What are the Price Effects of Trade? Evidence from the U.S. and Implications for Quantitative Trade Models*

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PRELIMINARY AND INCOMPLETE

Abstract

We estimate the impact of trade with China on U.S. consumer prices and use this evidence to discipline quantitative trade models. Using confidential price data from the U.S. Bureau of Labor Statistics and two complementary identification strategies from Pierce and Schott (2016) and Autor et al. (2013), we find that trade with China had a large impact on U.S. prices. Between 2000 and 2007, a one percentage point increase in Chinese import penetration in a given industry led to a three percentage point fall in the Consumer Price Index in that industry. This effect is large but plausible: for instance, benchmarking our estimates against those of Autor et al. (2013), our results imply that increased Chinese import penetration generated benefits to U.S. consumers through lower prices equal to $101,250 per lost manufacturing job (or a cumulative 1.97% fall in the aggregate U.S. CPI between 2000 and 2007). We then show that our estimates are one order of magnitude larger than what would be expected in the large class of trade models nested by Arkolakis et al. (2012). Decomposing our effect between domestic and foreign varieties, as well as between new and pre-existing domestic varieties, we find that the price response of domestic varieties plays a much bigger role than in standard quantitative trade models, which could be rationalized by endogenous markups *a la* Bertrand or endogenous innovations reducing marginal cost for domestic producers. Finally, we document that, for a given trade shock, the price response is substantially larger for product categories that cater to richer households; therefore the expenditure channel of trade may have significant distributional effects. Overall, our findings suggest that both the average gains from trade and their distributional effects may be substantially larger than previously thought.

JEL codes: F10, F13, F14

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I Introduction

How large are the gains from trade and how are they distributed in society? Recent research has developed reduced-form empirical strategies to estimate the distributional effects from trade in the labor market: for example, Autor et al. (2013) and Pierce and Schott (2016) have developed instruments to estimate the causal effect of trade with China on the loss of manufacturing jobs in the U.S. However, by and large such reduced-form methods have not been used to estimate the impact of trade on U.S. consumer prices, which is likely to be the key component of the gains from trade.[1] Data limitations explain the scarcity of evidence on this question, which can be answered only with comprehensive price data.

In the first part of this paper, we use confidential micro-data from the United States Bureau of Labor Statistics (BLS) to obtain comprehensive coverage of price dynamics across goods and services over a long panel, from the late 1980s to today. We first match price data from the Consumer Price Index to information on trade flows at the level of detailed industries. We then obtain plausibly exogenous variation in trade with China across industries over time using the instruments developed by Autor et al. (2013) and Pierce and Schott (2016). We can thus estimate the impact of trade with China on U.S. consumer prices across industries. We find large effects: on average, a one percentage point increase in the spending share on imports from China in a given industry leads to a three percentage point fall in U.S. consumer prices in that industry. This effect is large but not implausible in light of the large effects of trade with China on U.S. manufacturing employment documented in the prior literature. Benchmarking our estimates against those of Autor et al. (2013), we find that increased Chinese import penetration generated benefits to U.S. consumers through lower prices equal to $101,250 per lost manufacturing job. Applying our cross-industry estimates to changes in trade with China at the level of the U.S. as a whole over time, we obtain that between 2000 and 2007 the increased in trade with China reduced the U.S. Consumer Price Index by 1.97% (which is about one tenth of cumulative inflation during this period, equal to 19.91% according to the Consumer Price Index).

