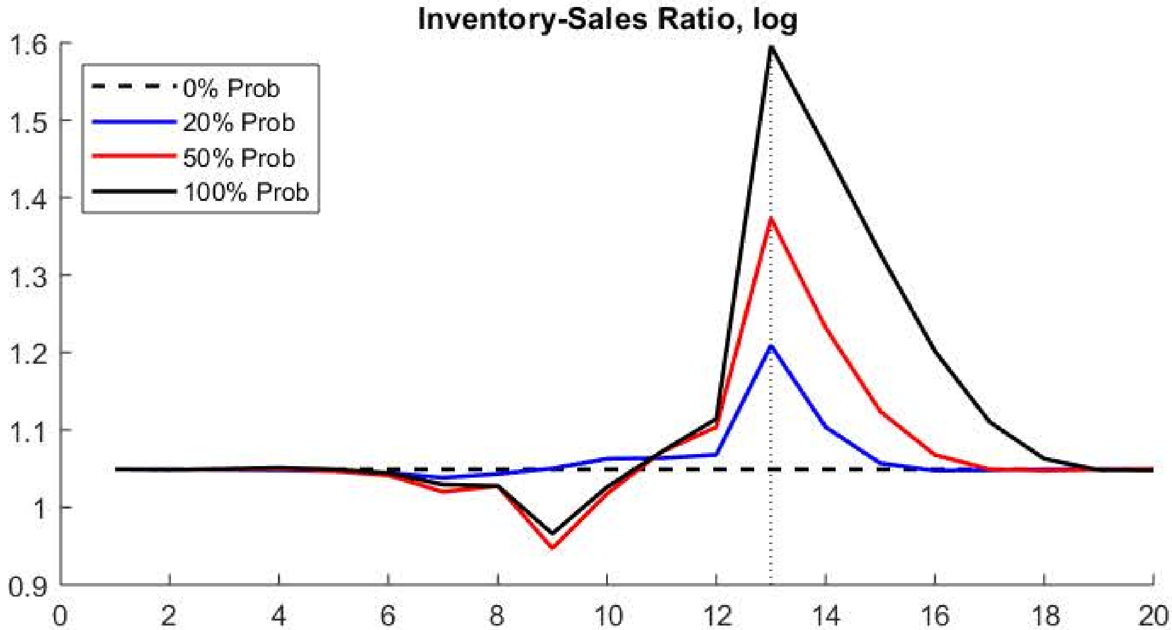
Note: The table presents results from the estimation of (11) and (12) on the simulations-generated data. It uses the calibration from Table A.5. The dependent variable in the first and second columns is the logged annual imports. The dependent variable in the third column is the logged annual HH index. The explanatory variables in the first two columns are logged HH index and its interaction with the dummy for China's pre-WTO period. Robust standard errors are in in the parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Import Response to Different Probabilities of 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



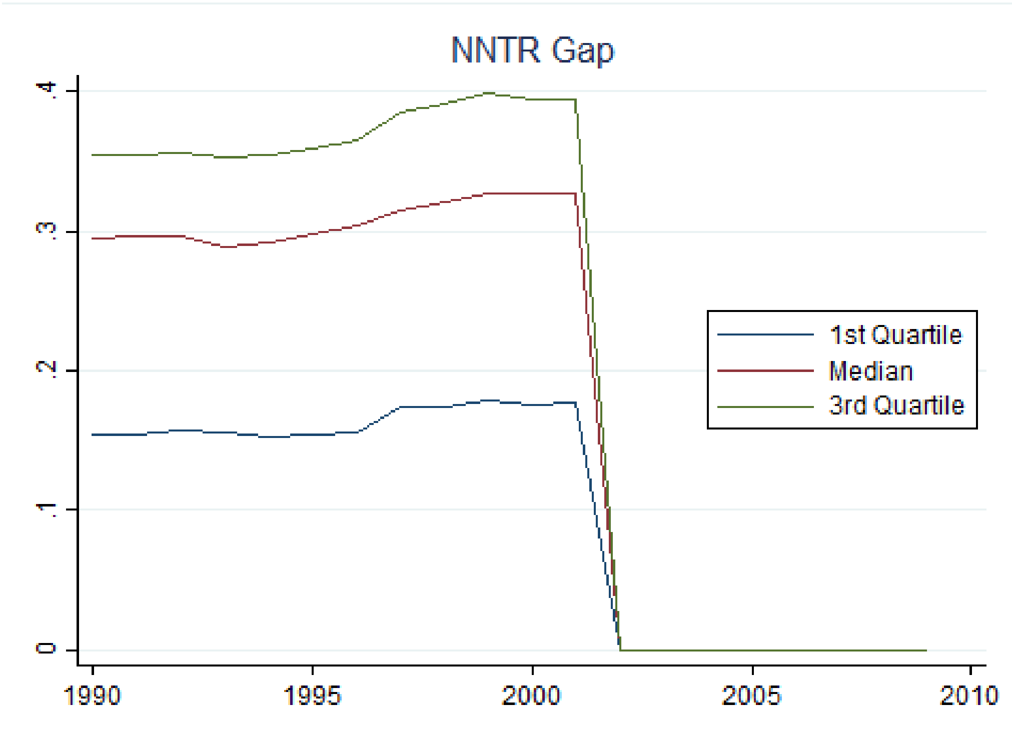
Note: This plot illustrates the anticipatory response of aggregate Inventory-Sales ratio to an uncertain change in tariff. We assign different probabilities to the event of 10% increase in tariffs 12 months ahead. The vertical dotted line denotes the time of the uncertainty resolution. In all cases,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

Figure 3: 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 S. 2808	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
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)	

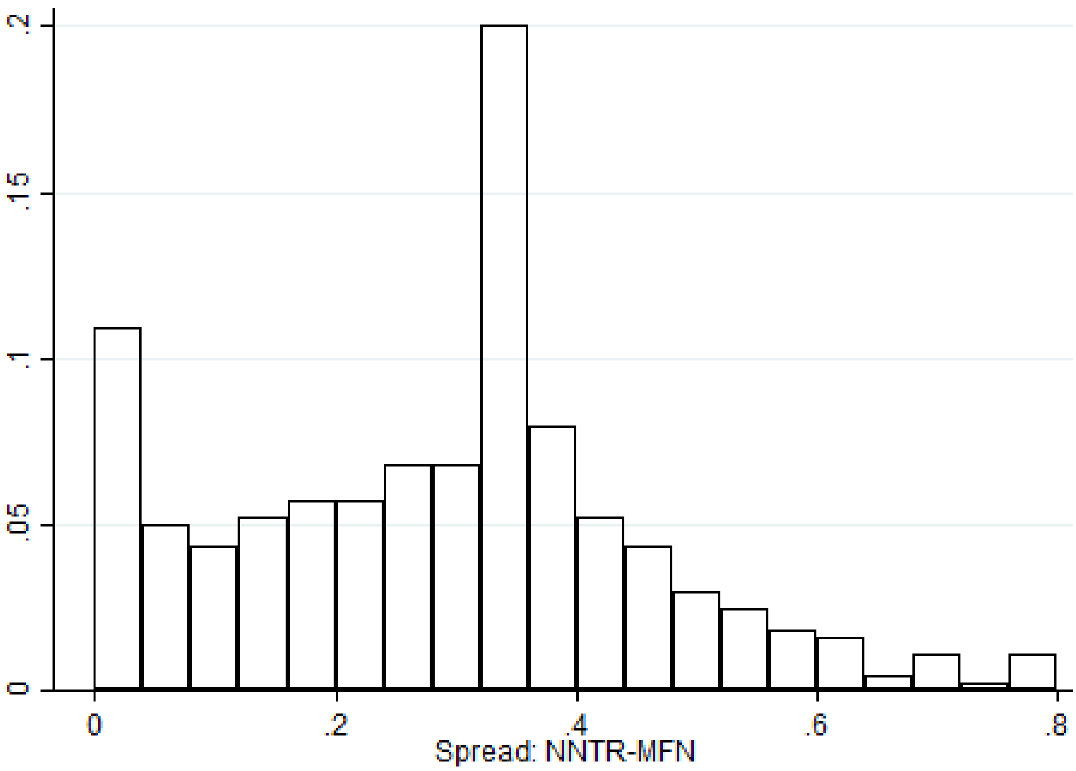
Source: Congressional Research Service, Report for Congress, "Voting on NTR for China Again in 2001, and Past Congressional Decisions".

