

## ABSTRACT

Title of dissertation: TRADE POLICY SHOCKS, U.S. IMPORTS AND CONSUMER PRICES

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How do trade policy shocks affect import and consumer prices? How does the impact on prices vary across consumers? Answers to these questions would help us better understand the transmission mechanism of trade policy shock and its implications for consumer welfare.

In my dissertation, I provide both theoretical and empirical evidence to these questions.<sup>1</sup> The first chapter examines the pass-through of import prices into consumer prices and the welfare implications of trade policy shocks. Using a novel dataset with both US import prices and barcode-level consumer prices, I find that the pass-through of import prices to consumer prices is incomplete: a 1% increase in import prices leads to a 0.3 to 0.4% increase in consumer prices. To explain these findings, I build on Burstein and Gopinath (2014) to model the retail margin with variable markups. I show that the pass-through rate depends on the magnitude of distribution margin and the markup elasticity.

In the second chapter, I extend the theoretical framework to explore the heterogeneity in pass-through rates across consumers. I show that a differential pass-through arises through two channels. The first one captures the fact that the pass-through rate varies across retail outlets for the same variety and the second channel focuses on the different expenditure shares across varieties with heterogeneous pass-through

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<sup>1</sup>The conclusions drawn from the Nielsen data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

rates. Exploiting the rich demographic information in Nielsen barcode data, I find that the pass-through rate is higher for consumers with lower income and in markets with higher retail industry competition. By decomposing the consumer-specific price index, I show that the differential pass-through rates are largely driven by the differences in expenditure shares across varieties.

I then conduct a quantitative exercise and show that the consumer prices of affected goods would increase 1-2% on average in response to a 25% tariff on consumer goods from China. The increases in prices are 50% higher for lower income and higher for consumers living in big cities of the Northeast region and West Coast.

The final chapter investigates the effect of trade policy uncertainty on US imports from China during the trade war episode. By comparing the differences in imports before and after the announcement of tariffs across products, I find that the decline in imports after tariff announcement is larger for products with larger increase in uncertainty (risk), which suggests uncertainty reduces imports. Furthermore, I find the intensive margin, the adjustment within HS10 products, plays a more important role in reducing imports. There is no significant difference in entry and exit rate across products with different changes in risk.

TRADE POLICY SHOCKS, U.S. IMPORTS AND  
CONSUMER PRICES

by

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# Chapter 1

## Import Price Pass-through into Consumers: Theory and Estimation

### 1.1 Introduction

In the past decades, trade barriers have continued to decrease all over the world, thus bringing gains to consumers through lower prices and more varieties. However, in recent years, we have witnessed a reversal of trade policy, through both higher import tariffs and higher policy uncertainty. How do these trade policy shocks affect consumer prices? In particular, how do import price changes caused by such shocks pass on to consumers? Does the import price pass-through vary across consumers, thus generating additional distributional effects? Answering these questions would help us better understand the welfare implications and the distribution consequences of trade policy shocks. The existing literature has paid little attention to tariff pass-

through, possibly due to the lack of variation in tariffs in the past years.<sup>1</sup> However, as the trade barriers increase dramatically in the recent trade war, an emerging literature examines the tariff pass-through into import prices. For example, Amiti et al (2019) and Khandelwal et al (2019) both find that the pass-through of tariffs into import prices at the border is complete, at least in the short-run.<sup>2</sup> However, we do not know how much of that increase in prices at the border is passed through to the prices the consumers pay at retail outlets and its welfare implications for consumers.

Using a unique dataset that links detailed US import prices with barcode-level consumer prices, I address the question by estimating the pass-through from import to consumer prices during the Great Trade Collapse (GTC). I find that the import price pass-through to consumer prices is incomplete: a 1% increase in import prices would lead to a 0.3 to 0.4% increase in consumer prices. In addition, the pass-through rate is increasing in the import penetration of the industry.

A key challenge in identifying the import price pass-through is the endogeneity of import prices. To address this problem, I exploit the exogenous variation in changes in trade policy uncertainty (TPU) across industries during the GTC. I show that the changes in TPU affected import prices across industries and thus can be used as an instrument for changes in import prices to identify the pass-through rate.

To explain the empirical findings, I develop a theoretical framework linking import prices and consumer prices following Burstein and Gopinath (2014). The framework features nontradable distribution margin and variable markups in the retail/wholesale sector, both of which could lead to incomplete pass-through. Specifically, the pass-through rate of import prices depends on: 1) the distribution margin, as prices of non-

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<sup>1</sup>One exception is Feenstra (1989), in which he estimated the pass-through of tariffs to prices of Japanese automobiles in 1980s. Other relevant studies mostly focus on how the decline in input tariffs affected manufacturing or export prices (Khandelwal et al (2016); Amiti et al (2018)) during the trade liberalization episodes.

<sup>2</sup>It is a surprising result given that the existing literature has documented incomplete pass-through of exchange rate shocks. It is also inconsistent with the estimated export supply elasticity in Broda, Weinstein and Limão (2008), which implies incomplete tariff pass-through.

tradable goods are insensitive to price shocks at the border; 2) the markup elasticity, which captures how retailers adjust their markups when facing a cost shock.

## 1.2 Literature

This paper contributes to the literature that examines the tariff or exchange-rate pass-through. Most of the existing literature focuses on how exchange rate shocks affect import prices and consumer prices. As reviewed by Burstein and Gopinath (2014), they find that the exchange rate pass-through is incomplete and the pass-through into consumer prices is well below that into border prices.<sup>3</sup> For tariff pass-through, dating back to 1980s, Feenstra (1989) finds the symmetry of exchange rate and tariff pass-through in the automobiles industry and shows that the tariff pass-through ranges from 0.6 to unity depending on the products. Other studies mostly focus on how the decline in trade barriers in trade liberalization episodes have affected prices (Amiti et al (2018); Jaravel and Sager (2019); Bai and Stumpner (2019)). For example, Jaravel and Sager (2019) find that the increased import penetration from China leads to a decline in consumer prices in the US, mostly due to the strategic complementarity of pricing decisions of domestic firms. In a similar study, Bai and Stumpner (2019) find that the imports from China decreased US consumer prices through lower prices of existing varieties and product entry. Using a similar dataset as the latter, I instead focus on transmission of import prices to consumers thus have more general implication on how trade shock affected consumer prices.

An emerging line of research starts to examine the price effect of US import tariffs during the recent trade war (Amiti et al (2019); Fajgelbaum et al (2019)). They find that the import tariffs are completely passed through into prices paid by US importers, at least in the short run. The results are at odds with previous findings of

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<sup>3</sup>For the US, they find that the pass-through is at least twice as high into border prices as it is into retail prices.

incomplete pass-through but also raise the question of how much of increases in prices at the border would pass through to the prices at the retail outlets. This paper addresses the question by estimating the import price pass-through into consumer prices using detailed price information. Contemporary to my work, two papers examine the pass-through of US tariffs to consumer prices. Flaaen, Hortacsu and Tintelnot (2019) estimate the price effect of US import tariffs on a specific consumer good: washing machines. They find that the pass-through of tariffs to consumer prices is negative for country-specific duties as multinationals shifted productions to tariff-free countries. However, the tariff elasticity is larger than one for 2018 tariffs that are imposed on all sourcing countries, mostly driven by the strategic pricing behavior by competing domestic firms. In another paper, Cavallo et al (2019) estimate the increase in prices both at the border and at the retail outlet using BLS data. Consistent with my finding, they find the retail price response to tariffs is small. By exploring the heterogeneous pass-through across consumers, this paper is closely related to Cravino and Levchenko (2017), which study the distributional effect of large exchange rate devaluations on consumers at different income levels. Following their work, this paper also explores how the differences in distribution margin shape the distributional effects across consumers. However, I allow for variable markups, which is an additional margin that would cause distributional effects.

This paper also is related to recent studies on trade policy uncertainty. Handley and Limão (2017) examine the effect of TPU on imports and import prices from China during its accession to WTO. They find that the decreased TPU led to export entry and technology upgrading of existing exporters, thus pushing down the import prices from China. Carballo et al (2018) focus on the increase in TPU during the Great Trade Collapse and its effect on export dynamics. Following their work, I explore the relationship between TPU and import prices during the GTC and use it as the basis of my empirical strategy.

### 1.3 Theoretical Framework

To examine how the changes in import prices are transmitted to consumer prices, I first develop a theoretical framework linking import prices and consumer prices following Burstein and Gopinath (2014). In this step, I derive a theoretically consistent import price pass-through into consumer prices by focusing on price changes of varieties that exist in both periods.

Suppose there is a retail/wholesale sector that distribute varieties from the port to the destination location. The retail price of variety  $v$  at time  $t$  is given by<sup>4</sup>

$$p_{vt}^r = (p_{vt}^T)^{(1-\eta_v)} (p_t^N)^{\eta_v} \underbrace{\gamma_{vt}}_{markup} = c_{vt} \gamma_{vt}(c_{vt}; \xi_{vt}) \quad (1.1)$$

where  $p_{vt}^T$  is the price of variety  $v$  at the dock. If it is a domestic variety, it presents the price at the factory gate. The retailer combines the good with distribution services in a Cobb-Douglas way with  $\eta_v$  represents the cost share of distribution service. Distribution service includes domestic transportation cost, marketing cost that uses the non-tradable goods and its price is  $p_t^N$ . We call  $\eta_v$  the distribution margin of variety  $v$  and assume non-tradable price  $p_t^N$  is not responsive to price shocks at the border. The retailer then charges a markup  $\gamma_{vt}$  over its marginal cost  $c_{vt}$ . We allow retailers to charge variable markups, which depends on its marginal cost and a demand parameter  $\xi_{vt}$ .<sup>5</sup>

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<sup>4</sup>A variety can be any disaggregated good within a product category. In my empirical analysis, a variety is defined at the barcode level.

<sup>5</sup>Burstein and Gopinath (2015) and Arkolakis (2017) review several models that would lead to variable markup including non-CES demand such as Kimball demand and oligoplistic competition as in Atkenson and Burnstein (2008). The idea is that heterogeneous firms would charge variable markups as elasticity of demand varies across firms. As shown in Arkolakis (2017) and Amiti et al (2018), firm's markup and cost pass-through depend on the relative price of the firm or the price vector the firm faces.

Re-writing equation (1.1) in logs:

$$\ln p_{vt}^r = (1 - \eta_v) \ln p_{vt}^T + \eta_v \ln p_t^N + \ln \gamma_{vt}(c_{vt}; \xi_{vt}) \quad (1.2)$$

We define variety pass-through as  $\rho_v = \frac{\partial \ln p_{vt}^r}{\partial \ln p_{vt}^T}$ , which captures how price shocks at the border transmit to consumer prices of the same variety.<sup>6</sup> It is straightforward to see that:

$$\rho_v = \frac{\partial \ln p_{vt}^r}{\partial \ln p_{vt}^T} = (1 - \eta_v)(1 - \theta_v) \quad (1.3)$$

where  $\theta_v = -\frac{\partial \ln \gamma_{vt}}{\partial \ln c_{vt}}$ , and we call it markup elasticity. Markup elasticity represents how variety's markup respond to cost shock. In the case of CES with monopolist competition, markup is constant and markup elasticity equals to zero. Thus the variety pass-through only depends on the distribution margin. In other scenario, when retailers engage in oligopolistic competition or face non-CES demand, markup elasticity could be positive as retailers absorb part of the cost.

As equation (1.3) makes clear, variety pass-through can be incomplete (less than one) due to the existence of distribution margin and variable markups. Because the prices of non-tradable goods are insensitive to import price shocks, the higher the distribution margin, the lower the pass-through. As markup elasticity captures how the markup responds to cost shock, the higher the markup elasticity, retailers absorb more of the cost shock, which in term results in lower pass-through.

As we cannot track the same variety from border to retail outlet, we aggregate price changes at variety level to product category level. For the purpose of deriving pass-through, we use varieties that exist in both periods. Log changes in consumer prices of product category  $g$  at time  $t$  is defined as:

$$\Delta \ln P_{gt}^R = \sum_{v \in g} w_{vt} \Delta \ln p_{vt}^r \quad (1.4)$$

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<sup>6</sup>For simplicity, we assume it does not vary over time.



The weight  $w_{vt}$  is the expenditure share of each variety  $v$ , which can be fixed or vary over time depending on how we define price index. For example, official CPI use fixed weights, so  $w_{vt} = w_v$ . Sato-vartia weights vary over time because they take into account the substitution effect in response to price change.

Note that the changes in retail price of variety  $v$  can be written as a function of variety pass-through and changes in import price/factory-gate price of variety  $v$ :

$$\Delta \ln p_{vt}^r = \rho_v \Delta \ln p_{vt}^T + \eta_v(1 + \theta_v) \Delta \ln p_t^N \quad (1.5)$$

Combining equation (1.9) and equation (1.5), we re-write consumer prices of product category  $g$ :

$$\Delta \ln P_{gt}^R = \sum_{v \in g} w_{vt} \rho_v \Delta \ln p_{vt}^T + \Delta \ln p_t^N \sum_{v \in g} w_{vt} \eta_v (1 + \theta_v) \quad (1.6)$$

By distinguishing between imported goods and domestic goods, I have:

$$\Delta \ln P_{gt}^R = \underbrace{s_{gt}^I \rho_g^I \sum_{v \in g} w_{vt}^I \Delta \ln p_{vt}^{T,I}}_{\text{imported}} + \underbrace{(1 - s_{gt}^I) \rho_g^D \sum_{v \in g} w_{vt}^D \Delta \ln p_{vt}^{T,D}}_{\text{domestic}} + \tilde{\delta} \Delta \ln p_t^N \quad (1.7)$$

where  $\tilde{\delta} = \sum w_{vt} \eta_v (1 + \theta_v)$ . Here I assume the variety pass-through is the same across imported (domestic) varieties in product category  $g$ .  $s_{gt}^I$  is the expenditure share on imported goods in product category  $g$ , whereas  $w_{vt}^I$  and  $w_{vt}^D$  are the expenditure share of a variety  $v$  within imported goods and domestic goods separately.

Define import price index of product  $g$  as  $\Delta \ln P_{gt}^I = \sum_{v \in g} w_{vt}^I \Delta \ln p_{vt}^{T,I}$ . Here I assume the same weight in consumption basket and in imported bundle, which is reasonable given the goods we focus on are mostly final goods. Similarly, I define domestic price index of product  $g$  as:  $\Delta \ln P_{gt}^D = \sum_{v \in g} w_{vt}^D \Delta \ln p_{vt}^{T,D}$ . I can rewrite the

above equation (1.7) as:

$$\Delta \ln P_{gt}^R = s_{gt}^I \rho_g^I \Delta \ln P_{gt}^I + (1 - s_{gt}^I) \rho_g^D \Delta \ln P_{gt}^D + \tilde{\delta} \Delta \ln p_t^N \quad (1.8)$$

I define import price pass-through at product category level as the changes in consumer prices in response to changes in import prices of the same product category. As we can see in equation (1.8), the pass-through into consumer prices depends on the interaction of the import share  $s_{gt}^I$  and variety pass-through  $\rho_g^I$ . The latter one is a function of distribution margin and markup elasticity. In addition, the changes in domestic price  $\Delta \ln P_{gt}^D$  might be a function of changes in import prices for two reasons: first, the strategic complementarities in pricing decisions of domestic and foreign exporters (Feenstra and Weinstein(2017); Amiti, Itskhoki and Konings(2018)); second, the use of imported intermediates in production of domestic goods. To fully account for the response of consumer prices, we might need to take into account both the direct effect of import prices and the indirect effect through domestic prices. Next, I discuss how I take equation (1.8) into data.

## 1.4 Empirical Analysis

### 1.4.1 Data and Measurement

To estimate the import price pass-through to consumer prices, I use a merged dataset from two data sources. The first one is the US quarterly import data during 2004Q1-2011Q4, which is available through US Census Bureau. This dataset contains customs value (CIF), quantity and unit value for each HS10-country combination. Our sample has 68 exporting countries, which include all US major trading partners and account for over 80% of total imports into the US.

The second dataset is the Consumer Panel from AC Nielsen company during

the same period and is available through Kilts marketing center of University of Chicago. Nielsen Consumer Panel (Nielsen data hereafter) contains transaction-level information such as price, quantities on barcoded goods from a representative sample of households in the US. In addition, it includes detailed household demographic and geographic information such as household income, size, zip-code etc. The products in Nielsen data are mostly consumer packaged goods, which account for about 30% of all expenditures on goods in CPI (Broda and Weinstein, 2010).

To merge the two datasets, I use a concordance developed by Bai and Stumpner (2018) which matches HS-6 digits in trade data with product codes (“product module”) in Nielsen data. The concordance covers 1175 HS6-digit codes and 1246 product modules, generating 359 new product categories.<sup>7</sup> The matched HS6s accounts for approximately 20% of total import value and mostly are final goods imports.

In addition, I obtain industrial PPI at NAICS level from two data sources. The first one is NBER-CES database, which is reported yearly, while the second one is quarterly-based PPI from BLS.

I calculate consumer price index for each product category using information in Nielsen data. The consumer price index is defined as a weighted average of price changes of continuing varieties:

$$\Delta \ln P_{gt}^R = \sum_{v \in g} w_{v0} \Delta \ln p_{vt}^r \quad (1.9)$$

where a variety is defined as a barcode (UPC). The price changes are calculated as the difference of (log) unit value at time  $t$  relative to that in the corresponding quarter of 2004. I use the expenditure share at base periods as weight. The calculated quarterly price index co-moves well with CPI, in particular, the food component of CPI as presented in Appendix Figure 1.A.1.

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<sup>7</sup>For example, the new product category “plain pasta” include 10 product modules ranging from Spaghetti to Lasagna, and 2 HS6s which are “unstuffed pasta that made with or without eggs”.

Import price index is calculated for the same product category using detailed import data, with a variety defined as a HS10-country. As the variety is more aggregated in import data than in the Nielsen data, I assume:  $\Delta \ln p_{Vt}^{T,I} = \sum_{v \in V} w_{v0}^V \Delta \ln p_{vt}^T$ . That is, the import price of a HS10-country combination  $V$  is the weighted average of the import prices at (unobserved) barcode-equivalent level ( $v$ ).