In the second part of this paper, we use our estimates to discipline quantitative trade models. Arkolakis et al. (2012) show that in a large set of standard trade models, the gains from trade have a simple expression in terms of two sufficient statistics: the change in the domestic expenditure share and the trade elasticity. Applying their logic to sectoral inflation in a multi-sector model,

[1] For a recent exception, see Bai and Stumpner (2018). The relationship between this paper and our work is discussed below.

it is straightforward to derive the IV specifications we run in the first part of the paper from the model. This exercise shows that in the class of trade models nested by Arkolakis et al. (2012), our estimates should be closely related to the (potentially sector-specific) trade elasticity. However, our IV estimates are one order of magnitude larger than what one would expect based on standard estimates of the trade elasticity. Of course, the trade elasticity varies across the models nested by Arkolakis et al. (2012) (see, e.g., Melitz and Redding (2015) and Simonovska and Waugh (2014)). But in the range of plausible elasticities, these models all predict that a one percentage point increase in the spending share on imports from China in a given industry should cause a fall in the U.S. price index close to about 30 basis points in that industry, while we find a decline of 3 percentage points. Given the seeming inconsistency between our empirical results and the prediction of the benchmark quantitative trade models, in ongoing work we conduct a decomposition of our estimate, distinguishing between: (1) the impact of price changes for foreign (Chinese) varieties; (2) the impact of price changes for domestic varieties, holding the distribution of domestic varieties constant; (3) the impact of price changes from selection effects across domestic varieties (i.e., entry and exit of domestic varieties). We conduct this decomposition using the data from the Consumer Price Index as well as from the Producer Price Index, which are both hosted by BLS. We find that the response domestic varieties play a much bigger role than in standard quantitative trade models, which could be rationalized by endogenous markups *a la* Bertrand or endogenous innovations reducing marginal cost for domestic producers.

Estimating the causal effect of trade with China on U.S. consumer prices poses several challenges. First, there could be reverse causality: for instance, China may decide to enter product categories where U.S. suppliers are easy to outcompete due to low TFP growth (implying higher U.S. inflation in these product categories and an upward bias of the OLS estimate); or China may decide to enter product categories where U.S. demand is growing (implying higher U.S. inflation if the marginal cost of U.S. producers is upward-sloping, hence another potential upward bias of the OLS estimate). Second, there may be omitted variable biases given that China has a comparative advantage in specific product categories, which may be on different inflation trends compared with other product categories. For instance, trade with China is primarily occuring in manufacturing rather than in services; since services tend to have higher inflation on average, the OLS coefficient may be biased downward. Likewise, within manufacturing trade with China is concentrated in specific product categories that may be on different inflation trends, such as computers, consumer electronics and other product categories characterized by high levels of innovation and low inflation (implying another potential downward bias for the OLS estimate).

Given these identification challenges, we use two complementary research designs borrowed from recent work by Pierce and Schott (2016) and Autor et al. (2014), who study the consequences of trade with China on employment across U.S. industries. The empirical strategy of Pierce and Schott (2016) exploits a policy change that reduced uncertainty over U.S. import tariffs on Chinese goods around 2000 and consequently boosted trade with China in subsequent years. The advantage of this research design is that the policy variation is transparent and lends itself to simple tests for pre-trends, in the 1990s. The main limitation is that using a change in uncertainty over import tariffs as an instrument for trade flows may potentially yield estimates with low external validity, because changes in policy uncertainty may have very different effects from more common permanent changes in tariffs (e.g., Handley and Limão (2017)).

To assess the stability and generalizability of our main estimates, obtained from the Pierce and Schott (2016) research design, we also use the empirical strategy of Autor et al. (2014). They instrument for the change in Chinese import penetration across U.S. industries with changes in Chinese import penetration across industries in eight comparable developed economies (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). This research design addresses threats to identification that stem from U.S.-specific supply or demand patterns, i.e. changes in U.S. supply or U.S. demand across industries that are not correlated with supply or demand changes in the group of eight comparable economies. A limitation of this approach is that reverse causality or omitted variable bias could potentially stem from supply and demand shocks that are in fact common to both the U.S. and the eight other developed economies. By using the sources of variation from both Pierce and Schott (2016) and Autor et al. (2014), we can assess whether we obtain stable plausibly causal estimate of the impact of trade with China on U.S. consumer prices.