Figure 4: NNTR Gap form 1990-2005



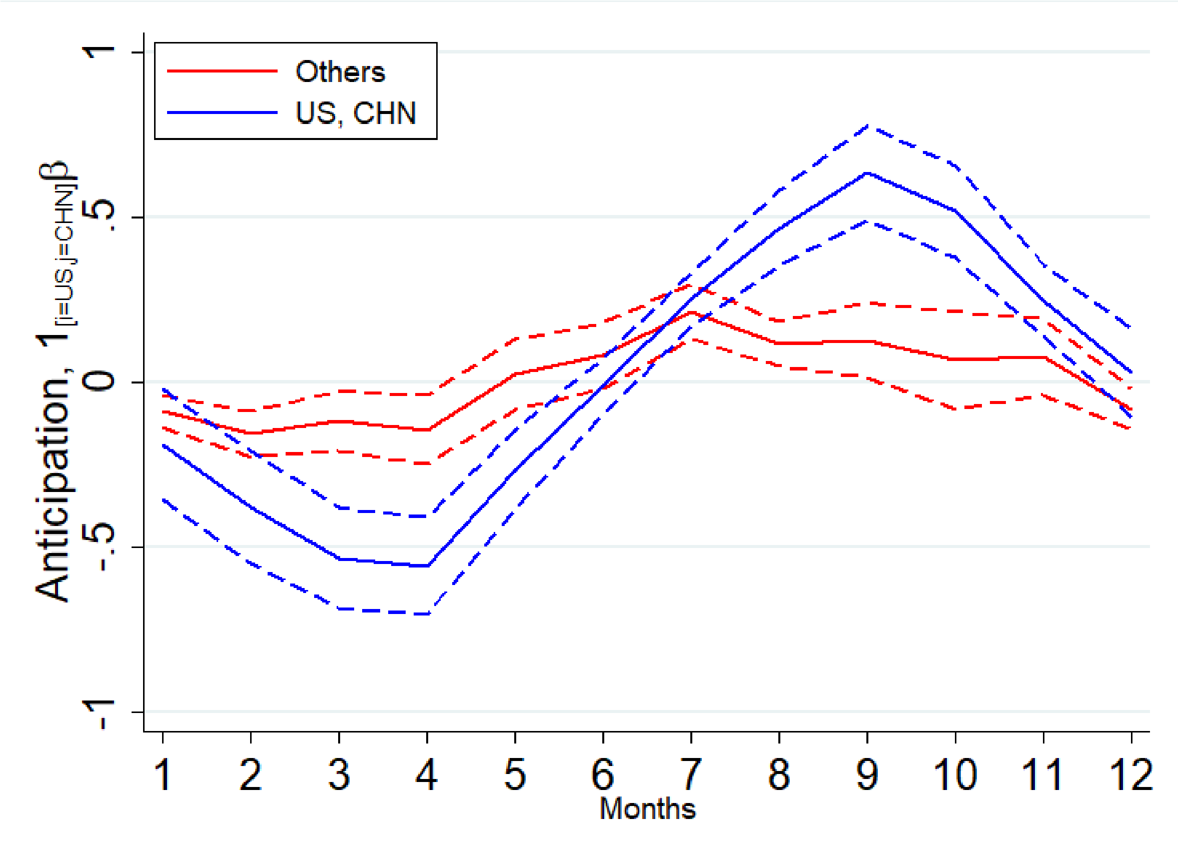
Note: Spread percentiles are calculated each year over 6-digit NAICS industries. Gaps are means over HS-8 product lines from Pierce & Schott (2016).

Figure 5: Distribution over HS-6 of the NNTR Gap in 1999



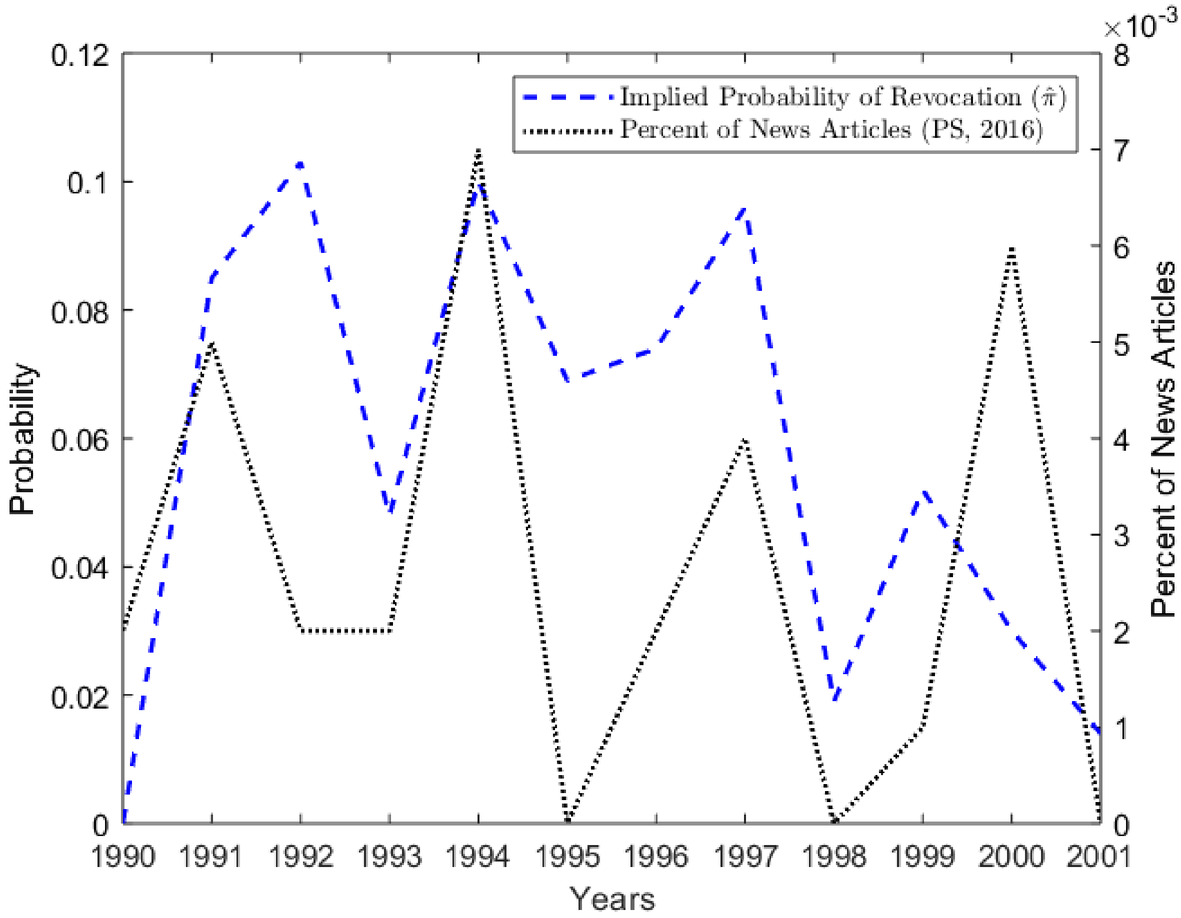
Note: NNTR gaps are at 6-digit NAICS industry level in 1999. NNTR gaps are means over HS-8 lines from Pierce & Schott (2016).