**Table 1.1:** Summary Statistics of Import and Consumer Prices

	Pre-Crisis	Crisis	Overall
Changes in Consumer Prices ( $\Delta \ln P_{gt}^R$ )	0.044 [0.117]	0.146 [0.173]	0.090 [0.154]
Changes in Import Prices ( $\Delta \ln p_{gt}^I$ )	0.057 [0.580]	0.224 [0.655]	0.133 [0.621]
Observations	3,577	2,971	6,548

Notes: Standard deviations are reported in the bracket. The Pre-Crisis period is defined as 2005Q1-2008Q3 and the Crisis period is defined as 2008Q4-2011Q4. All prices changes are relative to the corresponding quarter of 2004.

Table 3.3 reports the summary statistics of changes in import prices and consumer prices during the sample period. Column 1 is for pre-crisis period (2005Q1-2008Q3) and column 2 is for crisis period (2008Q4-2011Q4). As we see, both import and consumer prices increases during this period and the increase is larger during the crisis period. In addition, the import prices exhibit more variation than consumer prices.

## 1.4.2 Identification Strategy

Equipped with price indices, I take equation (1.8) into data by estimating the following equation:

$$\Delta \ln P_{gt}^R = \alpha + \beta \Delta \ln P_{gt}^I + \gamma \Delta \ln P_{gt}^D + \delta_t + \epsilon_{gt} \quad (1.10)$$

where  $\Delta \ln P_{gt}^R$  and  $\Delta \ln P_{gt}^I$  are changes in consumer prices and import prices of product category  $g$  respectively. I control for changes in domestic prices using US

industrial PPI. In doing so, I build a concordance between 359 product categories and 262 NAICS 6-digit industries.<sup>8</sup> I add time fixed effects to capture the changes in prices of non-tradable goods and other macro economic shocks that could affect all products equally. Because all price indices are calculated as price changes, the product fixed effects are differenced out.

One key challenge to identify the pass-through is the endogeneity of import prices. For example, a product-level demand shock would drive both import and consumer prices into the same direction, thus overestimating the effect. It is also possible that protectionism movement, that was prevalent during this period and can be product-specific, could cause import prices and consumer prices to change in opposite direction. In addition, the import prices could potentially have measurement error as we don't have barcode-level import prices, then the OLS estimate is subject to attenuation bias.

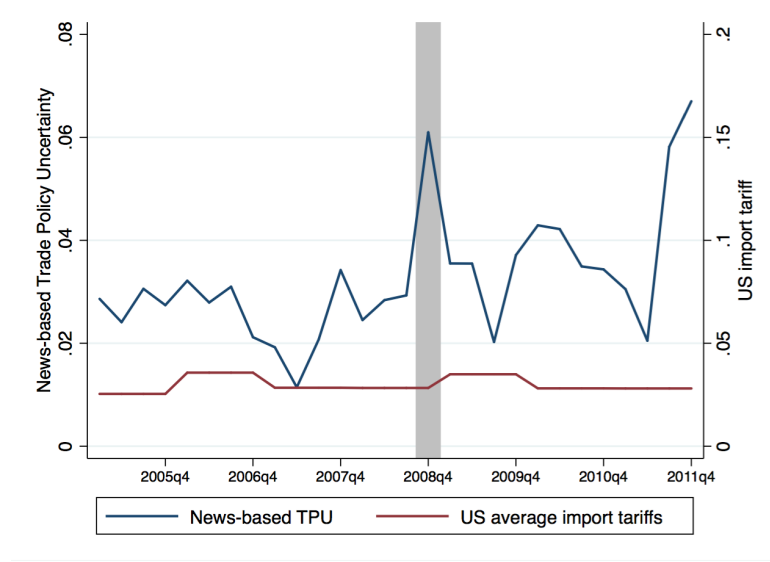
The event of Great Trade Collapse (GTC) provides us a unique setting to identify the import price pass-through as it generates exogeneous variations in import prices. During the 2008 financial crisis, as the economic condition worsened, there was widespread discussion of a possible trade war (Carballo et al, 2018). Though eventually the trade war didn't happen, it caused substantial increase in trade policy uncertainty during this period. Figure 1 plots the news-based trade policy uncertainty index constructed by Carballo et al (2018) and the average applied tariffs during this period. As we see, though the applied tariffs barely change, trade policy uncertainty increased substantially, especially in 2008Q4.

More importantly, the increases in TPU cause variations in import prices across industries. Recent studies, for example Handley and Limão (2017), have found that the import prices decreased more in industries with a larger decline in TPU during China's accession to WTO. Following their work, I show that an increase in TPU

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<sup>8</sup>I first use the concordance between NAICS6 and HS6 by Pierce and Schott(2009) and then link HS6 with product categories.

**Figure 1.1:** US Import Tariffs and Trade Policy Uncertainty



Notes: The news-based TPU index is constructed by Carballo et al (2018) and represents the mentions of “uncertainty” or “uncertain” in the set of articles about international trade or trade policy in major US newspapers. The US average imported tariffs are calculated as the weighted average of applied MFN tariffs.

during the GTC has led to lower import prices by exploiting variations in TPU across industries. More specifically, using US quarterly import data from 2004Q1-2011Q4, I find that the lower import prices are mainly driven by the lower prices of continuing varieties in industries that experience a larger increase in TPU. The results are reported in Appendix B.

More specifically, the different risk faced by each industry is measured by the gap between MFN tariffs and column-2 tariffs following Handley and Limão(2017). The basic idea is that in the case of trade war, the U.S. might switch to non-cooperative tariffs, which are product-specific and can be proxied by column-2 tariffs.<sup>9</sup> Moreover, as column-2 tariffs are set in Smoot-Hawley Act of 1930, the resulting risk measure is exogenous to other product-level shocks during the financial crisis. Therefore, the downward risk faced by industry  $i$  is measured as:

<sup>9</sup>Broda, Weinstein and Limão (2008) show the relationship between optimal non-cooperative tariffs and column-2 tariffs are positive.

$$Risk_i = 1 - \left(\frac{\tau_2^i}{\tau_m^i}\right)^{-\sigma} \quad (1.11)$$

where  $\tau_2^i$  and  $\tau_m^i$  are column 2 and MFN tariff rate for industry  $i$  respectively.<sup>10</sup> The downward risk is therefore measuring the proportion of profit loss if the worst-case tariffs (column-2) realize.

The arrival of financial crisis in 2008 indicates an increase in uncertainty, in particular, an increase in the probability of switching to non-cooperative tariffs (column-2). Thus the uncertainty shock could be measured by either a crisis dummy, which equals to one during 2008Q4-2011Q4 and zero otherwise, or a time-varying news index, which captures the overall sentiment of trade policy uncertainty over time. As shown in Figure 1, the quarterly news-based TPU index increased from an average of 0.026 before the crisis to 0.040 during the crisis. Especially, it shows a three-fold increase from 2008Q3 to 2008Q4, when the crisis just began. I therefore use the interaction between industrial risk level ( $Risk_i$ ) and the time-varying uncertainty measure ( $Crisis_t$  or  $News_t$ ) as the instrument for changes in import prices.

Due to similar reasons, the changes in domestic prices are endogenous as well. I instrument industrial PPI with one plausibly exogenous cost shock: the changes in energy prices. To do so, I interact the prices of five major energy sources with their corresponding cost shares in each industry.<sup>11</sup> Their annual price information is obtained through SEDS (State Energy Data System) of EIA. I use the average prices per BTU across the US to avoid any endogeneity issue. The expenditures data is available through Manufacturing Energy Consumption Survey (MECS), which reports each manufacturing industry's expenditures (in Million US dollars) on these five sources of energy every 4 years. I use the data from 2006.

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<sup>10</sup>In the baseline, the column 2 and MFN tariff rates for each industry are calculated as the simple average of HS8-level tariff rates. The elasticity of substitution  $\sigma$  takes the value of 3 following Handley and Limão(2017). In the robustness check, I try alternative risk measures including  $\ln\left(\frac{\tau_2^i}{\tau_m^i}\right)$ . The results are reported in the Appendix C.

<sup>11</sup>The five major energy includes: electricity, natural gas, residual fuel oil, distillate fuel and coal.

### 1.4.3 Estimation Results

**Table 1.2:** Import-Consumer Price Pass-through

	(1)	(2)	(3)
	OLS	IV	IV
Changes in Import Prices	0.014*** (0.003)	0.366*** (0.097)	0.338*** (0.088)
Industrial PPI	0.180*** (0.014)	0.524*** (0.107)	0.486*** (0.078)
Instrument		TPU× Crisis	TPU× News
First Stage F-Statistics		8.30	7.98
Time FE	Yes	Yes	Yes
N	5819	5635	5635

Notes: \*\*\*p<0.001, \*\*p<0.005, \*p<0.01. In both IV regressions, I instrument industrial PPI with changes in energy prices. The Cragg-Donald F statistics is 8.30 for column 2, which exceeds Stock and Yogo (2005) critical value of 7.03 (10% significance level) for two endogenous variables and two instruments. The Cragg-Donald F statistics is 7.98 for column 3.

Table 1.2 reports the results from the OLS and IV estimations. As we can see in Column 1, the OLS estimate is significant but small. However, after we instrument changes in import prices and domestic prices, the magnitude of coefficient increases substantially. Based on our IV estimates, the pass-through is between 0.3-0.4, suggesting that a one percent increase in import prices will lead to a 0.3 to 0.4 percent increase in consumer prices.<sup>12</sup> The first stage results are reported in Appendix Table 1.A.1.

In the baseline, I present the results using PPI from NBER-CES database. I do robustness check using BLS PPI and the results are reported in Appendix Table ???. To address the concern that there might be product-specific trend in prices, I control for department fixed effects in the robustness check. The results are similar and reported in Appendix Table 1.A.3.

<sup>12</sup>As reviewed by Gopinath and Burnstein(2015), the exchange rate pass-through at least twice as high into border prices as it is into retail prices for the U.S..



### 1.4.4 Accounting for Domestic Prices

As we discussed before, the domestic prices could potentially respond to import price changes due to two reasons: strategic complementarity and changes in production cost, i.e, the use of imported inputs in producing domestic goods. To fully capture the changes in consumer prices in response to import price changes, I take into account the indirect effect through domestic prices. To do so, I estimate the changes in domestic prices that are caused by import price shock and combine it with the domestic price pass-through we estimate to compute the overall effect.

**Table 1.3:** Response of Domestic Prices to Import Price Changes

	NBER-CES		BLS	
	(1)	(2)	(3)	(4)
Changes in Import Prices	1.391*	1.722**	1.760*	1.835**
	(0.574)	(0.600)	(0.768)	(0.662)
Instrument	TPU× Crisis	TPU× News	TPU× Crisis	TPU× News
First-Stage F Statistics	7.58	8.96	8.32	10.47
Time FE	Yes	Yes	Yes	Yes
N	5750	5750	5771	5771

Notes: \*\*\*p<0.001, \*\*p<0.005, \*p<0.01. The first two columns use NBER-CES PPI whereas the last two columns use BLS PPI.

Table 1.3 reports the estimation results for two PPI measures. As before, I instrument import prices with changes in TPU to address the endogeneity issue. The pass-through from import prices to domestic PPI is estimated to be roughly 1.4 after instrument and for PPI from NBER-CES database (column 1), which indicates that 1 percentage point increase in import prices cause about 1.4 percentage point increase in domestic prices. The large response of domestic prices is consistent with findings in the literature (e.g., Jaravel and Sager (2019); Flaaen, Hortacsu and Tintelnot (2019)), which suggest that competition between import and domestic goods drives the changes in domestic prices. As we mostly focus on final goods, the competition

effect might play a more important role as well.<sup>13</sup>

Combining it with our estimates of pass-through in Table 1.2, a one percentage point increase in import prices could lead to a 0.73 percentage point ( $1.39 \times 0.528$ ) increase in consumer prices through its indirect effect on domestic prices, which is even larger in magnitude compared with the direct effect of import prices.

Overall, when taking into account both direct and indirect effect, one percent increase in import prices would cause the consumer prices of the same product category to increase about 1.1 percentage point. Using estimates for BLS PPI (column 3) gives us similar results.

## 1.5 Conclusion

This chapter examines how did the changes in import prices caused by trade policy shock transmit to consumers during the GTC. I develop a theoretical framework linking import prices and consumer prices following Burstein and Gopinath (2014). The incomplete pass-through could arise both from the non-tradable distribution margin and variable markups in distribution sector. By exploiting the exogenous variations in trade policy uncertainty across industries, I estimate that the import price pass-through ranges from 0.3 to 0.4 after using changes in TPU as an instrument for import prices. Consistent with theoretical prediction, the pass-through rate is increasing in industrial import penetration. Lastly, I show that the import prices could have an indirect effect on consumer prices through its impact on domestic prices. Accounting for this channel, a one percentage point increase in import prices could lead to about a 1.1 percentage point increase in consumer prices.

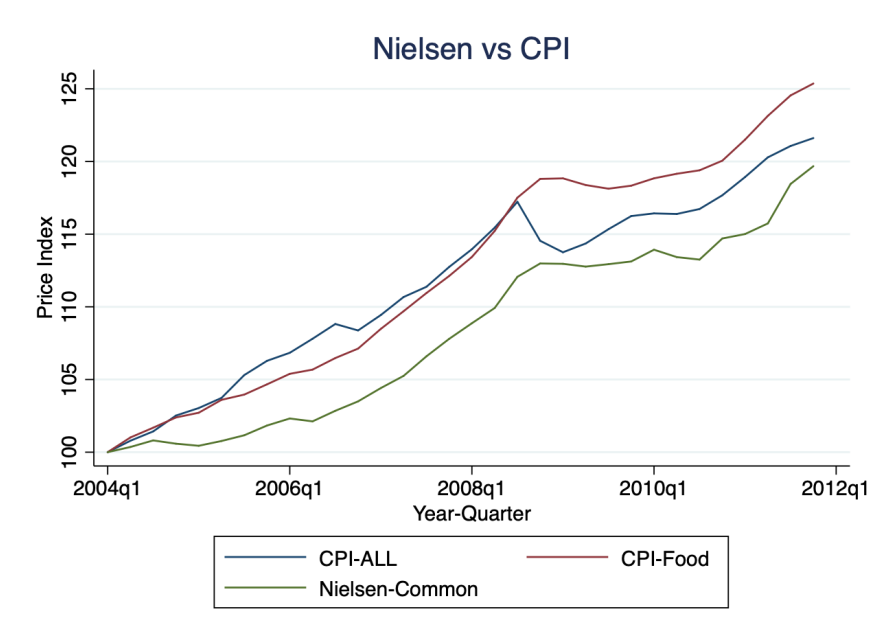
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<sup>13</sup>Of the 359 product categories, only 34 of them contain intermediates according to BEC. One example is “plumbing accessories” which belongs to the household supplies category. Those are goods that are mostly used as intermediates, but also can be directly consumed by consumers.

# Appendix

## 1.A Additional Figures and Tables

Figure 1.A.1: Nielsen Consumer Prices vs CPI



Notes: The CPI price indices are obtained from FRED database and have a base period of 2004Q1.

## 1.B TPU and Import Prices

In this section, I examine the effect of trade policy uncertainty (TPU) shock on import prices during the GTC. Recent literature documents that TPU affected imports and import prices. In particular, Handley and Limão (2017) show that the import prices

**Table 1.A.1:** Import Price Pass-through: First Stage

	Changes in Import Prices		PPI	
	(1)	(2)	(3)	(4)
TPU× Crisis	-0.167** (0.059)		-0.214*** (0.022)	
TPU× News		-3.508** (1.075)		-5.558*** (0.409)
Energe Prices(log)	0.100*** (0.029)	0.096** (0.029)	0.020*** (0.004)	0.013** (0.004)
F-Statistics	11.70	13.63	55.27	92.78
N	5834	5834	5992	5992
R-Squared	0.033	0.033	0.187	0.202

Notes: \*\*\*p&lt;0.001, \*\*p&lt;0.005, \*p&lt;0.01.

**Table 1.A.2:** Import-Consumer Price Pass-through: BLS PPI

	(1)	(2)	(3)
	OLS	IV	IV
Changes in Import Prices	0.007** (0.002)	0.563*** (0.168)	0.584*** (0.155)
Industrial PPI	0.076*** (0.011)	0.300** (0.096)	0.311*** (0.086)
Instrument		TPU× Crisis	TPU× News
First-Stage F Statistics		7.18	7.83
Time FE	Yes	Yes	Yes
N	5841	5629	5629

Notes: \*\*\*p&lt;0.001, \*\*p&lt;0.005, \*p&lt;0.01.

**Table 1.A.3:** Import-Consumer Price Pass-through: Department FE

	(1)	(2)	(3)
	OLS	IV	IV
Changes in Import Prices	0.013*** (0.004)	0.415* (0.231)	0.266* (0.148)
Industrial PPI	0.178*** (0.014)	0.502*** (0.106)	0.477*** (0.075)
Instrument		TPU× Crisis	TPU× News
First-Stage F Statistics		7.35	8.02
Department FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
N	5819	5635	5635

Notes: \*\*\*p&lt;0.01, \*\*p&lt;0.05, \*p&lt;0.1. In both IV regressions, I instrument industrial PPI with changes in energy prices. There are seven department categories in Nielsen data.

from China decreased more in industries with higher initial TPU during China’s accession to WTO.

Following their work, I exploit the variations in changes in TPU across industries. As shown in Figure 1, trade policy uncertainty in general increased during the crisis. More importantly, there is heterogeneity in TPU across industries because the potential threat tariffs are product-specific. Handley and Limão (2017) model trade policy uncertainty by allowing for three policy states: high, low and intermediate. The intermediate state is characterized by tariffs between high and low protection and that could change to either states with some probability. In our empirical setting, the trade policy was in intermediate state, specifically, low protection state (MFN tariff), before the crisis. The arrival of the crisis indicates an increase in probability of changing into high protection state, i.e, non-cooperative import tariffs.<sup>14</sup> We can therefore measure the increase in TPU each industry experienced during the crisis using the differences in MFN tariffs and non-cooperative tariffs (Column 2). Specifically, we define TPU for industry  $i$  as the following:

$$TPU_i = 1 - \left(\frac{\tau_2^i}{\tau_m^i}\right)^{-\sigma} \quad (1.12)$$

where  $\tau_2^i$  and  $\tau_m^i$  are Column 2 and MFN tariff for industry  $i$  respectively. In the baseline, I define an industry at the HS6-digit level and the industrial tariffs are the average of tariffs across HS8s within that industry. According to Handley and Limão(2017), in a standard trade model with TPU, it represents the potential profit loss if high protection state realizes.<sup>15</sup>

The definition of the import price index follows Feenstra(1994) and Broda and

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<sup>14</sup>In Handley and Limão(2017), when at the intermediate state, tariffs could change with probability  $\gamma$ , with  $\lambda$  to high protection and  $1 - \lambda$  to low protection state. In our empirical application, the intermediate state has tariff levels that are equal to low protection state. Thus, the probabilities of changing tariffs ( $\gamma$ ) and changing to high protection ( $\lambda$ ) are equivalent.