Using these two identification strategies, we find that U.S. consumer prices substantially decline in response to increased Chinese import competition. The magnitudes of the estimates are similar in both reseach designs. The results are robust to the inclusion of a variety of industry-specific time-varying controls as well as industry fixed effects. We document that the effect appears precisely in 2000 and that there is no significant effect in previous years, which makes the causal interpretation of the results plausible. Next, we examine heterogeneity in the price response to increased Chinese import penetration across industries. Matching spending shares from college-educated households (measured in the Consumer Expenditure Survey) to our detailed industries, we find that the impact of a given trade shock on U.S. inflation is substantially higher in product categories that cater more to college-educated households. Across industries, when the spending share from college graduates increase by one standard deviation, the price response to increased trade with China increases by 35% (in absolute value).

The finding that the inflation response is stronger in product categories that cater to more educated (i.e., richer) households has implications for the distributional effects of trade. Recent work has pointed out that high- and low-income households have similar spending shares on imports, in general but also from China specifically (e.g., Borusyak and Jaravel (2017) and Hottman and Monarch (2018)). These patterns suggest that the "expenditure channel" of trade may be distributionally neutral. In contrast, our estimates imply that for a given trade shock, the price response is substantially larger for product categories that cater to richer households; therefore the expenditure channel may in fact benefit richer households more.

Are our estimates of the price effects of increased trade with China consistent with benchmark quantitative trade models? As previously discussed, taken at face value our estimates appear to be "too large" (in fact, one order of magnitude too large) relative to what is expected from Arkolakis et al. (2012). However, several potential factors could reconcile our estimates with this class of models. First, if the sectors are sufficiently aggregated, then the elasticity of substitution between domestic and foreign varieties may be much lower than common estimates, which are based on more detailed data (within sectors). To alleviate the potential concern that the results are sensitive to aggregation choices, we conduct the analysis for both detailed sectors (based on the BLS official classification of products into detailed Entry-Level Item (ELI) categories) and less detailed 6-digit industries, as defined in the U.S. intput-output table. We obtain similar results across samples. Second, it could be that changes in import penetration from China are correlated with changes in the cost of production across U.S. indutries. For instance, a fall in the cost of intermediate inputs implies a fall in the cost of production in the U.S., hence falling prices and low inflation. To examine the importance of such effects, we repeat our IV estimation while controlling for other trade shocks that could be correlated with increasing import penetration from China and directly affect U.S. prices. Controlling for direct and indirect (via I-O linkages) imports of intermediates goods from China and from the rest of the world, as well as for exports, we continue to find that a large decline in U.S. consumer prices is induced by trade with China. We also check the robustness of the estimates to other potential concerns, such as the role of a small number of highly deflationary high-tech categories; we find that the results are similar when excluding these categories.

Given the robustness of our results across samples and specifications, how can we reconcile our (too large) estimates of the price effects of Chinese import competition with benchmark quantitative trade models? To examine where the price response comes from, we conduct the following decompositions: (1) we examine the extent to which the fall of U.S. consumer prices results from a fall in the price of products manufactured in the U.S., in China or in the rest of the world; we obtain this information by leveraging new data from "specification checklists" filled out by BLS data collectors, which keep track of product origin; (2) focusing on goods produced in the U.S., which we identify in the CPI data but also using a sample from confidential PPI data at the product level, we estimate the extent to which the fall in U.S. consumer prices results from falling prices holding the composition of U.S. products constant, or from a change in the composition of U.S. products (i.e., selection effects). Using these two decomposition as well as complementary data on TFP at the sector level from the NBER CES data and public-use PPI data at the sector level, we find that the pattern of U.S. inflation in response to increased trade with China are primarily explained by the price response of domestic U.S. producers. Our result are consistent with both falling markups or increasing productivity at the level of U.S. products. The key finding is that these changes occur in a way that is not consistent with the benchmark trade models nested by Arkolakis et al. (2012). Intuitively, these models require that a fall in U.S. domestic prices should occur only if domestic consumers substitute toward foreign goods (e.g., from China). A simple failure of these models would be the case of endogenous markups *a la* Betrand: because of the threat of Chinese competition, U.S. producers endogenously lower their markups, but there may be no substitution toward Chinese goods in equilibrium.