Figure 6: Monthly Coefficient of NNTR Gap



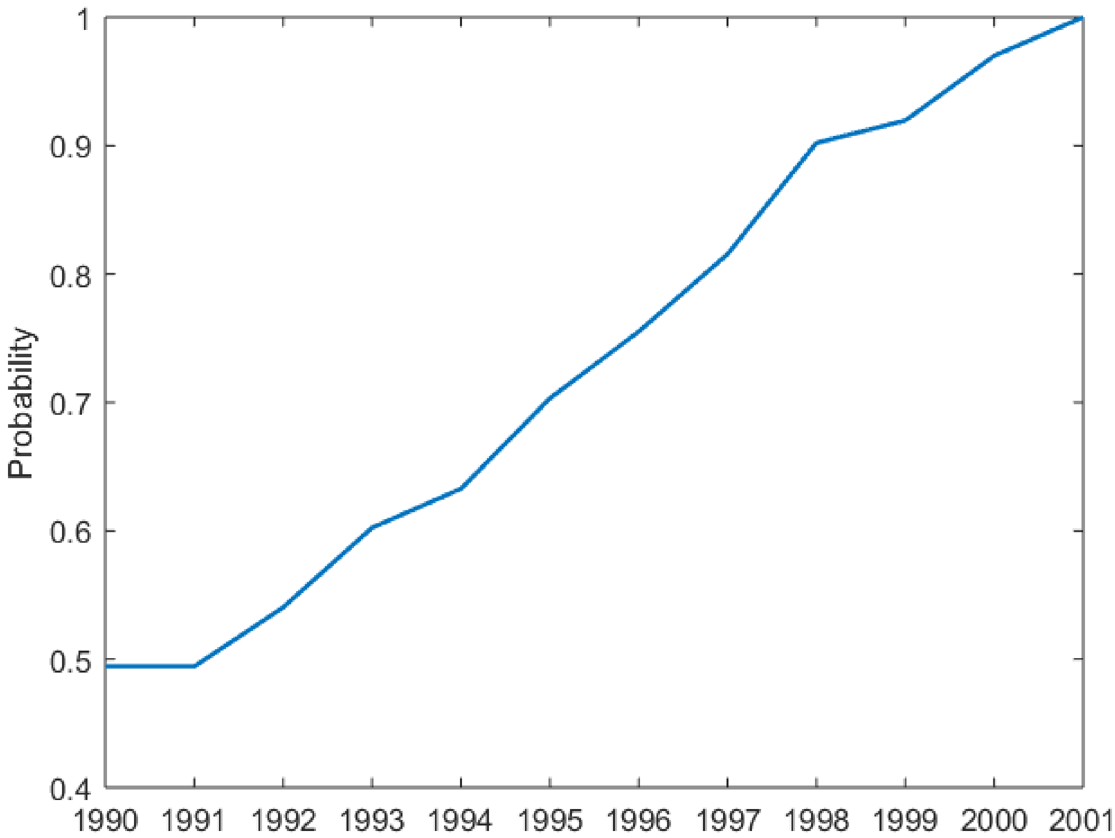
Note: These are the coefficients of $\hat{\beta}$ for each month $m_{res} = [1, 12]$ from estimating equation 6. Dashed lines are the [5%,95%] confidence interval. The month of September corresponds to our baseline estimate from estimating equation 5. Standard errors, in parentheses, are clustered at 2-digit NAICS industry level. Results corresponding to the figure are in the Table A.2 of the Appendix.

Figure 7: Model Estimated Probabilities of Revoked Access to MFN Rates



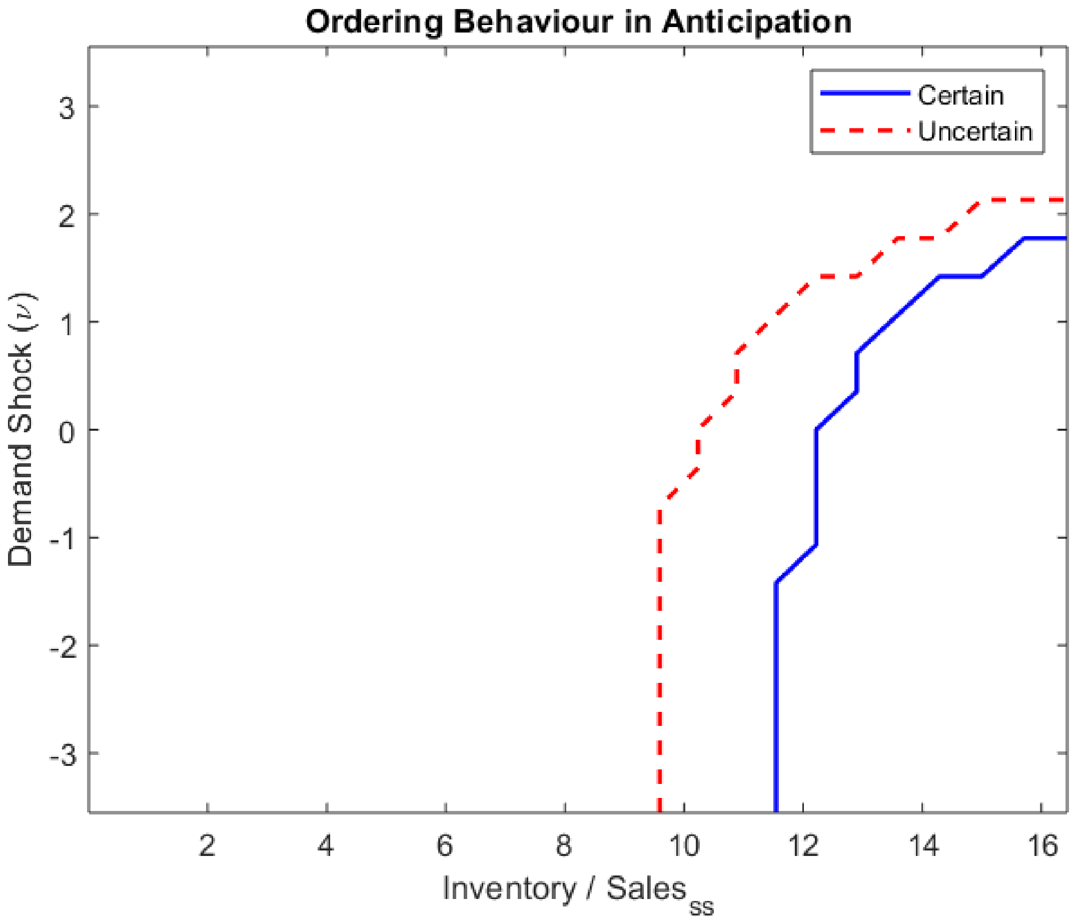
Note: On the left y-axis are our model implied probabilities from simulating the model for all 6-digit NAICS industries. Coefficients for β_t are reported in Table A.3 of the Appendix. On the right y-axis is the percent of news articles of the New York Times, Wall Street Journal, and the Washington Post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