<sup>15</sup>In the empirical analysis, I use  $\sigma=3$  following Handley and Limão(2017).

Weinstein(2006) and is specified as follows:

$$\Delta \ln P_{ict} = \sum_{\omega \in \bar{\Omega}_{ic}} w_t(\omega) \Delta \ln p_t(\omega) + \frac{1}{\sigma - 1} \ln \frac{\lambda_{ict}}{\lambda_{ict-1}} \quad (1.13)$$

where  $\ln P_{ict}$  is the log import price index of product  $i$  from country  $c$  at time  $t$ . The first component on the RHS is a weighted average of price changes of continuing varieties in that product-country cell, with sato-vatia weight  $w_t$  which takes into account of the substitution across periods.  $\Delta \ln p_t(\omega)$  is the log changes in variety-level prices and a variety is defined as a HS10-country combination. The second component accounts for the entry and exit of varieties, where  $\lambda_{ict}$  is the expenditure share of continuing varieties in all varieties at period  $t$ . Thus, the variety component increases as more varieties exit (lower  $\lambda_{ict-1}$ ) or less varieties enter (higher  $\lambda_t$ ).

To calculate the import price index, I use US quarterly import data from 68 countries during 2004Q1-2011Q4.<sup>16</sup> The sample includes all US major trading partners and imports from these countries account for more than 85% of all imports in 2004. The list of countries is in Appendix.

I estimate the effect of TPU on import prices by the following equation:

$$\begin{aligned} \Delta \ln P_{ict} = & \beta_1 Crisis_t \times TPU_i + \beta_2 Crisis_t \times TPU_i \times PTA_{ct} + \\ & \beta_3 TPU_i \times PTA_{ct} + \beta_4 TPU_i + \delta_{ct} + \varepsilon_{ict} \end{aligned} \quad (1.14)$$

where  $\Delta \ln P_{ict}$  is the changes in import prices relative to the corresponding quarter in 2004.  $Crisis_t$  is a dummy variable that equals to one for periods during 2008Q4-2011Q4, and equals to zero otherwise. I control for country-specific supply shocks using country by time fixed effects ( $\delta_{ct}$ ). I also divide exporting countries into PTA and non-PTA countries based on whether or not it has a Preferential Trade Agreement (PTA) with the United States. As shown by Carballo et al (2018), credible trade

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<sup>16</sup>The data is publicly available through US Census Bureau.

agreement could potentially reduce TPU as it provides extra commitment to trade policy relative to WTO.

**Table 1.B.1:** TPU and Import Prices

	Continuing		Varieties		Aggregate	
	(1)	(2)	(3)	(4)	(5)	(6)
TPU×Crisis	-0.072*** (0.010)	-0.068*** (0.010)	0.019*** (0.004)	0.015*** (0.004)	-0.053*** (0.011)	-0.052*** (0.011)
TPU			0.005** (0.002)		-0.009 (0.007)	
TPU×Crisis×PTA	-0.033 (0.021)	-0.027 (0.020)	-0.001 (0.008)	0.001 (0.007)	-0.034 (0.022)	-0.026 (0.021)
TPU×PTA	0.015 (0.013)	0.011 (0.013)	-0.004 (0.004)	-0.004 (0.005)	0.010 (0.013)	0.007 (0.014)
Country*Time FE	Yes	Yes	Yes	Yes	Yes	Yes
HS6 FE	No	Yes	No	Yes	No	Yes
N	795590	795573	795590	795573	795590	795573
R-Squared	0.018	0.048	0.005	0.050	0.017	0.049

**Table 1.B.2:** TPU and Import Prices: Matched Sample with Nielsen

	Continuing		Varieties		Aggregate	
	(1)	(2)	(3)	(4)	(5)	(6)
TPU×Crisis	-0.050** (0.016)	-0.057*** (0.016)	0.015* (0.006)	0.013* (0.006)	-0.035* (0.017)	-0.045** (0.017)
TPU			0.004 (0.003)		0.035*** (0.010)	
TPU×Crisis×PTA	-0.017 (0.033)	-0.012 (0.032)	-0.022 (0.014)	-0.019 (0.013)	-0.040 (0.035)	-0.031 (0.035)
TPU×PTA	0.061** (0.020)	0.057** (0.021)	-0.004 (0.008)	-0.009 (0.008)	0.057** (0.021)	0.048* (0.022)
Country*Time FE	Yes	Yes	Yes	Yes	Yes	Yes
HS6 FE	No	Yes	No	Yes	No	Yes
N	255750	255749	255750	255749	255750	255749
R-Squared	0.027	0.050	0.011	0.064	0.026	0.054

Table 1.B.1 represents the baseline results, where I use import price index defined at HS6-country level.<sup>17</sup> The first two columns use the price changes of continuing varieties as dependent variable. From the first column, we see that TPU has a significantly negative effect on import prices of continuing varieties during the crisis.

<sup>17</sup>Due to the measurement error in unit values, I trim observations with values that fall outside of median+/-3IQR range. These outliers account for about 3% of all observations.

The significant negative sign before  $TPU_i$  indicates that TPU had a negative effect even before the crisis. In addition, there is no significant difference between PTA and non-PTA countries in terms of the impact of TPU. In Column 2, I control for product-specific trend using fixed effect, and the results are similar.

To explain the negative effects, note that a variety is defined as a HS10-country combination. If the increased TPU induced less productive (potentially higher priced) firms to exit within the product-country category, the (average) unit value for the variety could be lower as the remaining firms are more productive and charging lower prices. In addition to the exit effect, it is possible that firms temporarily lowered their prices when facing higher TPU during the crisis with the expectation that TPU would decrease after the crisis.

Column 3-4 use the variety component as dependent variable. As we see in column 3,  $\beta_1$  is positive and significant, implying that in industries with higher TPU, there were more varieties exit and/or less varieties entry during the crisis. This is consistent with the theory that higher TPU would deter export entry if there is sunk entry cost. When adding the two component of price indices, the overall effect of TPU is negative as the price effect of continuing varieties outweigh the variety exit effect (column 5 and 6).

The results are robust when we use a matched sample of HS6s with Nielsen (Table 1.B.2). Products in Nielsen are mostly consumer packaged goods and constitute about one fifth of all import value. As we can see in Table 1.B.2, the magnitude of negative effect is slightly smaller and the signs and significance are the same with that in Table 1 except that the effect of TPU is positive before the crisis. I also do robustness checks using HS4 by country import price index. The results are reported in Appendix.

Because Crisis dummy hardly capture the variations in TPU over time, I replace it with the News-based TPU index as depicted in Figure 1. The regression results are reported in Table 1.B.3. For news index, I normalize it to have mean zero and



standard deviation of one. As we see, the results are similar to the specifications that use Crisis dummy. Table 1.B.4 provide robustness checks at the HS-4 industrial level.

**Table 1.B.3:** TPU and Import Prices: News-Based TPU Index

	Continuing		Varieties		Aggregate	
	(1)	(2)	(3)	(4)	(5)	(6)
TPU×News	-0.026*** (0.005)	-0.025*** (0.005)	0.005* (0.002)	0.004 (0.002)	-0.022*** (0.006)	-0.022*** (0.006)
TPU	-0.046*** (0.005)		0.013*** (0.002)		-0.032*** (0.005)	
TPU×News×PTA	0.000 (0.011)	0.001 (0.011)	-0.001 (0.004)	0.000 (0.004)	-0.001 (0.012)	0.001 (0.011)
TPU×PTA	-0.001 (0.010)	-0.002 (0.011)	-0.005 (0.004)	-0.004 (0.004)	-0.005 (0.011)	-0.005 (0.012)
Country*Time FE	Yes	Yes	Yes	Yes	Yes	Yes
HS6 FE	No	Yes	No	Yes	No	Yes
N	795590	795573	795590	795573	795590	795573
R-Squared	0.018	0.048	0.005	0.050	0.017	0.049

**Table 1.B.4:** TPU and Import Prices: HS4 by Country

	Continuing		Varieties		Aggregate	
	(1)	(2)	(3)	(4)	(5)	(6)
TPU×Crisis	-0.086*** (0.012)	-0.082*** (0.012)	0.014 (0.008)	0.009 (0.008)	-0.072*** (0.015)	-0.073*** (0.014)
TPU	-0.025** (0.007)		-0.007 (0.004)		-0.031*** (0.009)	
TPU×Crisis×PTA	0.019 (0.027)	0.024 (0.026)	0.011 (0.017)	0.016 (0.016)	0.030 (0.032)	0.039 (0.030)
TPU×PTA	-0.020 (0.017)	-0.025 (0.017)	-0.009 (0.009)	-0.008 (0.009)	-0.028 (0.019)	-0.033 (0.019)
Country*Time FE	Yes	Yes	Yes	Yes	Yes	Yes
HS4 FE	No	Yes	No	Yes	No	Yes
N	400226	400223	400226	400223	400226	400223
R-squared	0.028	0.054	0.009	0.055	0.024	0.054

In sum, I find that TPU has a negative impact on import prices during the GTC. In particular, industries that experienced larger increase in TPU have lower import prices for continuing varieties and less variety entry.

# Chapter 2

## Heterogeneity in Pass-through across Consumers: Estimation and Quantification

### 2.1 Introduction

In previous chapter, I discuss how shocks to import prices are passed through to the aggregate consumer prices. However, there are substantial differences in prices faced by consumers with different characteristics, even within the same product category. One explanation for the price differences is the differential spending patterns across products. For example, it is well established that high income consumers consume more of high-quality and high priced products within a product category (e.g., Fajgelbaum and Khandelwal (2017)). It could be also due to the fact that even for the same good, consumers pay different prices as they shop in different retail outlets (Handbury and Weinstein (2015); Handbury (2019)). Therefore, the shocks to prices at the border could lead to differential price changes across consumers and cause distributional consequences.

In this chapter, I investigate the heterogeneity in pass-through rates across consumers. To do so, I extend the theoretical framework in Chapter 1 to allow for heterogeneity in consumer prices. I show that a differential pass-through across consumers could arise through two channels. The first one captures the fact that consumers shop in different retail outlets for the same variety and the pass-through can be different across retail outlets. The second channel focuses on the different expenditure shares across varieties with different pass-through rates. For example, high income consumers spend more on varieties of higher quality, which have different pass-through rates than low-quality varieties.

In the empirical analysis, I explore the heterogeneity along two dimensions—income and geographic location—by using the rich demographic and geographic information in Nielsen data. I find that the pass-through rate is higher for consumers with lower income and in more competitive markets, which is measured by Herfindahl Index in local retail market.

I then investigate how each channel contributes to the differential pass-through across consumers. A price decomposition shows that the differences in expenditure shares across varieties with heterogeneous pass-through rates account for most of the differential pass-through. That is, consumers with lower income and at more competitive retail market spend more on varieties with higher pass-through rates.

For lower income consumers, the higher pass-through rate is possibly due to the fact that lower quality varieties they consume exhibit lower distribution margin compared with higher quality varieties and thus have higher pass-through rates. For consumers at more competitive retail markets, the higher pass-through might be because they spend more on varieties from relatively small retailers which have lower markup elasticity and thus higher pass-through rates.

This chapter contributes to the literature that studies the distributional consequences of international trade. This line of research focuses on how international

trade causes relative price changes both across sectors and within sectors and relates it to differential price changes across consumers. For example, Fajgelbaum and Khandelwal (2017) incorporates non-homothetic demand in a quantitative model and find that international trade is pro-poor because poor consumers spend more on sectors with a larger trade intensity and a lower elasticity of substitution between domestic and imported goods. Borusyak and Jaravel (2018) relax the assumption on demand structure and use micro-data on expenditure shares across sectors and goods. They show that consumers with various education levels have approximately the same expenditure share on imported goods and the expenditure channel is therefore almost neutral to different education groups. On the other hand, as price and expenditure data at more disaggregated product-level becomes available, some papers start to examine the effect of specific events on consumer welfare using micro-level data. Faber (2014) and Atkin, Faber and Navarro (2016) are two examples using barcode-level data to study separate events (the first one is about NAFTA and the second is on the arrival of foreign retail chains) on Mexican consumers. Similar to these studies, this paper also uses barcode-level price and expenditures. However, these papers did not distinguish between import prices and consumer prices. In contrast, this paper shows that the existence of domestic distribution sector creates a wedge between import and consumer prices and plays a role in generating distributional effects across consumers.

## 2.2 Consumer-specific Prices and Decomposition

In the first step, I define a consumer-specific price index by allowing for differences in expenditure share across varieties and variety-level prices, both of which could lead to differential pass-through. Specifically, the price index of product category  $g$  for consumer  $z$  is defined as

$$\Delta \ln P_{gt}^z = \sum_{v \in g} w_{vt}^z \Delta \ln p_{vt}^{zr} \quad (2.1)$$

where  $w_{vt}^z$  is the expenditure share on variety  $v$  for group  $z$  at time  $t$  and  $\Delta \ln p_{vt}^{zr}$  denotes the changes in prices of variety  $v$  for consumer  $z$ . The differences in variety-level price changes could arise because consumers shop the same variety (UPC) in different retail outlets or have different search intensity.

The differential import price pass-through across consumers depend on both factors. To see this, note that as consumers can pay different prices for the same variety, the same cost shock would lead to differential price adjustment at the variety-level. For example, a high and a low income consumer could buy the same imported good from a high-end retail store and a discount store respectively. Following an import price shock to that good, the two stores would adjust the prices on the shelf differently for reasons such as different demand elasticity. Therefore, even if consumers have the same expenditure share on each good, the differential price adjustment across retail outlets could lead to differential pass-through. This is the first channel which I call “outlet channel”. Second, as pass-through rates differ across varieties, the differential expenditure shares across varieties could also cause differential overall pass-through rate at the product category level. Again, the high income consumer could purchase a high quality variety and the low income consumer could purchase a low quality one within the same product category. If the pass-through rate varies across high and low quality varieties, the category-level pass-through rate can also be different across consumers. I call it the “composition channel”.

To investigate each channel in detail, I decompose the changes in consumer-specific price index into three components following Cravino and Levchenko (2017):<sup>1</sup>

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<sup>1</sup>Other papers such as Coibion et al (2015) use similar decomposition.

$$\begin{aligned}
\Delta \ln P_{gt}^z &= \sum_{v \in g} w_{vt}^z \Delta \ln p_{vt}^{z,r} = \sum_{v \in g} (w_{vt} + u_{vt}^z) \Delta \ln p_{vt}^{z,r} \\
&= \underbrace{\sum_{v \in g} w_{vt} \Delta \ln p_{vt}^{z,r}}_{\text{outlet channel}} + \underbrace{\sum_{v \in g} u_{vt}^z \Delta \ln p_{vt}^r}_{\text{composition channel}} + \sum_{v \in g} u_{vt}^z v_{vt}^z
\end{aligned} \tag{2.2}$$

where  $w_{vt}$  is the average expenditure share on variety  $v$  and  $u_{vt}^z$  is the deviation in expenditure share for consumer  $z$  from the average. Likewise,  $\Delta \ln p_{vt}^r$  is the average change in (log) price for variety  $v$  and  $v_{vt}^z$  is the deviation in price changes for consumer  $z$  from the average.

The first term uses the average expenditure share on each variety (across consumers) as weight and allow changes in unit prices to be consumer-specific, capturing the fact that consumers shop the same variety in different outlet thus facing differential retail price changes. The second term assumes the same change in variety-level price but allows for different expenditure patterns across varieties, thus measuring how differential expenditure shares across varieties contribute to the differential price index. Finally, the last term is the correlation between two deviations. For example, if high income consumers spend more on high quality goods, and the pass-through of high quality goods is disproportionately higher for high income consumers.

The decomposition highlights mechanisms that could cause differential price changes across consumers and therefore could be sources of heterogeneity in pass-through. In the following, I link each component of consumer-specific price indices with changes in import prices and investigate how each channel contributes to the differential pass-through.

## 2.2.1 The Outlet Channel

First, I examine how the price shocks in the border could cause differential changes in retail price for the same variety  $v$  across consumers. Note that retail price of variety  $v$  for group  $z$  can be written as:

$$\ln p_{vt}^{z,r} = (1 - \eta_v^z) \ln p_{vt}^T + \eta_v^z \ln p_t^N + \ln \gamma_{vt}^z(c_{vt}^z; \xi_{vt}^z) \quad (2.3)$$

Here I assume the price at the dock  $p_{vt}^T$  is the same for all consumers. However, the distribution margin, which captures the amount of domestic services being added to imported goods, and markup, which captures distributors' price setting behavior, can vary across consumers. The variety pass-through for consumer  $z$  is defined as follows:

$$\rho_v^z = \frac{\partial \ln p_{vt}^{z,r}}{\partial \ln p_{vt}^T} = (1 - \eta_v^z) \left(1 + \frac{\partial \ln \gamma_{vt}^z}{\partial \ln c_{vt}^z}\right) = (1 - \eta_v^z)(1 - \theta_v^z) \quad (2.4)$$

As we can see in equation (2.4), variety pass-through varies across consumers because of the differences in distribution margin and markup elasticity. These differences are possibly due to the fact that consumers shop the same variety (UPC) in different retail outlets and these retailer outlets attach different domestic services and have different pricing decisions when facing the same cost shock.<sup>2</sup>

Note that distribution margin  $\eta_v$  represents the proportion of non-tradable services that are provided with imported goods to consumers. It naturally varies across locations because of different domestic transportation costs. In addition, it could also vary across locations due to the differences in rent, labor costs etc. In the case of income, as high income consumers tend to shop in stores with higher amenity, these stores usually attach more domestic services such as offering more customer services, nicer shopping environment, thus having higher distribution margin.