Figure 8: Time-varying Estimated Probabilities of China maintaining MFN Access



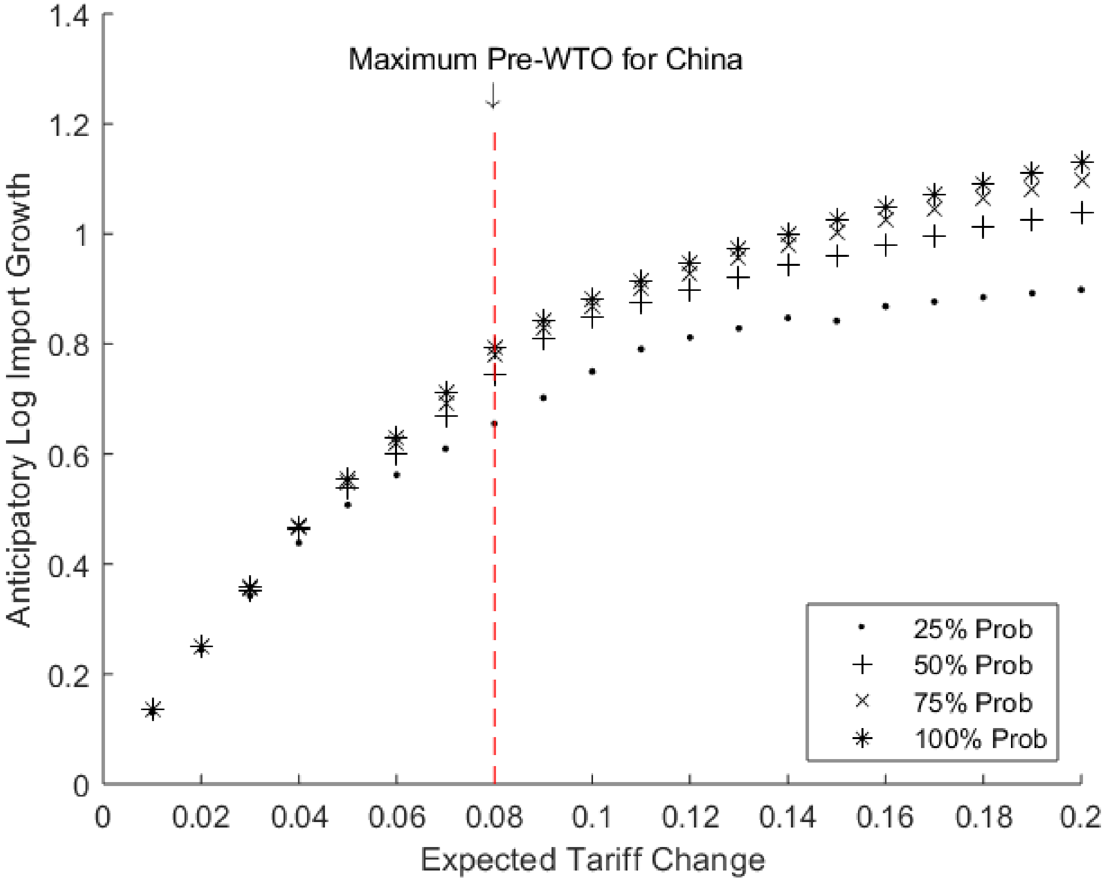
Note: On the y-axis are our model implied probabilities of China maintaining its MFN status till 2001 and years are on the x-axis. To obtain these we simulate the model for 6-digit NAICS industries and match the coefficients from (8) by changing probability input to the model.

Figure 9: Time-varying Estimated Probabilities of China maintaining MFN Access



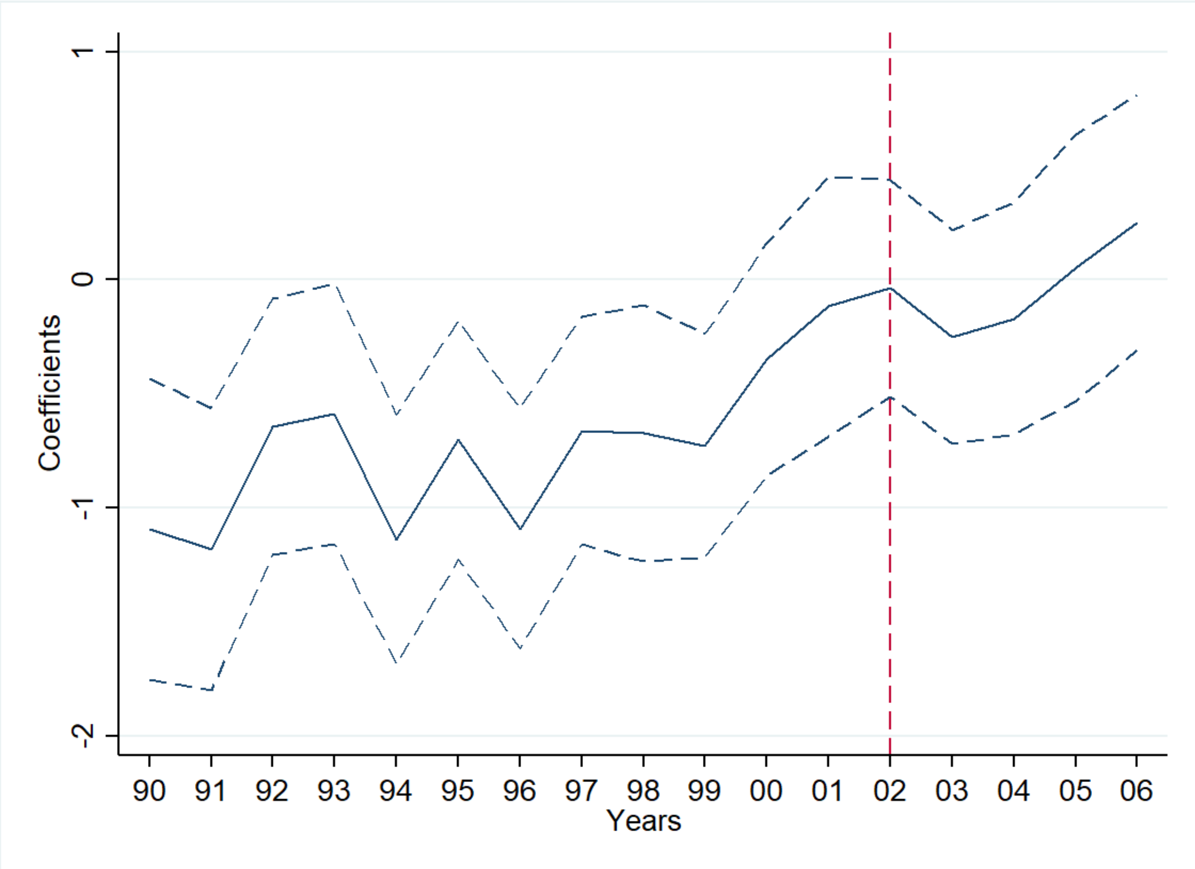
Note: On the y-axis is the level of demand shock and inventory holdings relative to steady-state average sales is on the x-axis. The area towards the top-left side of the curves is ordering region. Blue solid line shows the ordering cutoffs in the case of a 40% tariff change with certainty. Red dashed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

Figure 10: 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 11: Effects of Spreads on Annual US Imports from China



Note: These are the annual coefficients, $\beta_{t,i=US,j=CHN}$, from (10). Blue Dashed lines are the 95% confidence interval and red dashed line denotes the first year of China's WTO accession. Results correspond to Table A.4.

Appendix

A Comparison of Methodologies

In this section, we compare our difference-in-difference approach in Section 6 to the one applied in Pierce and Schott (2016). Although, their main variable of interest is industry-level employment, they also explore the channels of employment effects of uncertainty reduction. To do that, the paper considers the effect of uncertainty reduction on annual imports using a triple-difference strategy. They use the following specification at HS 8-digit level,

$$\ln(v^{j,h,t}) = \theta \mathbb{1}_{j=China} \mathbb{1}_{wto=1} X_h + \lambda \text{Tariff}_{j,h,t} + \gamma_{ct} + \gamma_{ch} + \gamma_{ht} + \alpha + \varepsilon_{j,h,t} \tag{13}$$

Where $v_{j,h,t}$ denotes the US import of good h from country c in year t and X_h is the product-specific NNTR spread. There are three notable differences between this specification and our equation (9). Firstly, while (13) uses exporter-product-year level import flows, we also add a reference importer in our analysis to control for the exporter-specific factors. This addition is particularly useful since it controls for the China-specific factors which were common to both US and EU such as structural changes within China. Similarly, we can use the EU to account for the difference in exporter-specific trends as shown in Figure A.2. Since the uncertainty was only US-China specific[38], adding a reference importer improves the identification of the uncertainty effect.

Secondly, the technical details of difference-in-difference methodology are different in our approach. We set US-China as our treatment group and US-RoW as the control group with the treatment being uncertainty driven by NNTR spreads. Accordingly, the intervention period is set to be China's pre-WTO period. In line with this, we employ a double-difference strategy instead of a triple-difference since our comparison is of high-spread US-China imports with low-spread US-China imports during the intervention period. As mentioned earlier, additional information from reference importer helps in controlling for the exporter-fixed factors.