Markup elasticity captures the fact that when facing the same cost shocks, the

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<sup>2</sup>Another possible explanation is that consumers have different search intensity.

markup adjustment could be different across retail outlets even for the same variety. In terms of income, it is possible that the high-amenity stores that cater to the rich have different markup elasticity due to the differences in demand elasticity between the rich and the poor. For consumers at different locations, the differences in market structure and local competition in retail industry can affect the markup elasticity. For example, Smith (2018) documented an overall increase in concentration in retail industry in the U.S and considerable variations in concentration levels across locations.

Note that we can write the changes in variety retail price as a function of variety pass-through and changes in prices at the dock:

$$\Delta \ln p_{vt}^{z,r} = \rho_v^z \Delta \ln p_{vt}^T + \eta_v^z (1 + \theta_v^z) \Delta \ln p_t^N \quad (2.5)$$

Denote the first component of consumer price indices in equation (2.2) as  $\Delta \ln P_{gt}^{z,1}$  and re-write it:

$$\Delta \ln P_{gt}^{z,1} = \sum_{v \in g} w_{vt} \Delta \ln p_{vt}^{z,r} = s_{gt}^I \rho_g^z \Delta \ln P_{gt}^I + (1 - s_{gt}^I) \rho_g^z \Delta \ln P_{gt}^D + \tilde{\delta} \Delta \ln P_t^N \quad (2.6)$$

When deriving the second equality, we distinguish between domestic and imported varieties and assume the variety pass-through is the same in product category  $g$ . As we can see in equation (2.6), the expenditure share across imported and domestic varieties is assumed to be the same across consumers. Therefore, if we find differential pass-through into the first component of price indices across consumers, it captures the differences in  $\rho_g^z$ : the variety-level pass-through. Note that

$$\rho_g^z = (1 - \eta_g^z)(1 - \theta_g^z) \quad (2.7)$$

The variety (product) pass-through is lower for consumers with higher distribution



margin or higher markup elasticity. In other words, as consumers shop in different retail stores for the same variety, it captures the heterogeneity in distribution margin or markup elasticity across retailers.

### **2.2.2 The Expenditure Channel**

The expenditure channel hinges on the fact that consumers consume different varieties within a narrow product category. To the extent that there is heterogeneity in pass-through across varieties in the same product category, the differential expenditure pattern could also result in different pass-through. One example is product quality. It is well known that high income consumers spend more on high quality varieties within a narrow product category. The high quality varieties might have a different pass-through rate than that of lower quality varieties due to differences in distribution margin or markup elasticity. Another example is the size of retailers. Some consumers tend to shop in large retail chains while others prefer small local stores. For example, there is evidence that high income consumers tend to spend more on products from large firms whereas low income consumers spend more on smaller firms (Faber and Fally (2014)). The spending patterns might also vary across different markets as some markets are dominated with a few large retailers while others have lots of local retailers to choose from. There is evidence that large firms tend to have a larger markup elasticity, i.e., they adjust their markup more intensively when facing cost shocks, than small firms (Amiti et al, 2019). Therefore, the differences in expenditure patterns across retailers of different size would result in differential pass-through rates as well.

Note that in addition to the above mentioned reasons, the differences in expenditure share across imported versus domestic varieties are also captured in this channel.

To see this, denote the second term of equation (2.2) as  $\Delta \ln P_{gt}^{z,2}$  and re-write it as:

$$\begin{aligned} \Delta \ln P_{gt}^{z,2} &= \sum_{v \in g} u_{vt}^z \Delta \ln p_{vt}^r \\ &= s_{gt}^{z,I} \sum_{v \in g,I} w_{vt}^{z,I} \rho_v \Delta \ln p_{vt}^{T,I} + (1 - s_{gt}^{z,I}) \sum_{v \in g,D} w_{vt}^{z,D} \rho_v \Delta \ln p_{vt}^{T,D} - \Delta \ln P_{gt} \end{aligned} \tag{2.8}$$

where  $s_{gt}^{z,I}$  and  $w_{vt}^{z,I}$  are the expenditure share on imported goods of consumer  $z$  and the expenditure share on imported variety  $v$  within imported varieties respectively. If we regress this component of price indices on a uniform import price index, the coefficient would increase in consumers  $z$ 's expenditure share on imported varieties. In other words, the import price has a larger impact on consumers that spend more on imported goods.

Within imported varieties, the differential pass-through is determined by the interaction between variety expenditure share  $w_{vt}^{z,I}$  and variety pass-through  $\rho_v$ . All the previously mentioned product characteristics including product quality, firm size are captured in this interaction. For example, if consumers spend more on high quality imported goods (higher  $w_{vt}^{z,I}$  with  $v$  denotes the high quality varieties), and if the pass-through of high quality variety  $\rho_v$  is lower, it would lead to overall lower pass-through for this group of consumers.

In any case, if we find the differential effect is significantly positive (negative) through this channel, it suggests this group of consumers spend more on varieties that have higher (lower) pass-through. However, we are unable to identify which product characteristics play a more important role unless we dig deeper into each possibility.

## 2.3 Empirical Evidence

### 2.3.1 Consumers with Different Income

To investigate whether the pass-through varies across consumers at different income levels, in the first step, I construct income-specific consumer price index as in equation (2.1) exploiting the rich demographic information in Nielsen data. Specifically, as a variety is defined as a unique UPC (barcode), I calculate the income-specific expenditure share on each UPC within a product category and income-specific unit price for each UPC. To avoid endogeneity issues, I use fixed expenditure share at the base period.

I divide households into ten income bins according to their income level. As to household income, I try two different measures. The first one is self-reported annual income, which is not in exact numbers but in income ranges. The second one is total spending by aggregating transaction-level expenditures in Nielsen data. Both measures are adjusted for household size.<sup>3</sup> I calculate income-specific price index for each product category and ten income groups.<sup>4</sup> Note that households with different income might consume different bundles of varieties within the same product category. Using the price changes of varieties consumed is equivalent to applying zero weights to unconsumed varieties.

I estimate a reduced form equation on the income-specific price indices to determine the direction of the differential effect, for example, if there is larger impact on low-income vs higher income. Because there are different forces affecting the pass-through and the direction of each force can be contradicting, the overall impact on different consumers is ambiguous in a theoretical perspective. Specifically, I estimate

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<sup>3</sup>The correlation between the two measures is about 0.3.

<sup>4</sup>One can calculate household-level price index. However, as each household consumes a limited number of varieties each period, we lose substantial price information when calculating price changes. For this reason, we calculate group-specific price index.

the following equation:

$$\Delta \ln P_{igt} = \alpha + \beta \Delta \ln P_{gt}^I + \gamma \Delta \ln P_{gt}^I \times D_z + \Delta \ln P_{gt}^D + \delta_{zt} + \epsilon_{zgt} \quad (2.9)$$

where  $\Delta \ln P_{igt}$  is the log changes in price index of income group  $i$  for product  $g$ .  $\Delta \ln P_{gt}^I$  represents import price index of product  $g$ .  $D_z$  are income dummies. In the baseline, I divide the ten income groups into two categories: high and low income.<sup>5</sup> I add income-time fixed effects to control for other shocks experienced by each income group.

Table 2.1 reports the regression results based on IV estimation. I use reported income in column 1-2 and total spending in column 3-4. As we can see in column 1-2, the pass-through into consumer prices of lower income is significant higher compared with that of higher income. The magnitude of the difference varies slightly across specifications. Overall, the pass-through into lower income is about 30% – 50% higher than that into higher income. The results are robust to using total spending as income measure.

**Table 2.1:** Import Price Pass-Through: Income

	Reported Income		Total Spending	
	(1)	(2)	(3)	(4)
Changes in Import Prices	0.268*** (0.029)	0.289*** (0.032)	0.261*** (0.028)	0.274*** (0.031)
Imp $\times$ Lower Income	0.115*** (0.021)	0.099*** (0.021)	0.102*** (0.021)	0.095*** (0.020)
Industrial PPI	0.401*** (0.035)	0.419*** (0.030)	0.441*** (0.036)	0.455*** (0.030)
Instrument	TPU $\times$ Crisis	TPU $\times$ News	TPU $\times$ Crisis	TPU $\times$ News
First-Stage F Statistics	117.6	111.5	115.2	108.8
Income*Time FE	Yes	Yes	Yes	Yes
N	61215	61215	61093	61093

Notes: \*\*\*p<0.001, \*\*p<0.005, \*p<0.01. This table reports only IV estimation results with different instruments. In all regressions, I use changes in energy prices to instrument for industrial PPI.

<sup>5</sup>I take the top 5 income groups as high income and the remaining 5 as low income

To dig deeper into the heterogeneity across income groups, I divide the sample into three categories: lower, middle and upper income.<sup>6</sup> Table 2.2 reports the results for three income categories. As we see, the pass-through into lowest income is significantly higher than that of highest income group. However, according to column 1-2, the pass-through into middle income group is not significantly different from that of highest income. It suggests the differences in pass-through across high and low income groups in previous table are mostly driven by the top and bottom income groups. Using total spending as income measure in column 3-4, the results are slightly different. Both the pass-through into lower income and middle income is significantly higher than that into higher income. A test of equality shows that there is no significant difference in pass-through between lower and middle income.

The results are robust to using other income measures including the total household income (total spending) without adjusting for household size, household income (total spending) adjusting for size and other demographics. These results are reported in Appendix Table 2.A.1 and Table 2.A.2.

**Table 2.2:** Import Price Pass-Through: 3 Income Categories

	Reported Income		Total Spending	
	(1)	(2)	(3)	(4)
Changes in Import Prices	0.271*** (0.031)	0.289*** (0.033)	0.234*** (0.031)	0.250*** (0.033)
Imp × Lower Income	0.131*** (0.028)	0.111*** (0.027)	0.143*** (0.028)	0.127*** (0.027)
Imp × Middle Income	0.037 (0.024)	0.039 (0.024)	0.088*** (0.024)	0.083*** (0.023)
Industrial PPI	0.401*** (0.035)	0.419*** (0.030)	0.442*** (0.036)	0.455*** (0.030)
Instrument	TPU × Crisis	TPU × News	TPU × Crisis	TPU × News
First-Stage F Statistics	113.2	111.1	117.7	109.2
Income*Time FE	Yes	Yes	Yes	Yes
N	61215	61215	61093	61093

Notes: \*\*\*p<sub>i</sub>0.001, \*\*p<sub>i</sub>0.005, \*p<sub>i</sub>0.01. In all regressions, I use changes in energy prices to instrument for industrial PPI.

<sup>6</sup>As we cannot split ten income groups into 3 categories of equal size, I assign top 3 income groups as upper income, bottom 3 groups as lower income and the middle 4 groups as middle income.

Note that the domestic pass-through into the consumer prices could be heterogeneous across consumers with different income levels as well. The heterogeneous response could be due to the similar reasons such as different spending patterns on domestic goods. Therefore, in Table 2.3 I interact the changes in domestic prices with high and low income dummies and instrument domestic prices with changes in energy prices. Using the two different instruments for import prices gives us very different results. Given the second instrument is subject to weak instrument problem, we focus on the results in column 1 and 3. As we see, the pass-through of domestic prices is slightly lower for lower income, which is in the opposite sign with the import price pass-through.

**Table 2.3:** Heterogeneity in Domestic Price Pass-through

	Reported Income		Total Spending	
	(1)	(2)	(3)	(4)
Changes in Import Prices	0.194*** (0.050)	0.542*** (0.130)	0.193*** (0.049)	0.586*** (0.143)
Imp Price $\times$ Lower Income	0.261*** (0.075)	-0.403 (0.236)	0.232** (0.075)	-0.506* (0.249)
Industrial PPI	0.413*** (0.037)	0.390*** (0.033)	0.454*** (0.036)	0.411*** (0.037)
PPI $\times$ Lower Income	-0.020* (0.008)	0.050* (0.025)	-0.018* (0.008)	0.060* (0.027)
Instrument	TPU $\times$ Crisis	TPU $\times$ News	TPU $\times$ Crisis	TPU $\times$ News
First Stage F-Statistics	41.48	4.63	40.80	4.53
Income*Time FE	Yes	Yes	Yes	Yes
N	61215	61215	61093	61093

Notes: \*\*\* $p < 0.001$ , \*\* $p < 0.005$ , \* $p < 0.01$ . In all regressions, I use changes in energy prices to instrument for industrial PPI. The first stage F Statistics reports the Cragg-Donald Wald F Statistics.

Theoretically, the differences in pass-through between import and domestic prices (PPI) could be due to the differences in expenditures on imported vs domestic goods and the variety-level pass-through. It is reasonable to assume that markup elasticity has little variation across domestic goods and imported goods, but the distribution margin, especially the transportation cost, could be quite different. If we define  $\xi_g^I$  as the import price pass-through and  $\xi_g^D$  as the domestic price pass-through for product

category  $g$ , according to equation (1.8), the ratio of the two could be written as:

$$\frac{\xi_g^I}{\xi_g^D} = \frac{s_g^I \rho_g^I}{(1 - s_{gt}^I) \rho_g^D} \quad (2.10)$$

Furthermore, the ratio of consumer-specific pass-through is:

$$\frac{\xi_g^{I,z}}{\xi_g^{D,z}} = \left( \frac{s_g^{I,z}}{1 - s_{gt}^{I,z}} \right) \left( \frac{\rho_g^{I,z}}{\rho_g^{D,z}} \right) = \left( \frac{s_g^{I,z}}{1 - s_{gt}^{I,z}} \right) \left( \frac{\rho_g^I}{\rho_g^D} \right) \quad (2.11)$$

The second term, the ratio of variety pass-through could be constant across different income groups. In other words, the differences in distribution margin, say transportation cost, across domestic and imported goods do not vary across high and low income. Therefore, the differences in pass-through ratio between high and low income can be written as:

$$\frac{\xi_g^{I,H} / \xi_g^{D,H}}{\xi_g^{I,L} / \xi_g^{D,L}} = \frac{s_g^{I,H} / (1 - s_{gt}^{I,H})}{s_g^{I,L} / (1 - s_{gt}^{I,L})} \quad (2.12)$$

As we see in equation (2.12), the diverging sign on the two interaction term in Table 2.3 captures the differences in expenditure share on imported and domestic goods. In particular, according to the estimates, the ratio is smaller than one ( $\frac{\xi_g^{I,H} / \xi_g^{D,H}}{\xi_g^{I,L} / \xi_g^{D,L}} < 1$ ), which suggests low income households spend more on imported goods compared with high income households. Overall, the results indicate that the different expenditure share on imported varieties plays an important role in driving the differential pass-through.

In addition, I investigate how each channel contributes to the higher pass-through into lower income by decomposing the income-specific price index into three components as in equation (2.2) and run the same regressions on each component. Table 2.4 reports the decomposition results using total reported income. As we see in column 1, the variety pass-through is higher for low income consumers but barely significant. The result in column 2 suggests the differential expenditures across varieties

with heterogeneous pass-through account for most of the differential effect. To be more specific, the positive and significant sign before the interaction implies that low income consumers spend more on varieties with higher pass-through compared with high income consumers. As suggested by previous results, it is likely due to the fact that lower income spend more on imported varieties. Lastly, the positive significant sign on the interaction term (column 3) indicates that the low income consumers also spend more on varieties that have disproportionately higher pass-through for low income consumers. The decomposition results are similar using TPU-News as instrument.

**Table 2.4:** Price Decomposition: Income

	(1) Outlet Channel	(2) Composition Channel	(3) Interaction
Changes in Import Prices	0.268*** (0.022)	0.245*** (0.021)	-0.024*** (0.005)
Imp $\times$ Lower Income	0.029 (0.019)	0.064*** (0.018)	0.012** (0.005)
Industrial PPI	0.604*** (0.026)	0.383*** (0.024)	0.011 (0.006)
Income*Time FE	Yes	Yes	Yes
N	63050	63050	63050

Notes: \*\*\* $p < 0.001$ , \*\* $p < 0.005$ , \* $p < 0.01$ . In all regressions, I use TPU\*Crisis as the instrument for import prices and changes in energy prices to instrument for industrial PPI.

### 2.3.2 Consumers at Different Locations

In this section, I investigate whether the import price pass-through into consumer prices varies across locations. A recent literature shows that the differences in prices across locations within countries are driven by both trade costs and markups (Atkin and Donaldson 2015, Hottman 2017). Note that these two factors play an important role in determining the pass-through in our theoretical model as trade costs account for a large fraction of distributional cost and markup captures local market structure. The consumer prices at different locations could therefore respond differently to price



shocks at the dock.

To proceed, I calculate the consumer price index for 50 markets in the US using Nielsen consumer panel, with the price index defined as in equation (2.1).<sup>7</sup> As in calculating income-specific price indices, we allow for market-specific expenditure shares and unit prices. I focus on two dimensions of locations. The first one is remoteness, which is a proxy for domestic distribution/trade cost. The second one is local market competition, which could play an important role in determining markup and markup elasticity. In the following, I discuss how I construct these measures and how each of them could affect pass-through into consumer prices across markets.

First, to capture the remoteness of each location, I measure minimum distance using information on each market’s distance to ports and port-level imports. To be more specific, I use the weighted average of (log) distance to 3 closest ports:

$$Dist_{gz}^w = \sum_p \ln d_{zp} \times s_{pg} \quad (2.13)$$

where  $d_{zp}$  is the distance of market  $z$  to port  $p$ , which is calculated as the fastest route using Google Maps and  $s_{pg}$  is the import share of port  $p$  of product  $g$ . I include 372 sea and land ports in the US and the port-level imports are available through US Census Bureau.<sup>8</sup>

Consumers at relatively remote locations might have different consumption basket from those by the coastline. In particular, they may consume less imported goods as there is higher distribution cost. Moreover, consumer prices of imported goods at remote locations contain larger proportion of non-tradable domestic transportation costs, thus having a higher distribution margin. Both channels could result in a

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<sup>7</sup>Nielsen defined 52 major scantrack markets with each market contains urban and suburban areas. I combine Suburban New York, Exurban New York and urban New York into one area as New York. Note that according to Nielsen, the sample of households in each market is representative of the whole population in that market. The market definition is also used in Handbury and Weinstein (2014).

<sup>8</sup>I dropped ports outside US mainland including those in Hawaii, Virgin Island, Puerto Rico and Alaska.

smaller pass-through rate to remote locations.