Our third departure from Pierce and Schott (2016) is related to the treatment variable. The NNTR spreads in (13) are set to be the same for all importing countries whereas actually the NNTR spreads were only a threat for imports coming from China. We account for this and use,

$$S_{i,j,s,t} = \begin{cases} X_{s,t} & \text{for} \quad i = US, j = China \\ 0 & \text{otherwise} \end{cases}$$

We use time-varying spreads as it is in the data, however most of the variation in the spreads is across industries. This expression for spreads also embeds the fact that the treatment was specific to the US-China import flows and not common across all exporting countries.

The double-difference approach is better at conforming to the data. We bring information from a reference importer to control for supply-related factors in the import demand equation. Moreover, since the treatment of uncertainty was only given to the US-China imports, we improve identification of the uncertainty effect by using the relevant control group i.e. low-spread US-China imports.

[38] EU granted China unconditional MFN status in 1980.

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: Anticipation - Monthly Responses to NNTR Gap

$\ln(v^{i,j,t,s}_{m_{res}-2:m_{res}}/v^{i,j,t,s}_{m_{res}-7:m_{res}-5})$	(1)
$\mathbb{1}_{\{m_{res}=January\}} \times \mathbb{1}_{\{US,China\}} \times X_{t,s}$	-0.19
	(0.12)
$\mathbb{1}_{\{m_{res}=February\}} \times \mathbb{1}_{\{US,China\}} \times X_{t,s}$	-0.38***
	(0.06)
$\mathbb{1}_{\{m_{res}=March\}} \times \mathbb{1}_{\{US,China\}} \times X_{t,s}$	-0.53***
	(0.02)
$\mathbb{1}_{\{m_{res}=April\}} \times \mathbb{1}_{\{US,China\}} \times X_{t,s}$	-0.55***
	(0.03)
$\mathbb{1}_{\{m_{res}=May\}} \times \mathbb{1}_{\{US,China\}} \times X_{t,s}$	-0.26***
	(0.04)
$\mathbb{1}_{\{m_{res}=June\}} \times \mathbb{1}_{\{US,China\}} \times X_{t,s}$	-0.01
	(0.02)
$\mathbb{1}_{\{m_{res}=July\}} \times \mathbb{1}_{\{US,China\}} \times X_{t,s}$	0.25***
	(0.01)
$\mathbb{1}_{\{m_{res}=August\}} \times \mathbb{1}_{\{US,China\}} \times X_{t,s}$	0.47***
	(0.03)
$\mathbb{1}_{\{m_{res}=September\}} \times \mathbb{1}_{\{US,China\}} \times X_{t,s}$	0.63***
	(0.07)
$\mathbb{1}_{\{m_{res}=October\}} \times \mathbb{1}_{\{US,China\}} \times X_{t,s}$	0.52***
	(0.06)
$\mathbb{1}_{\{m_{res}=November\}} \times \mathbb{1}_{\{US,China\}} \times X_{t,s}$	0.25***
	(0.07)
$\mathbb{1}_{\{m_{res}=December\}} \times \mathbb{1}_{\{US,China\}} \times X_{t,s}$	0.03
	(0.13)
2-Digit NAICS FE	✓
Destination-Source-Year FE	✓
Observations	215194
Adjusted R^2	0.01

Note: The dependent variable is the log growth rate in monthly averages of CIF value of imports between $m_{res}-2$ to m_{res} and $m_{res}-7$ to $m_{res}-5$. Sample period is from 1990 until 2001. Estimates are obtained from equation 6. We only report coefficients for $i = US, j = China$. Standard errors, in parentheses, are clustered at 2-digit NAICS industry level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Annual Anticipation 1990-2001

	(1)
$\mathbb{1}_{\{1990\}} \times \mathbb{1}_{\{i=US,j=CHN\}} \times X_{t,s}$	-0.25*
	(0.13)
$\mathbb{1}_{\{1991\}} \times \mathbb{1}_{\{i=US,j=CHN\}} \times X_{t,s}$	0.62***
	(0.07)
$\mathbb{1}_{\{1992\}} \times \mathbb{1}_{\{i=US,j=CHN\}} \times X_{t,s}$	0.75***
	(0.03)
$\mathbb{1}_{\{1993\}} \times \mathbb{1}_{\{i=US,j=CHN\}} \times X_{t,s}$	0.35**
	(0.11)
$\mathbb{1}_{\{1994\}} \times \mathbb{1}_{\{i=US,j=CHN\}} \times X_{t,s}$	0.73***
	(0.16)
$\mathbb{1}_{\{1995\}} \times \mathbb{1}_{\{i=US,j=CHN\}} \times X_{t,s}$	0.50***
	(0.11)
$\mathbb{1}_{\{1996\}} \times \mathbb{1}_{\{i=US,j=CHN\}} \times X_{t,s}$	0.54***
	(0.10)
$\mathbb{1}_{\{1997\}} \times \mathbb{1}_{\{i=US,j=CHN\}} \times X_{t,s}$	0.70***
	(0.20)
$\mathbb{1}_{\{1998\}} \times \mathbb{1}_{\{i=US,j=CHN\}} \times X_{t,s}$	0.14**
	(0.05)
$\mathbb{1}_{\{1999\}} \times \mathbb{1}_{\{i=US,j=CHN\}} \times X_{t,s}$	0.38**
	(0.12)
$\mathbb{1}_{\{2000\}} \times \mathbb{1}_{\{i=US,j=CHN\}} \times X_{t,s}$	0.22*
	(0.11)
$\mathbb{1}_{\{2001\}} \times \mathbb{1}_{\{i=US,j=CHN\}} \times X_{t,s}$	0.10
	(0.10)
2-Digit NAICS FE	✓
Destination-Source FE	✓
Observations	18743
Adjusted R^2	0.05

Note: This table contains the results from (8). Standard errors, in parentheses, are clustered at 6-digit NAICS industry level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Year-specific Effects on Annual Trade Flows

	(1) $\ln(v^{i,j,s,t})$
$\mathbb{1}_{1990} \times S_{i,j,s,t}$	-1.09**
$\mathbb{1}_{1991} \times S_{i,j,s,t}$	-1.18**
$\mathbb{1}_{1992} \times S_{i,j,s,t}$	-0.64*
$\mathbb{1}_{1993} \times S_{i,j,s,t}$	-0.59*
$\mathbb{1}_{1994} \times S_{i,j,s,t}$	-1.14***
$\mathbb{1}_{1995} \times S_{i,j,s,t}$	-0.70*
$\mathbb{1}_{1996} \times S_{i,j,s,t}$	-1.09***
$\mathbb{1}_{1997} \times S_{i,j,s,t}$	-0.66*
$\mathbb{1}_{1998} \times S_{i,j,s,t}$	-0.67*
$\mathbb{1}_{1999} \times S_{i,j,s,t}$	-0.73*
$\mathbb{1}_{2000} \times S_{i,j,s,t}$	-0.35
$\mathbb{1}_{2001} \times S_{i,j,s,t}$	-0.12
$\mathbb{1}_{2002} \times S_{i,j,s,t}$	-0.037
$\mathbb{1}_{2003} \times S_{i,j,s,t}$	-0.25
$\mathbb{1}_{2004} \times S_{i,j,s,t}$	-0.17
$\mathbb{1}_{2005} \times S_{i,j,s,t}$	0.054
$\mathbb{1}_{2006} \times S_{i,j,s,t}$	0.25
Dest-Ind-Year FE	✓
Source-Ind-Year FE	✓
N	46636
adj. R^2	0.91

Note: This table contains the results from (10). * $p < 0.32$, ** $p < 0.10$, *** $p < 0.05$.

Table A.5: Simulation Moments

	Data		Model	
NAICS	Spread	HH	HH	δ_s
111110	0.171	0.492	0.492	0.010
111120	0.056	0.309	0.309	0.025
111130	0.131	0.472	0.472	0.010
111140	0.057	0.403	0.403	0.014
111150	0.027	0.456	0.456	0.010
111160	0.002	0.106	0.106	0.217
111199	0.065	0.670	0.670	0.010
111211	0.116	0.713	0.713	0.010
111219	0.130	0.220	0.220	0.052
111310	0.001	0.280	0.280	0.031
111320	0.128	0.309	0.309	0.025
111331	0.020	0.263	0.263	0.037
111332	0.020	0.564	0.565	0.010
111333	0.017	0.613	0.613	0.010
111334	0.018	0.321	0.321	0.023
111335	0.029	0.294	0.294	0.028
111339	0.071	0.214	0.214	0.055
111411	0.090	0.171	0.171	0.089
111421	0.138	0.305	0.305	0.026
111422	0.126	0.098	0.098	0.248
111910	0.344	0.470	0.470	0.010
111920	0.017	0.511	0.511	0.010
111930	0.014	1.000	1.000	0.010
111940	0.035	0.355	0.355	0.019
111991	0.000	1.000	1.000	0.010
111992	0.094	0.960	0.960	0.010
111998	0.061	0.239	0.239	0.044
11211X	0.052	1.000	1.000	0.010
112210	0.000	1.000	1.000	0.010
1123XX	0.021	0.188	0.188	0.073
112410	0.119	0.171	0.171	0.090
112420	0.087	0.540	0.540	0.010
112511	0.003	0.233	0.233	0.047
112512	0.000	0.179	0.179	0.081
112910	0.043	0.121	0.121	0.166
112920	0.068	0.368	0.368	0.017
112930	0.039	1.000	1.000	0.010
112990	0.032	0.125	0.125	0.158
113210	0.084	0.135	0.135	0.138
113310	0.023	0.465	0.465	0.010
114111	0.018	0.233	0.233	0.047
114112	0.018	0.179	0.179	0.081
114119	0.055	0.098	0.098	0.249
211111	0.004	0.088	0.088	0.319
211112	0.000	0.502	0.502	0.010

	Data		Model	
NAICS	Spread	HH	HH	δ_s
212112	0.000	0.520	0.520	0.010
212113	0.000	0.117	0.117	0.177
212210	0.000	0.301	0.301	0.026
212221	0.016	0.407	0.407	0.014
212222	0.297	1.000	1.000	0.010
212231	0.333	1.000	1.000	0.010
212234	0.025	0.530	0.530	0.010
212291	0.000	0.290	0.290	0.029
212299	0.110	0.244	0.244	0.043
212311	0.244	0.149	0.149	0.115
212319	0.114	0.358	0.358	0.018
212322	0.020	0.135	0.135	0.138
212324	0.009	0.148	0.149	0.115
212325	0.062	0.500	0.500	0.010
212391	0.000	0.453	0.453	0.010
212392	0.000	1.000	1.000	0.010
212393	0.101	0.270	0.270	0.034
212399	0.021	0.477	0.477	0.010
311111	0.100	0.094	0.094	0.273
311119	0.143	0.208	0.208	0.057
311211	0.073	0.411	0.411	0.014
311212	0.053	0.156	0.156	0.105
311213	0.009	0.119	0.119	0.171
311221	0.107	0.232	0.232	0.047
311222	0.115	0.435	0.435	0.012
311223	0.059	0.229	0.229	0.049
311225	0.082	0.537	0.537	0.010
311230	0.087	0.147	0.147	0.116
31131X	0.054	0.304	0.304	0.026
311320	0.181	0.361	0.361	0.018
311340	0.150	0.122	0.122	0.162
311411	0.204	0.238	0.238	0.045
311421	0.212	0.187	0.187	0.073
311422	0.203	0.141	0.141	0.127
311423	0.078	0.391	0.391	0.015
311511	0.048	1.000	1.000	0.010
311512	0.083	0.419	0.419	0.013
311513	0.196	0.356	0.357	0.019
311514	0.113	0.478	0.478	0.010
311520	0.008	0.634	0.634	0.010
311611	0.096	0.392	0.392	0.015
311613	0.109	0.253	0.253	0.040
311615	0.087	0.247	0.247	0.042
311711	0.132	0.198	0.198	0.064
31181X	0.282	0.100	0.100	0.241

	Data		Model	
NAICS	Spread	HH	HH	δ_s
311822	0.093	0.335	0.335	0.021
311823	0.084	0.096	0.096	0.260
311911	0.082	0.631	0.631	0.010
311919	0.273	0.197	0.197	0.065
311920	0.034	0.199	0.199	0.063
311930	0.431	1.000	1.000	0.010
311941	0.257	0.100	0.100	0.241
311942	0.030	0.123	0.123	0.161
311991	0.024	0.226	0.226	0.050
311999	0.120	0.198	0.198	0.064
312111	0.074	0.459	0.459	0.010
312112	0.057	0.104	0.104	0.223
312113	0.000	0.158	0.158	0.102
312120	0.093	0.087	0.087	0.325
312130	0.207	0.204	0.204	0.060
312140	0.446	0.388	0.388	0.016
312221	0.479	0.100	0.100	0.238
312229	0.183	0.652	0.652	0.010
313111	0.322	0.296	0.296	0.027
313113	0.331	0.102	0.102	0.230
313210	0.441	0.503	0.503	0.010
313221	0.530	0.140	0.140	0.129
313230	0.552	0.156	0.156	0.105
313249	0.584	0.187	0.187	0.074
313312	0.252	0.764	0.764	0.010
313320	0.473	0.208	0.208	0.058
314110	0.426	0.158	0.158	0.103
314121	0.781	0.135	0.135	0.137
314129	0.586	0.187	0.187	0.074
314911	0.556	0.108	0.108	0.207
314912	0.500	0.212	0.212	0.055
314991	0.440	0.114	0.114	0.188
314992	0.251	0.107	0.107	0.211
314999	0.365	0.180	0.180	0.080
315111	0.640	0.338	0.338	0.021
315119	0.567	0.159	0.159	0.102
31511X	0.656	0.255	0.255	0.039
315221	0.632	0.437	0.437	0.012
315222	0.400	0.482	0.482	0.010
315223	0.435	0.526	0.526	0.010
315224	0.450	0.344	0.344	0.020
315228	0.483	0.369	0.369	0.017
315231	0.680	0.292	0.292	0.028
315232	0.540	0.317	0.317	0.023
315233	0.555	0.204	0.204	0.060

	Data		Model	
NAICS	Spread	HH	HH	δ_s
315234	0.468	0.316	0.316	0.024
315239	0.540	0.285	0.285	0.030
315291	0.564	0.301	0.301	0.026
315292	0.418	0.098	0.098	0.249
315991	0.362	0.248	0.248	0.041
315992	0.378	0.231	0.231	0.048
315993	0.463	0.509	0.509	0.010
315999	0.592	0.362	0.362	0.018
316110	0.211	0.204	0.204	0.060
316211	0.321	0.154	0.154	0.107
316212	0.274	0.280	0.280	0.031
316213	0.173	0.249	0.249	0.041
316214	0.201	0.224	0.224	0.050
316219	0.229	0.181	0.181	0.079
316991	0.311	0.120	0.120	0.168
316992	0.413	0.180	0.180	0.081
316993	0.405	0.134	0.134	0.140
316999	0.297	0.389	0.389	0.015
321113	0.043	0.314	0.314	0.024
321114	0.000	1.000	1.000	0.010
321211	0.321	0.212	0.212	0.056
321212	0.303	0.346	0.346	0.020
321213	0.239	0.175	0.176	0.085
321219	0.261	0.194	0.194	0.067
321911	0.280	0.086	0.086	0.350
321918	0.201	0.108	0.108	0.210
321920	0.149	1.000	1.000	0.010
321992	0.354	0.761	0.761	0.010
321999	0.292	0.142	0.142	0.126
322110	0.016	0.549	0.549	0.010
322121	0.255	0.316	0.316	0.024
322122	0.088	0.246	0.247	0.042
322130	0.273	0.260	0.260	0.038
322211	0.273	0.146	0.146	0.118
322212	0.329	0.090	0.091	0.296
322213	0.310	0.112	0.112	0.196
322214	0.329	0.170	0.170	0.091
322215	0.317	0.150	0.150	0.112
322222	0.249	0.117	0.117	0.177
322223	0.558	0.090	0.090	0.303
322232	0.320	0.112	0.112	0.193
322233	0.286	0.228	0.228	0.049
322291	0.302	0.096	0.096	0.261
322299	0.345	0.140	0.140	0.128
323116	0.225	0.154	0.154	0.108