Second, to measure the competition in local market, I construct Herfindahl-Hirschman Index (HHI) in retail industry for each market using the information on market share of each retailer in Nielsen data. Each transaction in Nielsen data includes information on the retail stores and retail chains. I define a retailer as the latter as evidence shows that the pricing decisions are often made at the retail chain level (DellaVigna and Gentzkow, 2019).

There are 849 different retailers in total and the median number of retailers operate in each market-product cell is 46. To test the robustness, I also construct alternative concentration measures using market shares of top 4, 8, 20 retailers following Autor et al (2014). To avoid endogeneity, all concentration measures are constructed using aggregate sales across products.

Models with oligopolistic competition would predict that firm's markup elasticity depends on its market share (Atkenson and Burnstein(2008)). Furthermore, using firm-level data, Amiti et al (2018) show that larger firms respond to its own cost shock with elasticity of 0.5, while small firms exhibit complete pass-through. As the import price pass-through varies across firms of different size, it could therefore vary across locations with different size distribution of firms, which is captured by market concentration measures.

Moreover, the remoteness and competition conditions in one market could be correlated. For example, the more remote market might exhibit less competition. Thus, we estimate the following equation:

$$\begin{aligned} \Delta \ln P_{zgt} = & \alpha + \beta \Delta \ln P_{gt}^I + \gamma_1 \Delta \ln P_{gt}^I \times Dist_{zg} + \gamma_2 \Delta \ln P_{gt}^I \times Concentr_z \\ & + \rho \Delta \ln P_{gt}^D + \delta_g + \delta_{zt} + \epsilon_{zgt} \end{aligned} \quad (2.14)$$

where on the left hand side is the changes in market-specific price index of product  $g$  for market  $z$ . On the right hand side, I add the interactions of changes in import

prices with both remoteness and concentration measures. As before, I control for domestic prices through PPI and add product and market-time fixed effects.

**Table 2.5:** Import Price Pass-through across Markets

	(1)	(2)	(3)	(4)
Changes in Import Prices	0.161** (0.053)	0.160** (0.052)	0.170** (0.052)	0.194*** (0.052)
Changes in Import Prices $\times Dist^w$	0.003 (0.004)	0.004 (0.004)	0.003 (0.004)	0.001 (0.004)
Changes in Import Prices $\times HHI$	-0.020** (0.010)			
Changes in Import Prices $\times Top 4$		-0.014 (0.010)		
Changes in Import Prices $\times Top 8$			-0.024** (0.010)	
Changes in Import Prices $\times Top 20$				-0.042*** (0.010)
Industrial PPI	0.256*** (0.045)	0.256*** (0.045)	0.258*** (0.045)	0.263*** (0.045)
First Stage F-Statistics	148.72	125.21	137.89	112.19
Market*Time FE	Yes	Yes	Yes	Yes
N	298639	298639	298639	298639

Notes: \*\*\*p<sub>i</sub>0.01, \*\*p<sub>i</sub>0.05, \*p<sub>i</sub>0.1. In all regressions, I use TPU\*Crisis as an instrument for import prices and changes in energy prices to instrument for industrial PPI.

Table 2.5 represents the regression results based on IV estimation. In terms of concentration measures, I use Herfindahl index, market shares of top four, eight and twenty retailers respectively in column 1-4. As we see across columns, the remoteness have no impact on the pass-through. One possible explanation is that distribution margin includes not only transportation costs, but also various other costs such as marketing, labor, rent. Some of the costs might work in the opposite direction of transportation costs, thus causing the coefficient to be insignificant.<sup>9</sup>

The concentration in retail industry has a negative and significant effect on the pass-through rate, suggesting that the pass-through to more concentrated market is lower. To explain it, consider the previously mentioned findings that cost pass-

<sup>9</sup>For example, rent and labor costs might be less expensive in more remote places.

through is lower for larger firms. The more concentrated market is dominated with a few large retailers which generally have lower pass-through, thus making the average pass-through lower for that market.

**Table 2.6:** Import Price Pass-through across Markets: Robustness

	(1)	(2)	(3)	(4)
Changes in Import Prices	0.136*** (0.015)	0.135*** (0.015)	0.067* (0.034)	0.028 (0.026)
Changes in Import Prices $\times Dist^w$	0.035*** (0.010)	0.030** (0.010)	0.109*** (0.027)	0.117*** (0.026)
Changes in Import Prices $\times HHI$	0.027 (0.015)		-0.085 (0.061)	
Changes in Import Prices $\times Top8$		0.037* (0.015)		-0.099** (0.030)
PPI	0.224*** (0.049)	0.220*** (0.050)	0.222*** (0.052)	0.213*** (0.051)
PPI $\times Dist^w$			-0.081* (0.036)	-0.093** (0.036)
PPI $\times HHI$			0.144 (0.080)	
PPI $\times Top8$				0.148*** (0.034)
First Stage F-Statistics	149.94	134.53	25.93	41.19
Product*County FE	Yes	Yes	Yes	Yes
County*Time FE	Yes	Yes	Yes	Yes
N	279285	279285	279285	279285
R-Squared	0.280	0.277	0.269	0.275

Notes: \*\*\*p<0.001, \*\*p<0.005, \*p<0.01. In all regressions, I use TPU\*Crisis as an instrument for import prices and changes in energy prices to instrument for industrial PPI.

There might be different trend in prices of different product across different markets. Therefore I add the product-by-market fixed effect in Table 2.6. As we can see in the first two columns, the pass-through is increasing with remoteness measure and the sign on concentration interactions becomes positive, suggesting pass-through is higher more more concentrated market. The results are at odds with previous results without product-market fixed effects, thus raising concerns on the robustness of previous results.

Moreover, in column 3-4, I add the interaction between PPI and concentra-

tion/remoteness measures. Both the interactions between remoteness and concentration are in the opposite signs with import prices, suggesting they are mostly driven by different expenditure shares between imported vs domestic goods.

I repeat the price decomposition exercise for markets. Table 2.7 shows the decomposition results. As we see, the variety pass-through is not significantly different across market with different concentration levels, while the differential expenditure patterns across markets explains all of the differential effect. The negative and significant sign before the interaction term in column 2 suggests that consumers in more concentrated markets tend to spend more on varieties that have lower pass-through. It is consistent with the fact that large retailers have lower pass-through and consumers in more concentrated markets tend to spend more on varieties from large retailers.

**Table 2.7:** Price Decomposition: Markets

	(1) Outlet Channel	(2) Composition Channel	(3) Interaction
Changes in Import Prices	0.172*** (0.042)	0.033 (0.034)	-0.052 (0.028)
Imp $\times$ <i>Dist</i> <sup>w</sup>	0.002 (0.003)	0.005* (0.003)	0.002 (0.002)
Imp $\times$ HHI	0.003 (0.006)	-0.022*** (0.005)	0.000 (0.004)
Industrial PPI	0.927*** (0.027)	0.065** (0.022)	-0.003 (0.018)
Market*Time FE	Yes	Yes	Yes
N	347400	347400	347400

Notes: \*\*\*p<0.001, \*\*p<0.005, \*p<0.01. In all regressions, I use TPU\*Crisis as an instrument for import prices and changes in energy prices to instrument for industrial PPI.

### 2.3.3 Pass-through into Different Markets: County-level Evidence

Retail market competition is mostly at the local level as it is very costly for consumers to purchase goods far away from home (Rossi-Hansberg, Sarte and Trachter, 2018;

Argarwal, Jensen and Monte, 2020). Previously we define a market as a Nielsen defined “scantrack market”. The advantage is that it has a large and representative sample of households in each location, but the limitation is that its size is too large to be counted as a single local retail market. For example, one scantrack market contains 31 counties on average. Therefore, we repeat the exercise by narrowing our market definition as a county.

**Table 2.8:** County-level Pass-Through

	(1)	(2)	(3)	(4)
Changes in Import Prices	0.083*** (0.006)	0.060*** (0.007)	0.087*** (0.006)	0.065*** (0.007)
Import Price $\times$ HHI	-0.014** (0.005)	-0.016*** (0.005)	-0.009 (0.005)	-0.010 (0.005)
Import Price $\times$ Dist		0.034*** (0.006)		0.028* (0.011)
PPI	0.627*** (0.019)	0.586*** (0.021)	0.635*** (0.019)	0.593*** (0.020)
PPI $\times$ HHI			0.124*** (0.018)	0.133*** (0.018)
PPI $\times$ Dist				0.007 (0.012)
Product*County FE	Yes	Yes	Yes	Yes
County*Time FE	Yes	Yes	Yes	Yes
N	2273224	2273224	2273224	2273224
R-Squared	0.288	0.293	0.287	0.292

Notes: \*\*\* $p < 0.001$ , \*\* $p < 0.005$ , \* $p < 0.01$ . In all regressions, I use TPU\*Crisis as an instrument for import prices and changes in energy prices to instrument for industrial PPI. Both HHI and Distance variables are market-product specific.

The results, as reported in Table 2.8, indicate that the pass-through of import prices is lower for more concentrated county, which is consistent with previous scantrack market level results. In column 2, we also find the pass-through is higher for more distant county, which contradicts with our prediction. One possible explanation is that the more remote market might have lower labor cost or rent, which outweighs the effect of higher transportation cost.

In addition, we find that the domestic price pass-through is higher for more concentrated market (column 3-4), which is in the opposite sign with the pass-through

of import prices. It provides us with additional evidence on which factor drives the different pass-through across markets. As it is reasonable to assume retailers' markup elasticity varies little with regard to import price shock or domestic price shock, the differences sign might capture the differences in expenditure share on imported vs domestic goods across markets with different concentration levels.<sup>10</sup> That is, consumers in more concentrated county purchase less imported varieties and more domestic varieties compared with those in less concentrated county. Lastly, we find the pass-through of domestic prices does not vary across markets with different distance to port, which makes sense as it mainly captures the transportation cost for imported good. The results are robust to use market-level concentration measures.

## 2.4 Quantification Exercises

The goal of the exercise is to assess the effect of trade war on consumer prices using our estimates on pass-through rate. Suppose the US imposes a 25% tariff on all consumer goods from China, which is highly likely as the Trump Administration already imposes 15% tariffs on 125 billion imports from China that includes considerable amount of consumer goods starting Sep 4, 2019 and threatens to increase these tariffs further.

Based on recent findings of complete tariff pass-through into import prices during the trade war (Amiti et al (2019); Fajgelbaum et al (2019)), I take the tariff changes as the changes in import prices. Therefore, the log changes in import prices of product  $g$  at period  $t$  are:

$$\Delta \ln P_{gt}^T = \sum_i w_{ig} \Delta \ln P_{igt}^T \quad (2.15)$$

Assuming the import prices from the unaffected countries constant, the increase in import prices of product  $g$  equals to the share of imports from China times the

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<sup>10</sup>Import price shock and domestic price shock are both cost shock for retailers.

increase in prices of Chinese imports.<sup>11</sup> For the expenditure share on Chinese imports of all imports, I use the average expenditure share on Chinese imports among Nielsen goods, which is 0.185. Thus, the import prices of affected products increase 4% on average.

**Table 2.9:** Increases in Consumer Prices in response to Tariffs

	(1)	(2)	(3)
	Aggregate Prices	Lower Income	Higher Income
Changes in Consumer Prices	1.2%	1.53%	1.07%
Adjusted for Domestic Prices	4.4%	3.71%	3.37%
Estimated Pass-Through Rate	0.3	0.38	0.27

Notes: The estimated pass-through rates are based on regressions using TPU\*Crisis as instruments. The increases in domestic prices are calculated using a pass-through rate of 0.5 for aggregate prices. The domestic pass-through is 0.393 for lower income and 0.413 for higher income.

From our estimates in Table 1.2 , the pass-through from an increase in import price to aggregate consumer prices is about 0.3-0.4. Keeping the prices of domestic goods  $g$  and prices of non-tradables constant, the log changes in consumer prices of product  $g$  are given by  $\Delta \ln P_{gt} = \theta \Delta \ln P_{gt}^T$ , which are a product of pass-through and changes in import prices. For an average product with a 4% increase in import prices, the increase in consumer prices ranges from roughly 1.2% to 1.6%.

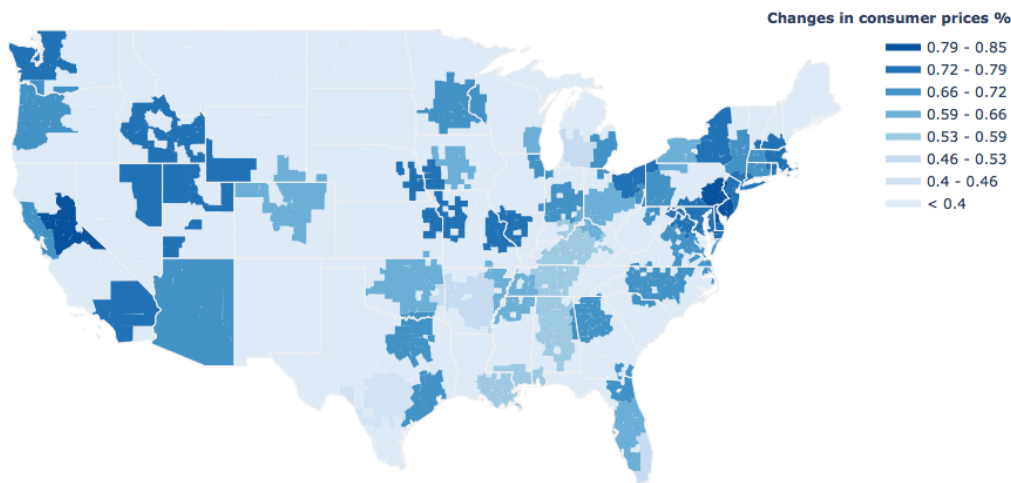
As discussed in the first chapter, due to strategic complementarity and changes in product cost, the domestic prices would increase as well in response to increases in import price. I therefore calculate the indirect effect on consumer prices through the changes in domestic prices. Overall, a 4% increase in import prices would lead to a 4.4% increase in consumer prices, which is significantly higher than previous estimates by only taking into account the direct effect. Our estimates are consistent with findings in the literature. For example, Fajgelbaum et al (2019) find a positive relationship between domestic PPI and import tariffs during the US-China trade

<sup>11</sup>Note that the tariff-inclusive import price of product  $g$  from country  $i$  is  $P_{igt}^T = (1 + \tau_{igt})P_{igt}^*$ , where  $P_{igt}^*$  is the price exporters charge. Thus  $\Delta \ln P_{igt}^T = \ln(1 + \tau_{igt})$ , if we assume complete pass-through and zero tariffs at base period.



war.<sup>12</sup> By estimating the response of PPI for changes in import prices instead of import tariffs, our estimates are slightly larger in magnitude.<sup>13</sup>

**Figure 2.1:** Changes in Consumer Prices across US markets



To see how the increases in import prices translate to differential changes in consumer prices, I apply the estimates of consumer-specific pass-through rates. I find that a 25% tariff leads to a 1.53% increase in consumer prices for lower income households and a 1.07% increase for higher income households. If we take into account the increase in domestic prices, the numbers become 3.71% for low income and 3.37% for high income.

Figure 2.1 shows the impact of trade war on consumer prices across markets, where the darker color represents a larger increase in consumer prices.<sup>14</sup> As we see, consumers in large cities of the Northeast region and Western Coast experienced larger increases in consumer prices, while consumers in the South received the least impact. Meanwhile, the Mountain West and Midwest experienced modest increases in

<sup>12</sup>Amiti et al (2019) has similar findings by distinguishing between input tariffs and output tariffs.

<sup>13</sup>They estimate a tariff elasticity of 0.13, indicating that a 25% increase in tariffs would lead to a 2.9% increase in domestic prices. Multiplying it with the domestic price pass-through (about 0.5) we estimate, it would result in an additional 1.45% increase in consumer price index. Adding it together, the consumer prices of affected goods would increase by 2.65% to 3.05% on average.

<sup>14</sup>The pass-through across markets are calculated by taking into account of different concentration levels in the form of HHI. The effect of distance is not accounted for it is not precisely estimated. The increases in consumer prices for each market is reported in Appendix.

consumer prices. The differential effects are mostly driven by the differences in retail industry concentration across markets. That is, the large cities usually have more competitive retail market while small cities have less competition in retail industries.

Using a general equilibrium quantitative model, Fajgelbaum et al (2019) estimate that prices of tradable goods increased 1.5% on average during the trade war, which is consistent with our estimates before taking into account of domestic prices. Across different regions, they find that counties in Rust Belt and Southeast experienced relatively large increase in nominal wages in tradable sector. However, according to my estimates, some of the Rust Belt cities such as Pittsburgh, Detroit and Baltimore have relatively high pass-through rates and therefore experience larger increases in cost of living during the trade war.

## 2.5 Conclusion

This chapter explores the heterogeneity in pass-through rates across consumers by extending the framework to allow consumer-specific prices. I find the pass-through rate is higher for consumers with lower income and at more competitive markets. The results are robust to using alternative income and concentration measures.

I distinguish two channels that could cause differential pass-through. The first one captures that fact that consumers shop in different retail outlets for the same variety (UPC) and thus face differential retail price adjustment following an import price shock. The second channel focuses on the different expenditure shares across varieties and heterogeneous pass-through across varieties within a narrow product category. A price decomposition shows that for consumers with different income, both variety pass-through and differential expenditure shares contribute to the higher pass-through into consumer prices of lower income, with the latter plays a more important role. For consumer prices across markets with different concentration, the variety

pass-through is not significantly different across markets. However, consumers in more concentrated markets spend more on varieties with lower pass-through.

I then provide a quantification on the effect of trade war on consumer prices based on my estimates. I find that the consumer prices are estimated to increase 1.2% to 1.6% in response to 25% tariffs on Chinese imports of consumer goods. In addition, I find that a 25% tariffs lead to 1.53% increase in consumer prices for lower income households and 1.07% increase for higher income households. Across locations, consumers in big cities of the Northeast and Western Coast experienced larger increase in consumer prices, while consumers in the South received the least impact.