	Data		Model	
NAICS	Spread	HH	HH	δ_s
323117	0.000	0.113	0.113	0.191
323118	0.301	0.100	0.100	0.240
323119	0.119	0.109	0.109	0.204
323122	0.391	0.120	0.120	0.169
324110	0.059	0.174	0.174	0.087
324121	0.022	0.136	0.136	0.137
324122	0.290	0.168	0.168	0.093
325110	0.080	0.477	0.477	0.010
325120	0.216	0.553	0.553	0.010
325131	0.175	0.141	0.141	0.126
325132	0.464	0.145	0.145	0.120
325181	0.103	0.320	0.320	0.023
325182	0.200	0.131	0.131	0.146
325188	0.167	0.226	0.226	0.050
325191	0.103	0.148	0.148	0.115
325192	0.170	0.209	0.209	0.057
325193	0.615	0.183	0.183	0.077
325199	0.259	0.232	0.232	0.047
325211	0.265	0.113	0.113	0.190
325212	0.201	0.123	0.123	0.160
325221	0.369	0.302	0.302	0.026
325222	0.366	0.137	0.137	0.134
325311	0.011	0.219	0.219	0.052
325312	0.000	0.615	0.615	0.010
325320	0.191	0.277	0.277	0.032
325411	0.225	0.243	0.244	0.043
325412	0.194	0.198	0.198	0.064
325414	0.029	0.817	0.817	0.010
325510	0.216	0.117	0.117	0.178
325520	0.204	0.176	0.176	0.085
325611	0.235	0.151	0.151	0.111
325612	0.222	0.115	0.115	0.185
325613	0.217	0.207	0.207	0.058
325620	0.641	0.105	0.105	0.219
325910	0.082	0.144	0.144	0.122
325920	0.231	0.198	0.198	0.064
325992	0.205	0.126	0.126	0.154
325998	0.189	0.162	0.162	0.098
326113	0.263	0.095	0.095	0.264
326121	0.330	0.325	0.325	0.022
326122	0.325	0.170	0.171	0.090
326160	0.770	0.105	0.105	0.218
326191	0.497	0.110	0.110	0.202
326192	0.351	0.396	0.396	0.015
326199	0.574	0.108	0.108	0.207

	Data		Model	
NAICS	Spread	HH	HH	δ_s
326211	0.165	0.095	0.095	0.265
326212	0.112	0.219	0.219	0.052
326220	0.257	0.101	0.101	0.234
326299	0.350	0.117	0.118	0.176
327111	0.534	0.088	0.088	0.319
327112	0.456	0.092	0.092	0.287
327113	0.501	0.097	0.097	0.254
327121	0.136	0.575	0.575	0.010
327122	0.365	0.090	0.090	0.303
327123	0.315	0.248	0.248	0.041
327124	0.268	0.086	0.086	0.342
327125	0.280	0.302	0.302	0.026
327211	0.370	0.159	0.159	0.101
327212	0.476	0.127	0.127	0.152
327213	0.200	0.125	0.125	0.157
327215	0.447	0.121	0.121	0.165
327310	0.023	0.285	0.286	0.030
327331	0.258	0.117	0.117	0.178
327390	0.268	0.391	0.391	0.015
327410	0.079	0.507	0.507	0.010
327420	0.188	0.253	0.253	0.040
327910	0.098	0.107	0.107	0.210
327991	0.394	0.103	0.103	0.229
327992	0.175	0.137	0.137	0.134
327993	0.366	0.214	0.214	0.055
327999	0.265	0.248	0.248	0.041
331111	0.150	0.228	0.228	0.049
331112	0.135	0.327	0.327	0.022
331221	0.213	0.091	0.091	0.291
331222	0.198	0.129	0.129	0.149
331311	0.052	0.086	0.086	0.342
331312	0.149	0.339	0.339	0.020
331314	0.233	1.000	1.000	0.010
331315	0.156	0.286	0.286	0.030
331316	0.264	0.178	0.179	0.082
331319	0.218	0.299	0.299	0.027
331411	0.099	0.333	0.333	0.021
331419	0.133	0.329	0.329	0.022
331421	0.273	0.251	0.251	0.040
331422	0.246	0.225	0.225	0.050
331491	0.351	0.160	0.160	0.100
331492	0.223	0.278	0.278	0.032
331511	0.251	0.121	0.121	0.165
332115	0.417	0.091	0.091	0.288
332211	0.493	0.104	0.104	0.222

	Data		Model	
NAICS	Spread	HH	HH	δ_s
332212	0.299	0.107	0.107	0.211
332213	0.219	0.104	0.105	0.221
332214	0.417	0.106	0.107	0.213
332312	0.385	0.234	0.234	0.046
332321	0.335	0.136	0.136	0.136
332323	0.407	0.196	0.196	0.066
332410	0.383	0.258	0.258	0.038
332420	0.326	0.259	0.259	0.038
332431	0.322	0.149	0.149	0.114
332439	0.301	0.124	0.124	0.159
332510	0.385	0.097	0.097	0.256
332611	0.360	0.089	0.089	0.308
332618	0.323	0.122	0.122	0.162
332722	0.281	0.092	0.092	0.283
332911	0.362	0.100	0.100	0.241
332912	0.320	0.180	0.180	0.080
332919	0.380	0.101	0.101	0.238
332991	0.542	0.100	0.100	0.242
332992	0.369	0.383	0.383	0.016
332994	0.423	0.306	0.306	0.025
332995	0.502	0.580	0.580	0.010
332997	0.464	0.121	0.121	0.165
332998	0.369	0.193	0.193	0.068
332999	0.314	0.112	0.112	0.195
333111	0.079	0.269	0.269	0.035
333120	0.312	0.244	0.244	0.043
333131	0.375	0.216	0.216	0.054
333132	0.366	0.220	0.220	0.052
333210	0.308	0.504	0.504	0.010
333220	0.306	0.141	0.142	0.126
333291	0.335	0.179	0.179	0.081
333292	0.368	0.208	0.208	0.057
333293	0.181	0.117	0.117	0.177
333294	0.292	0.189	0.189	0.071
333295	0.324	0.158	0.158	0.102
333298	0.296	0.211	0.211	0.056
333311	0.327	0.144	0.144	0.121
333313	0.274	0.095	0.096	0.261
333314	0.398	0.100	0.100	0.240
333315	0.281	0.123	0.123	0.160
333319	0.329	0.233	0.233	0.047
333412	0.329	0.088	0.088	0.319
333414	0.368	0.207	0.207	0.058
333415	0.342	0.162	0.162	0.098
333511	0.311	0.142	0.142	0.125

	Data		Model	
NAICS	Spread	HH	HH	δ_s
333512	0.262	0.363	0.363	0.018
333513	0.269	0.247	0.247	0.042
333514	0.340	0.111	0.111	0.198
333515	0.410	0.104	0.104	0.225
333516	0.271	0.230	0.230	0.048
333611	0.229	0.331	0.331	0.021
333612	0.331	0.100	0.100	0.242
333613	0.386	0.090	0.090	0.296
333618	0.273	0.101	0.101	0.238
333911	0.334	0.128	0.128	0.151
333912	0.327	0.130	0.130	0.147
333913	0.332	0.119	0.119	0.170
333921	0.338	0.384	0.384	0.016
333922	0.338	0.183	0.183	0.078
333923	0.338	0.122	0.122	0.163
333924	0.349	0.114	0.114	0.188
333991	0.293	0.092	0.092	0.287
333992	0.333	0.133	0.133	0.142
333993	0.319	0.203	0.203	0.060
333994	0.360	0.143	0.143	0.123
333995	0.261	0.173	0.173	0.088
333996	0.332	0.114	0.114	0.187
333997	0.418	0.121	0.121	0.164
333999	0.305	0.158	0.158	0.102
334111	0.341	0.161	0.161	0.099
334112	0.347	0.103	0.103	0.226
334119	0.341	0.094	0.094	0.271
334210	0.308	0.097	0.097	0.254
334220	0.298	0.103	0.103	0.227
334290	0.343	0.109	0.109	0.206
334310	0.311	0.105	0.105	0.219
334411	0.343	0.141	0.141	0.126
334412	0.316	0.088	0.088	0.320
334413	0.339	0.092	0.092	0.285
334414	0.287	0.089	0.089	0.309
334415	0.311	0.091	0.091	0.290
334416	0.322	0.086	0.086	0.344
334417	0.309	0.091	0.091	0.294
334418	0.344	0.100	0.100	0.238
334419	0.336	0.094	0.094	0.271
334510	0.330	0.104	0.104	0.224
334511	0.350	0.147	0.147	0.118
334512	0.340	0.103	0.103	0.228
334513	0.393	0.113	0.113	0.191
334514	0.461	0.212	0.212	0.055

	Data		Model	
NAICS	Spread	HH	HH	δ_s
334515	0.371	0.098	0.098	0.250
334516	0.376	0.108	0.108	0.209
334517	0.333	0.127	0.127	0.153
334518	0.568	0.189	0.189	0.072
334519	0.407	0.129	0.129	0.149
334612	0.438	0.122	0.122	0.163
334613	0.677	0.094	0.095	0.267
335110	0.230	0.095	0.095	0.265
335121	0.357	0.104	0.104	0.223
335129	0.360	0.107	0.107	0.213
335211	0.359	0.130	0.130	0.147
335212	0.331	0.161	0.161	0.100
335221	0.384	0.113	0.113	0.191
335222	0.331	0.152	0.152	0.110
335224	0.328	0.175	0.175	0.086
335228	0.356	0.279	0.279	0.032
335311	0.329	0.159	0.159	0.102
335312	0.336	0.125	0.125	0.157
335313	0.307	0.114	0.114	0.188
335314	0.359	0.094	0.094	0.272
335911	0.356	0.097	0.097	0.255
335912	0.308	0.097	0.097	0.252
335921	0.591	0.148	0.148	0.115
335929	0.322	0.098	0.098	0.249
335931	0.311	0.088	0.088	0.315
335991	0.371	0.098	0.098	0.251
335999	0.314	0.106	0.106	0.215
336111	0.075	0.105	0.105	0.218
336120	0.151	0.651	0.652	0.010
336211	0.106	0.253	0.253	0.040
336212	0.432	1.000	1.000	0.010
336214	0.178	0.372	0.372	0.017
33631X	0.266	0.171	0.171	0.089
336321	0.323	0.111	0.112	0.196
336322	0.301	0.088	0.088	0.314
336330	0.112	0.109	0.109	0.206
336340	0.180	0.114	0.114	0.189
336350	0.157	0.096	0.096	0.257
336360	0.312	0.091	0.091	0.291
336391	0.333	0.087	0.087	0.327
336399	0.248	0.133	0.133	0.142
336411	0.301	0.569	0.569	0.010
336412	0.312	0.733	0.733	0.010
336413	0.281	0.269	0.269	0.035
336415	0.330	0.611	0.611	0.010

	Data		Model	
NAICS	Spread	HH	HH	δ_s
336419	0.138	0.169	0.169	0.092
336510	0.340	0.393	0.393	0.015
336611	0.061	0.765	0.765	0.010
336612	0.302	0.532	0.532	0.010
336991	0.174	0.116	0.116	0.182
336992	0.350	1.000	1.000	0.010
337110	0.338	0.156	0.156	0.104
337121	0.380	0.091	0.091	0.291
337124	0.427	0.093	0.093	0.277
337127	0.424	0.110	0.110	0.200
337129	0.175	0.134	0.134	0.140
337211	0.386	0.252	0.252	0.040
337214	0.414	0.094	0.094	0.272
337215	0.465	0.122	0.122	0.162
337910	0.380	0.201	0.201	0.062
337920	0.482	0.107	0.107	0.211
339112	0.453	0.100	0.100	0.242
339113	0.352	0.115	0.115	0.185
339114	0.331	0.090	0.090	0.299
339115	0.395	0.087	0.087	0.330
339911	0.706	0.097	0.097	0.252
339912	0.447	0.108	0.108	0.207
339913	0.139	0.144	0.144	0.121
339914	0.702	0.101	0.101	0.234
339920	0.339	0.162	0.162	0.098
339931	0.663	0.103	0.103	0.230
339932	0.508	0.110	0.110	0.201
339941	0.453	0.088	0.089	0.312
339942	0.280	0.114	0.114	0.187
339943	0.551	0.088	0.088	0.320
339944	0.335	0.097	0.097	0.255
339950	0.456	0.084	0.084	0.400
339991	0.292	0.088	0.088	0.321
339992	0.350	0.127	0.127	0.153
339993	0.350	0.092	0.092	0.282
339994	0.311	0.093	0.093	0.277
339999	0.447	0.121	0.121	0.166
910000	0.057	0.282	0.282	0.031
920000	0.120	0.140	0.140	0.129
980000	0.000	0.100	0.100	0.239
990000	0.207	0.185	0.185	0.076

Figure A.1: Import Response to a Mean-preserving Uncertainty Spread

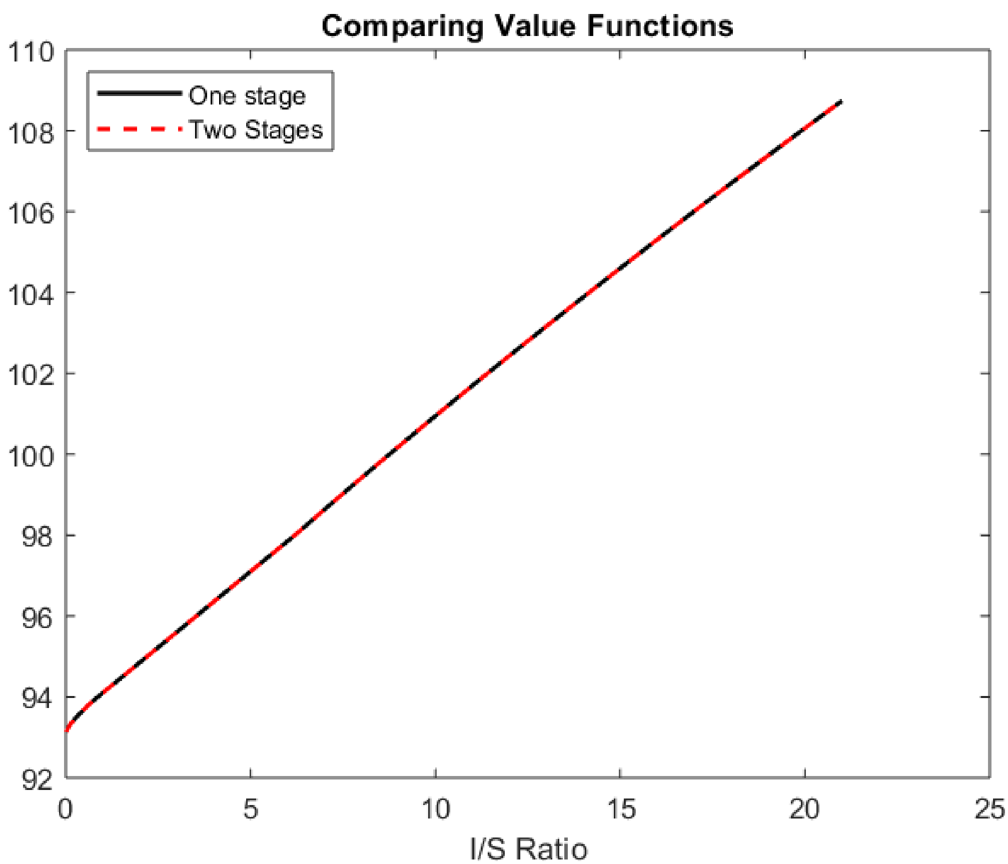


Figure A.2: Total Annual Imports