# Appendix

## 2.A Tables

**Table 2.A.1:** Pass-Through Across Income: Unadjusted Income

	Reported Income				Total Spending	
	(1) OLS	(2) IV	(3) IV	(4) OLS	(5) IV	(6) IV
Changes in Import Prices	0.016*** (0.002)	0.083* (0.040)	0.006 (0.038)	0.004*** (0.001)	0.323*** (0.039)	0.218*** (0.036)
Imp × Lower Income	0.028*** (0.002)	0.324*** (0.015)	0.311*** (0.014)	0.001 (0.002)	0.052** (0.016)	0.058*** (0.014)
Industrial PPI	0.253*** (0.013)	0.096*** (0.027)	0.142*** (0.025)	0.316*** (0.013)	0.109*** (0.026)	0.166*** (0.024)
Instrument		TPU × Crisis	TPU × News		TPU × Crisis	TPU × News
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Income*Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	68537	66233	66233	75201	72681	72681

**Table 2.A.2:** Income Adjusted for Household Size and other demographics

	Reported Income				Total Spending	
	(1) OLS	(2) IV	(3) IV	(4) OLS	(5) IV	(6) IV
Changes in Import Prices	0.007*** (0.002)	0.291*** (0.039)	0.194*** (0.037)	0.007*** (0.001)	0.335*** (0.040)	0.240*** (0.036)
Imp × Lower Income	0.007*** (0.002)	0.102*** (0.016)	0.093*** (0.014)	0.001 (0.002)	0.056*** (0.016)	0.061*** (0.014)
Industrial PPI	0.307*** (0.013)	0.104*** (0.027)	0.160*** (0.025)	0.321*** (0.013)	0.108*** (0.027)	0.159*** (0.025)
Instrument		TPU × Crisis	TPU × News		TPU × Crisis	TPU × News
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Income*Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	75220	72700	72700	75213	72693	72693

**Table 2.A.3: Total Spending: Decomposition**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	Variety Pass-through IV	IV	OLS	Expenditure Patterns IV	IV	OLS	Interaction IV	IV
Changes in Import Prices	0.010*** (0.001)	0.469*** (0.046)	0.322*** (0.035)	-0.003** (0.001)	-0.122*** (0.021)	-0.076*** (0.022)	0.001 (0.001)	-0.018 (0.010)	-0.016 (0.011)
Imp × Lower Income	0.001 (0.001)	0.018 (0.018)	0.013 (0.014)	0.002 (0.002)	0.042*** (0.012)	0.050*** (0.011)	0.002* (0.001)	-0.000 (0.005)	-0.001 (0.005)
Industrial PPI	0.370*** (0.013)	0.109*** (0.032)	0.189*** (0.025)	-0.058*** (0.010)	-0.010 (0.013)	-0.037** (0.014)	0.001 (0.003)	0.011* (0.005)	0.010 (0.006)
Instrument		TPU × Crisis	TPU × News		TPU × Crisis	TPU × News		TPU × Crisis	TPU × News
Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income*Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	72560	70040	70040	72560	70040	70040	72560	70040	70040

**Table 2.A.4: Changes in Consumer Prices across Markets**

Market	Pass-Through	Increase in Consumer Prices	Domestic Adjusted
Philadelphia	0.194	0.80%	1.52%
Sacramento	0.190	0.79%	1.51%
Washington DC	0.189	0.78%	1.50%
Suburban NY	0.187	0.77%	1.49%
Baltimore	0.185	0.77%	1.48%
Syracuse	0.185	0.76%	1.48%
Cleveland	0.183	0.76%	1.48%
Los Angeles	0.179	0.74%	1.46%
San Diego	0.178	0.73%	1.45%
Omaha	0.178	0.73%	1.45%
Boston	0.176	0.73%	1.45%
Salt Lake City	0.175	0.72%	1.44%
Kansas City	0.175	0.72%	1.44%
St. Louis	0.175	0.72%	1.44%
Seattle	0.174	0.72%	1.44%
Portland OR	0.172	0.71%	1.43%
Indianapolis	0.169	0.70%	1.42%
Phoenix	0.169	0.70%	1.42%
Richmond	0.169	0.70%	1.42%
Raleigh - Durham	0.169	0.70%	1.42%
Chicago	0.167	0.69%	1.41%
Hartford - New Haven	0.167	0.69%	1.41%
Pittsburgh	0.166	0.68%	1.40%
Charlotte	0.165	0.68%	1.40%
Detroit	0.165	0.68%	1.40%
Atlanta	0.165	0.68%	1.40%
Albany	0.165	0.68%	1.40%
San Francisco	0.165	0.68%	1.40%
Minneapolis	0.163	0.67%	1.39%
Jacksonville	0.163	0.67%	1.39%

Notes: The third column is the increase in consumer prices after adjusting for the increase in domestic manufacturing prices.

**Table 2.A.5:** Changes in Consumer Prices across Markets (Continued)

Market	Pass-Through	Increase in Consumer Prices	Domestic Adjusted
Dallas	0.163	0.67%	1.39%
Houston	0.161	0.66%	1.38%
Denver	0.158	0.65%	1.37%
Oklahoma City - Tulsa	0.154	0.64%	1.36%
Orlando	0.152	0.63%	1.34%
Columbus	0.151	0.62%	1.34%
Memphis	0.149	0.62%	1.34%
Milwaukee	0.148	0.61%	1.33%
Buffalo - Rochester	0.148	0.61%	1.33%
Tampa	0.145	0.60%	1.32%
Cincinnati	0.143	0.59%	1.31%
Des Moines	0.143	0.59%	1.31%
Nashville	0.140	0.58%	1.30%
Birmingham	0.139	0.58%	1.29%
New Orleans - Mobile	0.132	0.55%	1.27%
Louisville	0.130	0.54%	1.26%
Grand Rapids	0.124	0.51%	1.23%
Miami	0.123	0.51%	1.23%
Little Rock	0.122	0.50%	1.22%
San Antonio	0.103	0.42%	1.14%

Notes: The third column is the increase in consumer prices after adjusting for the increase in domestic manufacturing prices.

# Chapter 3

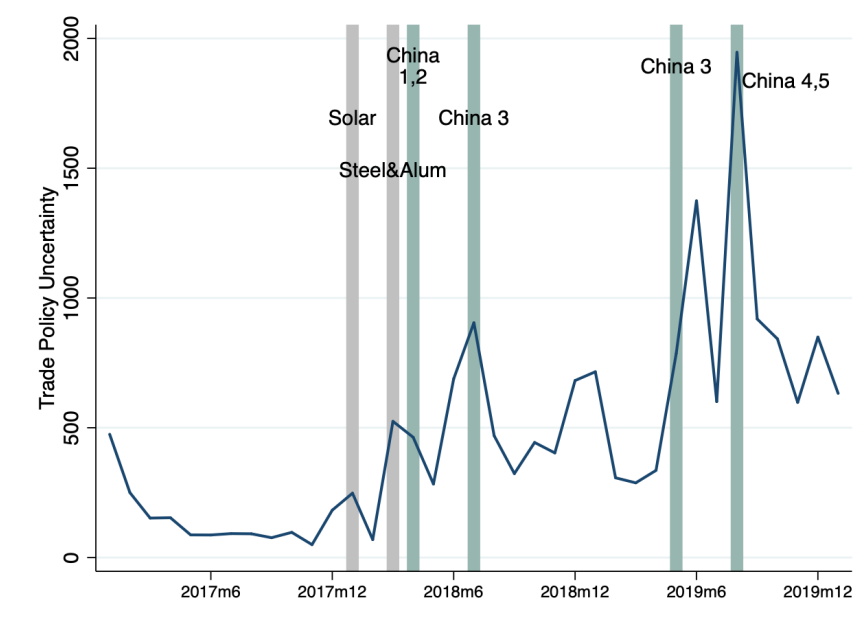
## Trade Policy Uncertainty and US Imports in the Trade War

### 3.1 Introduction

Starting from Jan 2018, the Trump administration has implemented a series of trade policies that substantially increased trade barriers into the US, or the so called “trade war”. The average import tariffs on imports from China rose from 3.1% on Jan 2018 to 21% on Jan 2020 (Bown, 2019). At the same time, the uncertainty about trade policy surged as well. Figure 1 plots the news-based trade policy uncertainty index (solid blue line) developed by Baker, Bloom and Davis (2016) as well as the timing of tariff increase announcement (vertical lines). As we see, the uncertainty about trade policy increases substantially over the course of the “trade war” and reaches its peak on August 2019, when the US announced tariffs on \$300 billion imports from China.

This chapter aims to evaluate the effect of trade policy uncertainty on US imports during the “trade war” episode. The key challenge in identifying the effect of TPU on imports is how to separate it from the effect of increases in import tariffs. Unlike previous studies on trade policy uncertainty where the changes in tariffs are minimal,

**Figure 3.1:** Trade Policy Uncertainty and Import Tariff Waves



Notes: TPU and EPU indices are from Baker, Bloom and Davis (2016). Grey vertical lines denote timing of announcement of tariff waves targeting on solar panels & washing machines, and steel & aluminum. Green vertical lines represent tariff waves on Chinese imports, which are categorized into 5 waves with detailed definition in section 2.

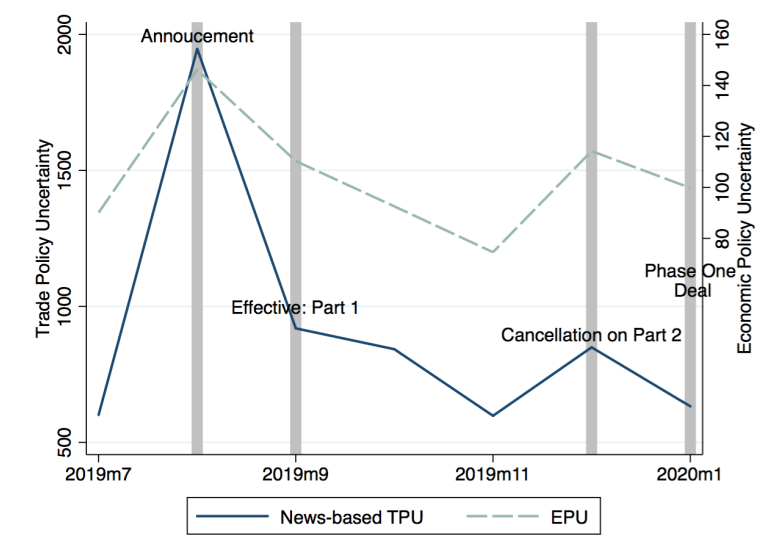
the threat to increase trade barriers realized during this period, which makes it difficult to disentangle the effect of uncertainty from the anticipation effect of tariffs. To address this problem, I exploit the variations in uncertainty after tariff announcement across different products according to its changes in risk, which can be considered as exogenous.

As shown in Figure 1, the trade policy uncertainty peaks when new tariffs were announced.<sup>1</sup> Intuitively, when the U.S. proposes or threatens additional tariffs, the probability of worst-case scenario (higher trade barrier) increases while there are also chances the proposed tariffs would cancel if both sides reach an agreement, which indicates an increase in trade policy uncertainty (TPU) in the framework of Handley and Limão (2017). However, when the higher tariffs realize, the products are in a high protection state. Though there is still uncertainty about whether the tariffs would

<sup>1</sup>Note that the first two waves of tariffs on imports from China are announced at the same time, on April 2018.



**Figure 3.2:** Trade Policy Uncertainty During Wave 4/5



Notes: The two waves are announced at the same time, Aug 2019. Wave 4 went to effect on Sep 1, 2019 and wave 5 was scheduled to take effect on Dec 15, 2019 until it is cancelled during December 2019.

escalate or cancel, the overall uncertainty level decreases. To be more clear, Figure 2 shows how the TPU index involves in the course of the final two waves, which target \$300 billion imports from China. The figure shows that the uncertainty is the highest when the tariffs are announced and much lower when the tariffs realize.<sup>2</sup> For this wave, there is a slightly increase in uncertainty in December when Trump canceled December tariffs and a decrease when Phase one deal with China was announced. The other waves exhibit similar patterns though there are some overlapping periods between different waves.

Motivated by these facts, if a product is announced to have tariff increases in the near future, I assume that the probability of tariff increases for this product increases. However, the risk level of each product, which is defined as the profit loss if worse case scenario realizes according to Handley and Limão (2017), changes into different directions after tariff announcement. More specifically, if a product’s prior belief about worst-case tariff is higher than the announced tariff level, which could be

<sup>2</sup>Note that the high uncertainty level in August, 2019 includes not only uncertainty about import tariffs, but also the uncertainty about retaliation.

thought as the updated belief about tariffs, the risk faced by this product surprisingly decreases after the announcement. Note that the changes in risk for each product are independent from the probability of tariff change, which is often captured by the overall TPU index and does not vary across products in the same wave. Therefore, the changes in overall uncertainty, which depends on both the probability of tariff increases and the changes in risk, can be different across products. In particular, the products with risk increases would have higher uncertainty after tariff announcement as both factors increase. However, the changes in uncertainty faced by products with risk decreases are ambiguous as the probability increases but the risk falls.

I employ a diff-in-diff identification strategy by comparing the differences in imports before and after the tariff announcement across products with different changes in risk. If the stockpiling does not vary across products with different changes in risk, its effect would cancel out using our DID strategy. However, as the stockpiling behavior might be correlated with additional tariffs, I control for the anticipated increase in tariffs during announcement period to further separate the effect of TPU from the anticipation effect.

Another concern is that the changes in risk might be correlated with other product-level shocks, thus subject to omitted variable bias. Given that the column-2 tariffs were set in the Smoot-Harley Act of 1930 and the additional tariffs are almost uniform in one wave. It is reasonable to assume the changes in risk, which are constructed by comparing the two tariff rates, are exogenous to other product-level shocks.

I find that uncertainty reduces imports as the decline in imports after tariff announcement is larger for products with higher increase in uncertainty (risk). In fact, for products with average expected increase in tariffs, those with an increase in risk experience lower imports after tariff announcement whereas those with a decrease in risk experience higher imports. I also find the anticipation effect is more pronounced for products with higher expected increase in tariffs, which is consistent with the

findings in Alessandria et al (2019).

I find the intensive margin, the adjustment within HS10 products, plays a more important role in reducing imports. There is no significant difference in entry and exit rate across products with different changes in risk. However, I find lower product entry after tariff announcement for almost all products, which can be seen as evidence of higher uncertainty, in particular, higher probability of tariff increases, reduced product entry.

I also examine the uncertainty during the pre-war period (2014m1-2017m12) and find that the higher trade policy uncertainty caused by Trump's election led to lower imports for higher risk industries at HS6 digit level, where the risk is measured as the difference between column-2 and mfn tariffs. The results inform us that the column-2 tariffs are valid conjecture on firms' prior belief about worst-case tariff rates before the trade war.

**Literature** This chapter contributes to the growing literature on trade policy uncertainty. Handley and Limão (2017) examine how the decrease in trade policy uncertainty through China's accession to WTO contributes to the export boom from China to the US. Using Chinese firm-level data, Feng, Li and Swenson (2017) investigate how the same event affects Chinese firms' entry and exit decisions. Other studies focus on how the trade agreements, especially PTAs, affect export and its dynamics in different contexts (Handley and Limão(2015); Carballo, Handley and Limão (2018)). These studies mostly examine the effect of TPU reduction on exports. However, in recent years, there is an upward trend in trade policy uncertainty around the world and the uncertainty reaches its peak during the trade war episode. Therefore, it is of interest to see if the increase in uncertainty has non-asymmetric effect on exports or imports. Some recent studies have started to look at the effect of increases in uncertainty in different contexts. For example, Crowley, Song and Meng (2018) find that Chinese firms less likely to enter and more likely to exit if they face a rise in trade

policy uncertainty. More recently, Graziano, Handley and Limão(2019) examine the effect of Brexit on EU-UK exports and find that an increase in probability of Brexit reduces EU-UK exports and net export entry. A closely related paper, Alessandria, Khan and Khederlarian (2019), examines the effect of increases in trade policy uncertainty on US imports from China during 1991-2000 when China faced annual MFN status renewal. This paper complements the literature in the following ways:

First, this paper is the first one to explore the changes in firms' belief about (worst-case) tariffs during an event. Previous studies mostly focus on the events that led to an increase in probability of tariff increase (decrease) with the worst-case tariffs constant throughout the event. Therefore, it allows us to develop a new identification strategy by exploiting the differential changes in risk across products before and after the event.

Second, unlike previous events that there is a one time change in uncertainty which applies to all products, the uncertainty changes continuously during this period as new wave of tariffs are announced. Moreover, the changes in uncertainty, in particular, the probability of tariff increase, are different across products with those covered in the announcement have higher uncertainty. This setting would be useful for us to probably examine the spillover effect of uncertainty on products that are not targeted.

Third, in contrast to other events where the threat to increase trade barriers rarely realize, during this episode, the additional tariffs actually took effect, which enables us to compare the effect of TPU vs the increased trade barriers on imports.

This chapter is also related to the recent literature studying the effect of trade war on US imports and other outcomes (Amiti et al (2019); Fajgelbaum et al (2019)). They find that the imposed tariffs reduce import value of affected products and raise prices for the US firms and consumers. Instead of tariffs, this paper mainly focuses on the effect of trade policy uncertainty on US imports, which might be an important force in reducing US imports from China during current period and play an important

role on US-China trade in the long run.

## 3.2 Background and Stylized Facts

The “trade war” episode started when President Trump approved tariffs on imports of solar panels and washing machines on January 2018. Later in March 2018, the US announced tariffs on steel and aluminum for all trading partners.<sup>3</sup>

In April 2018, the Trump administration announced additional 25 percent tariffs on \$50 billion imports from China based on their investigation under Section 301. Through almost two years (2018-19), the US has imposed five waves of tariffs on imports from China, covering \$522 billion imports from China. Those imports account for 90% of total imports from China in 2018. Though the 5th wave of tariffs were cancelled in December 2019 due to the Phase One Deal with China, the tariffs in place still cover 63% of total imports from China. At the same time, China retaliates with several rounds of tariffs on American goods.

This paper focuses on the effect of both trade policy uncertainty and five waves of tariffs on imports from China. More specifically, the five waves of tariffs are defined as follows:<sup>4</sup>

- **wave 1:** 25 percent tariffs on \$34 billion imports, announced on April 3, 2018, effective on July 6, 2018.
- **wave 2:** 25 percent tariffs on \$16 billion imports, announced on April 3, 2018, effective on August 23, 2018.
- **wave 3:** 10 percent tariffs on \$200 billion imports, announced on July 10, 2018, effective on Sep 24, 2018, increased to 25 percent on May 10, 2019.

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<sup>3</sup>There were tariff exemptions on specific partners such NAFTA and EU later.

<sup>4</sup>Thanks to Chad Bown for summarizing the timeline of the trade war.

- **wave 4:** 15 percent tariffs on \$112 billion imports, announced on August 1, 2019, effective on September 1, 2019.
- **wave 5:** 15 percent tariffs on \$160 billion imports, announced on August 1, 2019, planned to take effect on December 15, 2019, cancelled in December, 2019.

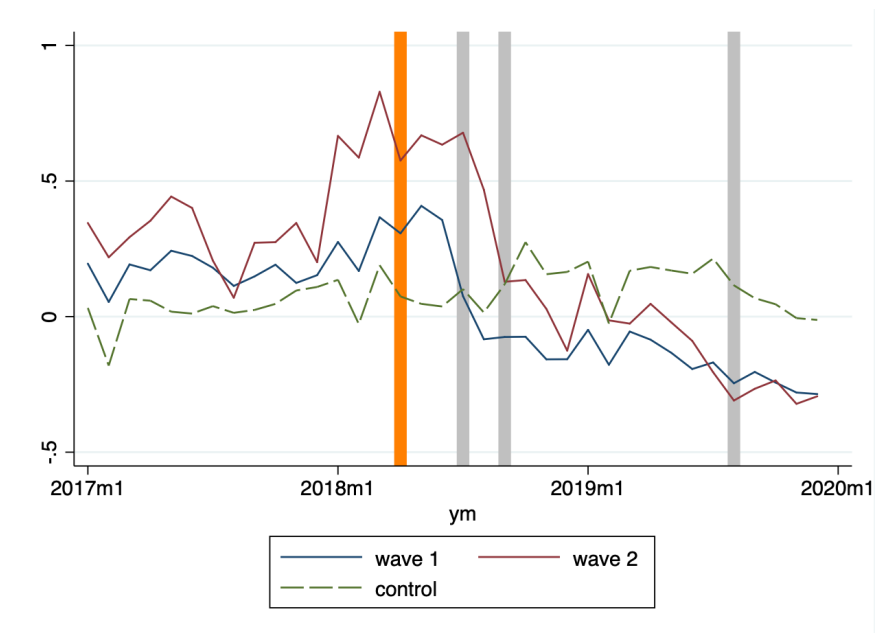
To see how the imports of each wave evolve during this period, I plot the imports from China that are hit by the first two waves of tariffs and also the imports from China that are not subject to 2018 tariffs (labelled as control group).<sup>5</sup> Note that both waves are announced at the same time - April, 2018 - and are implemented in two phases, with the first wave (blue line) took effect on July 6th, 2018 and second wave (red line) on Aug 23, 2018. The orange vertical line denotes the month of announcement and the two grey lines denote the months of implementation.

As Figure 3 makes clear, the imports of wave 1 and control group were basically following the same trend before the trade war. After the announcement, the wave 1 imports didn't immediately decrease and even increased before the tariffs actually took effect, which might be due to the fact that firms tried to stockpile during this period. The imports of both waves decline sharply in the month the tariffs took effect and continue to decrease in the subsequent month, which can be seen as the lagged effect of tariffs. However, the continued decrease in imports for the next year (2019) might indicate that uncertainty of trade policy also plays a role in dampening the import in the longer run given that there were no tariff changes for those products during this period. The imports of other waves exhibit similar patterns and are reported in the Appendix Figure 3.A.1.

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<sup>5</sup>Note that the later does not include imports subject to tariffs on solar and washing machines, and tariffs on steel and aluminum. To avoid complication, it also does not include imports that are subject to third wave of tariffs that took effect on Sep 2018.

**Figure 3.3:** US Imports from China and Tariff Waves



Notes: The monthly US imports data is obtained from US Census Bureau. The imports are normalized as the proportional changes relative to the corresponding month in 2016. Blue and red lines denote changes in imports from China that are subject to the first two waves of tariffs. Dotted green lines represents changes in imports of control group, which includes imports from China that are not subject to 2018 tariffs. Note that the later does not include imports subject to tariffs on solar and washing machines, and tariffs on steel and aluminum. To avoid complication, it also does not include imports that are subject to third wave of tariffs that took effect on Sep 2018.

### 3.3 Pre-War Period

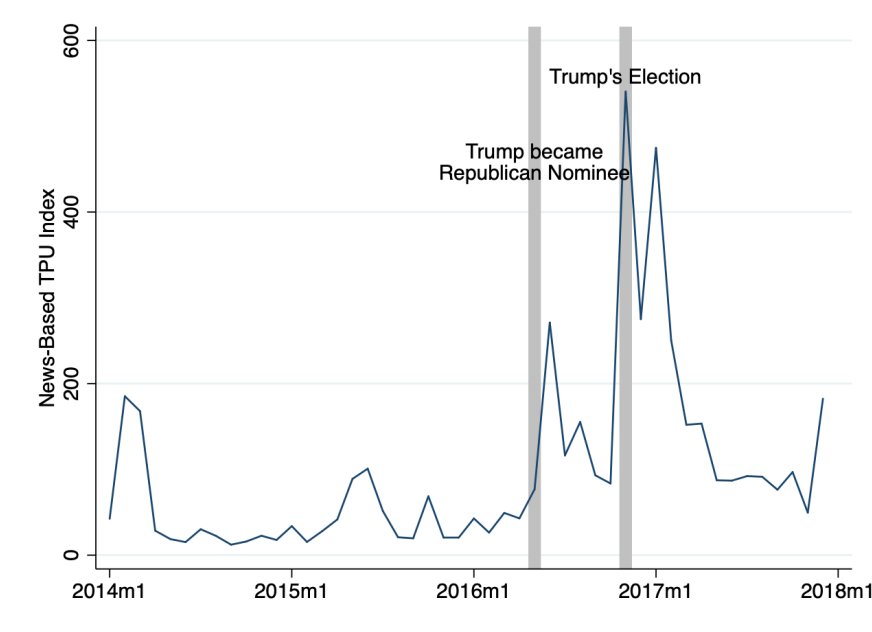
Before I formally identify the effect of TPU on imports during the trade war episode, I first examine firms' prior beliefs about potential tariffs and the changes in uncertainty during the pre-war period, in particular, around Trump's presidential election. This analysis is important as it gives us information on how the arrival of trade war changed uncertainty for each product.

To examine exporters' prior beliefs about potential (worst-case) tariffs, we exploit the variation in trade policy uncertainty over time during the pre-war period (2014m1-2017m12), in particular, the changes in uncertainty around the 2016 US presidential election. During Trump's presidential campaign, he frequently threatened to withdraw from current trade agreements, for example NAFTA, and impose tariffs on imports from specific countries such as Mexico and China (Handley and Limão, 2017b). These threats substantially increased uncertainty on trade policy, specially after he won the presidential election in Nov, 2016. Figure 3.4 plots the news-based trade policy uncertainty index constructed by Baker et al (2016) during the Pre-War period. As we can see, the uncertainty was at a very low level before Trump's campaign and there was an increase when Trump became the Republican Presidential Candidate in May 2018. Furthermore, the TPU Index increased dramatically and reached its peak after Trump' election as the US president.

Based on these facts, we can reasonably identify the effect of uncertainty by comparing the imports before and after Trump's election. Moreover, we explore the variations in risk faced by different industries and examine if the differences in imports vary across industries with high vs low risk. In terms of risk, one potential scenario is that exporters expect the US switch to column-2 tariffs, which are the tariffs imposed on countries with non-Normal Trade Relation (non-NTR) with the



**Figure 3.4:** News-based TPU Index during the Pre-War Period



Notes: The news-based TPU index is constructed by Baker et al (2016).

US.<sup>6</sup> Therefore, the risk faced by industry  $i$  before the trade war is gap between the MFN tariff rate and column-2 tariff rate:

$$Risk_i^{pre} = 1 - \left(\frac{\tau_2}{\tau_{mfn}}\right)^{-3} \quad (3.1)$$

Following Handley and Limão (2017), I construct the risk variable using the column-2 and mfn tariff rates at HTS8 level in 2016.<sup>7</sup> Both column-2 and mfn tariffs are calculated as the ad valorem equivalent(AVE) tariff rates.<sup>8</sup>

The hypothesis is that if the uncertainty increased after Trump's election, we would expect the imports are lower for higher risk products after the election. To

<sup>6</sup>Before China's accession to WTO, the Congress voted annually to renew China's MFN status. If the MFN status were not renewed, the US would impose non-NTR tariffs on Chinese imports.(Handley and Limão (2017); Alessandria et al(2019))

<sup>7</sup>There is little variation in column-2 tariffs across years. The reason of not using column-2 in previous years like in Pierce and Schott (2016) is its limited coverage of new HTS8s in recent years. More specifically, about 1/4 of HTS8s in the sample period are not covered in 2001 HTS schedule. The column-2 tariffs for these HTS8s are therefore missing.

<sup>8</sup>According to WTO, AVE=ad valorem rate + specific rate/unit price.

test this hypothesis, we run the following estimation

$$\log(\text{imp}_{vt}) = \beta \text{Risk}_i^{\text{pre}} \times \text{Election}_t + \ln \tau_{it} + \delta_v + \delta_t + \epsilon_{vt} \quad (3.2)$$

where on the left hand side is the monthly (log) imports of product  $v$  (HS10) from China to the US during 2014m1-2017m12. On the right hand side, I include the interaction between industrial (HS8) *risk* and an *election* dummy, which equals to one after November 2016 and zero otherwise. If the uncertainty about trade policy increased after Trump’s election, we expect  $\beta$  to be negative as higher risk industries have disproportionately lower imports after uncertainty increased. In addition, I include the product and time fixed effects to control for time-invariant product-specific characteristics and unobserved economic shocks that affect imports equally.

Table 3.1 reports the regression results. In the first column, we can see that higher risk industries had lower imports during the entire period, confirming that column-2 is the relevant worst-case tariff in the pre-war episode. However, there is no significant difference in imports before and after Trump’s election. The results hold when we control for HS10 fixed effects in column 2. The lack of effect might be due to our definition of election dummy, which assumes a one time increase in uncertainty. Thus in column 3-4, I replace the election dummy with the time-varying News Index, which captures not only the increase in uncertainty during Trump’s presidential election, but also the variations in uncertainty during Trump’s campaign, such as when he became the Republican presidential nominee. The results are similar: there is no significant difference in imports across periods with high or low uncertainty. Results in column-4 suggest that there is even slightly higher imports when uncertainty is high.

The higher uncertainty might affect the entry and exit of HS10s, which are not captured in the HS-10 level regression. Therefore, in the following, I aggregate imports to the HS-6 level to investigate if the uncertainty increase during Trump’s election

**Table 3.1:** Imports and Uncertainty During the Pre-War Period

	(1)	(2)	(3)	(4)
$Risk_i^{Pre}$	-0.596***		-0.590***	
	(0.039)		(0.038)	
$Risk_i^{Pre} \times Election_t$	0.021	0.016		
	(0.032)	(0.016)		
$Risk_i^{Pre} \times News_t$			0.016	0.015*
			(0.015)	(0.007)
Tariffs	0.075	-1.842*	0.075	-1.809*
	(0.109)	(0.745)	(0.109)	(0.742)
HS6 FE	Yes	No	Yes	No
HS10 FE	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
N	231727	231727	231727	231727
R-Squared	0.520	0.887	0.520	0.887

Notes: \*\*\*p<0.001, \*\*p<0.005, \*p<0.01. The standard error is clustered at HS10 level. Election dummy equals to one after Nov 2016. Tariffs are at HS8 level.

**Table 3.2:** Pre-War Episode: HS6

	(1)	(2)	(3)	(4)
$Risk_i^{Pre} \times Election_t$	-0.049*	-0.061*		
	(0.021)	(0.031)		
$Risk_i^{Pre} \times News_t$			-0.023**	-0.000
			(0.011)	(0.017)
Tariffs	-5.995***	-2.004	-5.684***	-1.737
	(1.188)	(1.276)	(1.180)	(1.274)
HS6 FE	Yes	No	Yes	No
HS2 $\times$ Time FE	No	Yes	No	Yes
Time FE	Yes	No	Yes	No
N	157430	157278	157430	157278
R-Squared	0.899	0.904	0.899	0.904

Notes: \*\*\*p<0.001, \*\*p<0.005, \*p<0.01. Election dummy equals to one after Nov 2016. HS6-level Risk is calculated using the simple average of mfn and column-2 tariffs within a HS6. The parameter before interaction of risk with news index includes the current and two months lagged effect of news index.

affects HS-6 level imports from China. Table 3.2 presents the results. As we can see in column 1, the higher risk industries experienced lower imports after Trump's election. The effect is robust to controlling for sector(HS2) by time fixed effects in column 2. As I didn't find evidence of adjustment at HS10-level, the results suggest that higher uncertainty caused by Trump's election led to lower entry or higher exit of HS10s.

I replace the election dummy with uncertainty news index in column 3-4. To control for the lagged effect of uncertainty, I include the interaction of risk with two monthly lags of news index. As we can see in column 3, the high the uncertainty, the lower the imports for higher risk industries.

In sum, I find that the higher trade policy uncertainty caused by Trump's election led to lower imports for higher risk industries at HS6 digit level, where the risk is measured as the difference between column-2 and mfn tariffs. The adjustment was mostly through the entry and exit of HS10s within a HS6 instead of reduction in HS10 level imports.

## **3.4 Trade War Episode**

### **3.4.1 Theoretical Framework**

To examine the effect of uncertainty during the trade war, I derive a theoretical prediction on change in uncertainty factor and its effect on US imports from China in the framework of Handley and Limão (2017).

The arrival of trade war, in particular, the announcement of tariffs, could indicate: 1) an increase in probability of tariff change; 2) changes in risk for each product. The latter happens because the announced additional tariffs, which are concentrated at 10 percent or 25 percent, are different from exporters' prior beliefs about worst-case tariff level. It potentially changes the overall uncertainty for different products into

opposite directions. Consider a product with prior belief on tariffs that are higher than the announced (additional) 25 percent, the announcement of tariffs would lead to a decrease in risk and an increase in probability of tariff changes. The overall change in uncertainty for this product is therefore ambiguous and depends on the relative magnitude of each force. To see it more clearly, we put it in the framework of Handley and Limão (2017) and rewrite the uncertainty factor  $U(\omega, \gamma)$ , which governs how the uncertainty affects export entry and industrial export.

$$U(\omega, \gamma) = \left[1 + \frac{\mu(\gamma)}{1 + \mu(\gamma)}(\omega - 1)\right]^{\frac{1}{\sigma-1}} \quad (3.3)$$

where the risk is defined as the ratio of potential profit loss:

$$Risk = 1 - \omega = 1 - \left(\frac{\tau_2}{\tau_1}\right)^{-\sigma} \quad (3.4)$$

Note that  $\tau_2$  is the worst-case tariffs and  $\tau_1$  is the current tariffs. According to previous analysis, the prior belief about worst-case tariffs is potentially the column-2 tariff rates, which have a median of roughly 35 percent. After the announcement of tariffs, exporters updated their beliefs on tariffs and the worst-case tariffs could be equal to the announced tariff levels, which are not necessarily higher than the column-2 tariff rates. Therefore, the announcement of tariffs might lead to an increase in risk for some products but a decline in risk for others.

The other term in the equation (3.3),  $\mu(\gamma)$ , depends on the probability of policy shock  $\gamma$ , the probability of tariff increase  $\lambda_2$  and the probability of surviving  $\beta$  :

$$\mu(\gamma) = \gamma \lambda_2 \frac{\beta}{1 - \beta} \quad (3.5)$$

The announcement of tariffs in the trade war causes an increase in  $\mu(\gamma)$  as it raises the probability of tariff increase ( $\gamma \lambda_2 \uparrow$ ) for all products. Note that the overall

uncertainty factor  $U(\omega, \gamma)$  depends on both risk level  $(1 - \omega)$  and probability of tariff increases  $(\mu(\gamma))$ :

$$\frac{\partial U}{\partial(1 - \omega)} < 0, \quad \frac{\partial U}{\partial\mu(\gamma)} < 0 \quad (3.6)$$

That is, the higher the risk and the higher the probability of tariff increases, the lower the uncertainty factor. Note that  $U(\omega, \gamma) < 1$  and a lower uncertainty factor is equivalent to higher uncertainty.

To see this more clearly, I re-state the uncertainty augmented gravity equation in Handley and Limão (2017) and write it in differences between Pre-war and Post-announcement period:

$$\Delta \ln R_v = (k - \sigma + 1)(\ln U_v^{ann}(\omega_w, \gamma_w) - \ln U_v^{pre}(\omega_p, \gamma_p)) - \frac{\sigma}{\sigma - 1}k\Delta \ln \tau_v - k\Delta \ln d_v + \epsilon_v \quad (3.7)$$

For products with increased risk  $(1 - \omega \uparrow)$  during the trade war, according to equation (3.6), we have:

$$\Delta \ln U_v = \ln U_v^{war}(\omega_w, \gamma_w) - \ln U_v^{pre}(\omega_p, \gamma_p) < 0 \quad (3.8)$$

That is, the announcement of tariffs would decrease imports for these products because the overall uncertainty increased (lower uncertainty factor). For products with a fall in risk  $(1 - \omega \downarrow)$ , the differences in uncertainty factor are uncertain as the two forces are contradicting with each other. If we define the changes in risk for product  $v$  as:

$$\Delta Risk_v = Risk_v^{war} - Risk_v^{pre} = \left(\frac{\tau_v^{col2}}{\tau_v^{mfn}}\right)^{-\sigma} - \left(\frac{\tau_v^{war}}{\tau_v^{mfn}}\right)^{-\sigma} \quad (3.9)$$

where the  $\tau_v^{war}$  equals to current MFN tariffs plus the announced additional tariffs and column-2 represents the prior beliefs about worst-case tariffs. We would expect the increase in uncertainty is higher for products with larger differences in risk  $(\Delta Risk_v)$ .

That is:

$$\frac{\partial \Delta \ln U_v}{\partial \Delta Risk_v} < 0 \quad (3.10)$$

### 3.4.2 Identification Strategy

After establishing the relationship between uncertainty and imports in equation (3.7),

I propose to run the following estimation:

$$\begin{aligned} \ln imp_{vt} = & \alpha + \beta_1 Announce_{vt} \times \Delta Risk_v + \beta_2 Announce_{vt} + \beta_3 Announce_{vt} \times \Delta \ln \tau_v^{war} \\ & + \beta_4 Effect_{vt} + \beta_5 \ln \tau_{vt} + \delta_v + \delta_t + \epsilon_{vt} \end{aligned}$$

where  $Announce_{vt}$  is a dummy variable that equals to one after the tariffs on product  $v$  is announced and before the tariffs realized. It represents the increase in probability of tariff increases ( $\gamma\lambda_2$ ) for all affected products. The changes in risk before and after the announcement are defined as in equation (3.9). We expect  $\beta_1$  to be negative as it capture the differential effect of uncertainty on imports.

The sign of  $\beta_2$ , which measures the differences in average import before and after the announcement for products without changes in risk, is ambiguous. It captures not only the effect of increases in uncertainty but also the effect of anticipatory stockpiling. The idea is that if firms expect future, uncertain tariff increases, they tend to stockpile before the uncertainty resolves. Alessandria et al (2019) find evidence of anticipatory stockpiling behavior for China's MFN status renewal during the 1990s. We find similar pattern of imports during the trade war episode as in Figure. In sum, the stockpiling leads to a positive  $\beta_2$  while the increase in uncertainty might cause a negative  $\beta_2$ . It is hard to disentangle each other through a single parameter.

More importantly, our difference-in-difference identification strategy separates the effect of uncertainty from the anticipation effect. If the stockpiling behavior does not

vary across products with different changes in risk, the parameter of interest  $\beta_1$ , which compares differential import growth across products, only captures the effect of uncertainty on imports as the stockpiling effect has been cancelled out. However, Alessandria et al (2019) find that the higher the expected increases in tariffs, the more stockpiling. As the magnitude of (expected) increases in tariffs might be correlated with the changes in risk, the stockpiling might be different across products. To address this concern, I add an interaction term of  $Announce_{vt}$  and  $\Delta \ln \tau_v^{war}$ , which is the expected tariff increases for product  $v$ :  $\ln \tau_v^{war} - \ln \tau_v^{mfn}$ , to control for the differential stockpiling behavior across products.

Lastly, I include a  $Effect_{vt}$  dummy, which equals to one after the tariffs took effect. It captures the differences in average import between the pre-war and the after (tariff) realization period after controlling for the changes in applied tariffs. The differences in import could be due to changes in uncertainty between the two periods and/or the decline in imports due to stockpiling in previous period. I also control for changes in tariffs and product, time fixed effects.

### 3.4.3 Data

I combine data from several data sources. The US monthly import data at HS10-level is obtained from the US Census Bureau. The balanced sample includes HS10s that exist in every month of 2017-2019 and accounts for about 91% of total imports from China.

The tariffs data, which includes MFN and Column-2 tariff rates at HTS8 level as well as additional tariffs on Chinese imports, is obtained from USITC.<sup>9</sup> Note that USITC tariff schedules include both ad valorem tariff rates and specific tariff rates. We only make use of the ad valorem rates because the specific rates are almost

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<sup>9</sup>The list of products that are subject to additional tariffs can be found in Chapter 99 of USITC tariff schedules. The additional tariffs are mostly at the HTS8 level, with some exemptions on HS10 products within HTS8.



constant during this period. Exploiting these information, I construct monthly tariffs for Chinese imports at HS10 level. To construct the changes in risk  $\Delta Risk_v$ , I use the column-2 and MFN tariff rates in 2017. To summarize, of the 2,737 HS6s imported from China, 2,620 HS6s are hit by tariffs during this period and they account for about 94% of the total imports from China in 2017.

The  $Announce_{vt}$  and  $Effect_{vt}$  dummies are constructed from the timeline of the trade war, as summarized by Chad Bown.<sup>10</sup> Note that if the announcement/effective date is after 15th of a month, I count the next month as the beginning month. For example, the second wave of tariffs took effect on Aug 23, 2018. The  $Effect_{vt}$  dummy equals to one starting from September 2018. Table 3.3 presents the summary statistics.

It is worth mentioning that almost all affected products experienced one time increase in tariffs except products in wave 3. For wave 3 products, there was a 10 percent increase in tariffs in September, 2018 (announced in June, 2018) and a subsequent increase to 25 percent in May, 2019 (announced in the same month). However, as there is no gap between announcement and execution in the second announcement. The further increase is not captured in the regression.

**Table 3.3:** Summary Statistics

	Mean	SD	Median	N
Import (log)	12.28	2.53	12.36	340,408
Changes in Risk ( $\Delta Risk_v$ )	-0.23	0.22	-0.26	340,408
Risk Dummy ( $D_v^{risk}$ )	0.13	0.34	0	340,408
Anticipated Tariff Increase ( $\Delta \ln \tau_v^{war}$ )	0.12	0.05	0.09	340,408
Announce(Binary)	0.07	0.25	0	340,408
Effective(Binary)	0.28	0.28	0	340,408
Entry	0.20	0.40	0	236,147
Exit	0.11	0.31	0	360,686

Notes: The import value are reported for the unbalanced sample.

<sup>10</sup>The timeline is available on PIIE's website.

### 3.4.4 Baseline Results

**Table 3.4:** TPU and Imports: Baseline Results

	(1)	(2)	(3)	(4)
Announce	0.067*** (0.010)	0.035*** (0.011)	0.048*** (0.012)	-0.012 (0.013)
Announce $\times D_v^{risk}$	-0.063** (0.021)	-0.060** (0.021)		
Announce $\times \Delta Risk_v$			-0.054 (0.032)	-0.165*** (0.034)
Announce $\times \Delta \ln \tau_v^{war}$		0.074*** (0.008)		0.087*** (0.008)
Effect	0.091*** (0.016)	0.075*** (0.016)	0.092*** (0.016)	0.075*** (0.016)
Tariffs( $\ln \tau_{vt}$ )	-2.333*** (0.104)	-2.285*** (0.104)	-2.336*** (0.104)	-2.283*** (0.104)
HS10 FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	341276	340408	341276	340408
R-Squared	0.875	0.875	0.875	0.875

Notes: \*\*\*p<0.001, \*\*p<0.005, \*p<0.01. The standard error is clustered at HS10 level. The anticipated tariff increase ( $\Delta \ln \tau_v^{war}$ ) is normalized.

Table 3.4 reports the baseline results using the full, unbalanced sample of HS10-level imports. In the first column, I interact *Announce* with a dummy variable  $D_v^{risk}$ , which equals to one if the product's announced war tariffs are larger than column-2 tariffs and thus experienced an increase in risk after the tariff announcement.<sup>11</sup> The significantly negative sign before the interaction term in column 1 suggests that compared with products that have a risk decrease, products that experience risk increases have lower imports after the announcement. In column 2, I add the interaction of announcement dummy and the anticipated increase in tariffs. The coefficient before this interaction is positive and significant, indicating the stockpiling effect is more pronounced for products with higher anticipated increase in tariffs. This is consistent with the findings in Alessandria et al (2019). Moreover, the results on uncertainty is robust to adding the anticipation term. Combined with coefficients on

<sup>11</sup>Approximately 25% of HS10s have an increase in risk.

other terms, a product with an increase in risk and average expected increase in tariffs ( $\Delta \ln \tau_v^{war} = 0$ ) would have 2.5 log points lower imports after the announcement on average. The higher the anticipation effect, the smaller the decline in imports. However, a product with a decrease in risk ( $D_v^{risk} = 0$ ) and average expected increase in tariffs has 3.5 log points higher imports after the announcement.

In column 3 and 4, I replace the risk dummy variable with the actual changes in risk. The coefficient before the interaction term is negative but not significant in column 3 and becomes significantly negative after I add the anticipation term in column 4. This is probably due to the fact the anticipated increase in tariffs is positively correlated with the changes in risk. Thus the interaction with risk can capture the increased stockpiling if we are omitting the anticipation effect. The negative and significant sign before the interaction with risk suggests that the larger the increase in uncertainty, the smaller the increase in imports. In other words, higher uncertainty reduces imports, which is consistent with our hypothesis.

The results using balanced sample of HS10s are reported in Appendix Table 3.A.1. The interaction with the risk dummy is still negative but not significant (column 1-2), which might be due to fact that the balanced sample omit the adjustment through the extensive margin. We also find a smaller elasticity of risk in column 4, which is consistent with the extensive margin hypothesis. In the next section, I replace the import value with the entry and exit dummies to formally investigate the effect of uncertainty on product entry and exit.

### 3.4.5 Product Entry and Exit

The previous results using import value suggest that extensive margin might play a role in reducing import. In the framework of Handley and Limão (2017), a main channel that uncertainty affects import is through the changes in entry cutoff. Therefore, it is important to examine how the extensive margin responded to changes in

uncertainty during this period. In the following, I examine this channel by constructing an entry and exit sample and run a linear probability model. More specifically, the entry sample includes products that were not imported in  $t - 12$  and exit sample are products that were imported in  $t - 12$ . Therefore, the entry is defined as products that were not imported in  $t - 12$  but were imported in  $t$  while exit is defined as products that are imported in  $t - 12$  but not in  $t$ . Our sample, which includes entry and exit for 2017m1-2019m12, has an average entry rate is about 20% and the exit rate is about 11%.<sup>12</sup>

**Table 3.5:** Product Entry

	(1)	(2)	(3)	(4)
Announce	-0.001 (0.005)	-0.021** (0.008)	-0.006 (0.005)	-0.020** (0.008)
Announce $\times D_v^{risk}$	-0.011 (0.006)	0.002 (0.009)		
Announce $\times \Delta Risk_v$			-0.012 (0.010)	0.001 (0.016)
Announce $\times \Delta \ln \tau_v^{war}$		0.021*** (0.006)		0.021*** (0.006)
Effect	0.012* (0.006)	0.009 (0.010)	0.012* (0.006)	0.009 (0.010)
Tariffs( $\ln \tau_{vt}$ )	-0.234*** (0.036)	-0.354*** (0.057)	-0.234*** (0.037)	-0.354*** (0.057)
HS10 FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	200713	132642	200713	132642
R-Squared	0.444	0.368	0.444	0.368

Notes: \*\*\*p<0.001, \*\*p<0.005, \*p<0.01. The standard error is clustered at HS10 level. Entry is defined as if the product that was not imported in  $t - 12$  but exist in  $t$ . The entire entry sample includes products that are not present in  $t - 12$ .

Table 3.5 presents the results on product entry. As we can see in column 1, there was less product entry after tariff announcement for higher risk products. However, the effect disappears when I control for anticipation effect in column 2. Instead, I find that there was more product entry for products with higher expected increase in tariffs. According to column 2, a product with average expected increase in tariffs

<sup>12</sup>To construct entry and exit for 2017, I use imports information in 2016.

had lower entry rate after the announcement, which can be seen as evidence of higher uncertainty, in particular, higher probability of tariff increases, reduced product entry.<sup>13</sup> The results using actual changes in risk (column 3) indicate that there was no significant differences in product entry across products with different changes in risk. After adding anticipation effect, the results are similar. The results are robust to using other criteria of entry as reported in Appendix Table 3.A.2.

**Table 3.6:** Product Exit

	(1)	(2)	(3)	(4)
Announce	0.003 (0.002)	0.003 (0.002)	0.000 (0.003)	0.001 (0.003)
Announce $\times D_v^{risk}$	-0.008 (0.005)	-0.008 (0.005)		
Announce $\times \Delta Risk_v$			-0.007 (0.008)	-0.006 (0.009)
Announce $\times \Delta \ln \tau_v^{war}$		-0.001 (0.002)		-0.001 (0.002)
Effect	0.006 (0.003)	0.006 (0.003)	0.006 (0.003)	0.006 (0.003)
Tariffs( $\ln \tau_{vt}$ )	0.153*** (0.020)	0.152*** (0.020)	0.153*** (0.020)	0.152*** (0.020)
HS10 FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	337998	337261	337998	337261
R-Squared	0.491	0.482	0.491	0.482

Notes: \*\*\*p<0.001, \*\*p<0.005, \*p<0.01. The standard error is clustered at HS10 level. Exit is defined as if the product that were imported in  $t - 12$  but not imported in  $t$ .

Table 3.6 reports results on product exit. The results show no significant impact of uncertainty on product exit. It is surprising that the entry and exit do not vary across products with different risk. One possible explanation is that most entry and exit at the firm-level has not been captured in the product-level data. It is also possible that uncertainty affects entry only in industries with high fixed entry cost as shown in Handley and Limão (2017).

<sup>13</sup>The anticipated increase in tariffs  $\Delta \ln \tau_v^{war}$  has been normalized to have a mean zero.

## 3.5 Conclusion

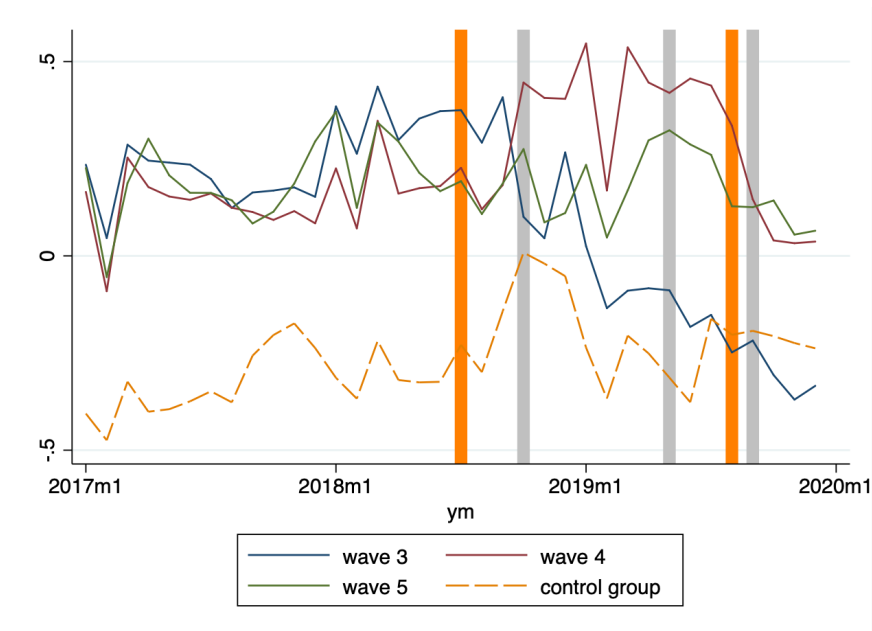
This chapter investigates the effect of trade policy uncertainty on US import from China during the trade war episode. By comparing the differences in imports before and after the announcement of tariffs across products, I find that the decline in imports after tariff announcement is larger for products with higher increase in uncertainty (risk), which suggests uncertainty reduces imports. Furthermore, I find the intensive margin, the adjustment within HS10 products, plays a more important role in reducing imports. There is no significant difference in entry and exit rate across products with different changes in risk.

In addition, I find the anticipation effect is more pronounced for products with higher expected increase in tariffs, which is consistent with the findings in Alessandria et al (2019). I also examine the uncertainty during the pre-war period (2014m1-2017m12) and find that the higher trade policy uncertainty caused by Trump's election led to lower imports for higher risk industries at HS6 digit level, where the risk is measured as the difference between column-2 and mfn tariffs. The results inform us that the column-2 tariffs are valid conjecture on firms' prior belief about worst-case tariff rates before the trade war.

# Appendix

## 3.A Additional Figures and Tables

Figure 3.A.1: Imports and Tariff Waves: 3-5th Waves



The first orange bar indicates the time when the wave 3 tariffs are announced. The first grey bar denotes the time when the wave 3 tariffs went effect and the second grey bar indicates the increase in tariffs to 25 percent for wave 3 products. The second orange bar represents the time when wave 4/5 tariffs were announced and the third grey bar denotes when the wave 4 tariffs realized.

**Table 3.A.1:** TPU and Imports: Balanced Sample

	(1)	(2)	(3)	(4)
Announce	0.077*** (0.009)	0.047*** (0.010)	0.077*** (0.012)	0.012 (0.014)
Announce $\times D_v^{risk}$	-0.030 (0.025)	-0.034 (0.024)		
Announce $\times \Delta Risk_v$			0.012 (0.034)	-0.122** (0.038)
Announce $\times \Delta \ln \tau_v^{war}$		0.067*** (0.007)		0.076*** (0.008)
Effect	0.109*** (0.016)	0.094*** (0.016)	0.109*** (0.016)	0.094*** (0.016)
Tariffs( $\ln \tau_{vt}$ )	-2.282*** (0.112)	-2.239*** (0.111)	-2.281*** (0.111)	-2.238*** (0.111)
HS10 FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	221635	221383	221635	221383
R-Squared	0.887	0.887	0.887	0.887

Notes: \*\*\*p<0.001, \*\*p<0.005, \*p<0.01. The standard error is clustered at HS10 level. The anticipated tariff increase ( $\Delta \ln \tau_v^{war}$ ) is normalized. The balanced sample only includes HS10s that were imported in every month of 2017-2019. Those HS10s account for 92% of total imports from China in 2017.

**Table 3.A.2:** Product Entry

	(1)	(2)	(3)	(4)
Announce	-0.000 (0.006)	-0.019 (0.010)	-0.006 (0.005)	-0.020* (0.009)
Announce $\times D_v^{risk}$	-0.012* (0.006)	-0.005 (0.011)		
Announce $\times \Delta Risk_v$			-0.012 (0.010)	-0.001 (0.019)
Announce $\times \Delta \ln \tau_v^{war}$		0.017* (0.008)		0.017* (0.008)
Effective	0.015** (0.005)	0.016 (0.012)	0.015** (0.005)	0.016 (0.012)
Tariffs( $\ln \tau_{vt}$ )	-0.155*** (0.035)	-0.257*** (0.068)	-0.156*** (0.035)	-0.257*** (0.068)
HS10 FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	154255	85401	154255	85401
R-Squared	0.431	0.362	0.431	0.362

Notes: \*\*\*p<0.001, \*\*p<0.005, \*p<0.01. The standard error is clustered at HS10 level. Entry is defined as if the product that was not imported in  $t - n$ , where  $n = 11, 12, 13$ , but was imported in  $t$ . The entire entry sample includes products that are not present in  $t - 12$ .



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