This paper builds and contributes to several literatures. First, we heavily rely on Pierce and Schott (2016) and Autor et al. (2014), who have introduced instruments for Chinese import penetration. Second, we confront our empirical estimates to the predictions of the quantitative trade models nested by Arkolakis et al. (2012). Our estimates reject a key prediction of this class of model, as we find a much bigger price response to a given increase in spending on imported products. Finally, in a closely related paper, Bai and Stumpner (2018) estimate the response of U.S. consumer prices to increased trade with China using data on consumer packaged goods (where prices are measured in scanner data on products found in supermarkets, tracked by a marketing company, Nielsen). Our analysis differs from theirs in several way. First, our data differs from Nielsen data as follows: (i) we have full coverage of the consumption basket, while the Nielsen data covers under 15% of overall consumption; in particular, the Nielsen data does not offer adequate coverage for some of the key product categories in which much of trade with China occurs, such as electronics and apparel; (ii) our data goes back to before the "China shock" (around 2000), which allows us to document pre-trend tests to assess the plausibility of a causal interpretation of the estimates; in contrast, the Nielsen data only starts in 2004. Second, we obtain different results due to the choice of sample: (i) the impact of trade with China on inflation we find is much larger than their estimates, which we can show is because the effect is larger in product categories that are not well covered in Nielsen (such as electronics or other high-tech product categories); (ii) we find that the effect is substantially larger in product categories catering to more educated (i.e., richer) households, implying that trade can have substantial distributional effects through the expenditure channel (in contrast, Bai and Stumpner (2018) find no such distributional effects, likely due to the choice of sample). Third, we use our estimates to point out that quantitative trade models are not consistent with the patterns found in the data; we do so by showing how to derive our cross-industry regression specifications from a simple multi-sector model *a la* Arkolakis et al. (2012) and by showing that potential confounding factors, such as trade in intermediate inputs, cannot account for the patterns.[2]

The remainder of this paper is organized as follows. Section II presents the data and summary statistics; Section III presents the research designs and empirical estimates of the impact of trade with China on U.S. consumer prices; and Section IV discusses the implications for the average gains from trade, the distributional effects of trade, and quantitative trade models.

II Data

In this section, we describe the data sources, define the samples and key variables we use in the analysis, and present summary statistics.

II.A Data Sources, Samples and Variable Definitions

Our analysis relies primarily on four data source: inflation data from the Bureau of Labor Statistics; trade data from the input-output tables and Autor et al. (2013); instruments for trade with China borrowed from Pierce and Schott (2016) and Autor et al. (2013); and a set of industry characteristics, primarily measured in the input-output table.

[2] Bai and Stumpner (2018) use the (country-level) formula from Arkolakis et al. (2012) to motivate their (cross-industry) regression but are not attempting to reject or discipline quantitative trade models. In fact, their preferred estimate suggests that the effect is much lower than what we find, which is likely due to the difference in the sample of goods we consider.

Inflation. Our outcome variable is inflation across U.S. industries. We measure this variable in confidential data from the Bureau of Labor Statistics. Although we observe price changes at the product level, we aggregate these product-level price changes into category-level changes following the procedure of the BLS. We obtain 207 product categories spanning the full range of final consumption goods and services. These categories, called Entry Level Item (ELI) categories, are the most detailed cateogries in the BLS' product classification. They are ideal for our purposes because they offer a comprehensive coverage of consumption and are sufficiently detailed such that we expect product substitution to occur primarily within, rather than across categories.[3]

Weights are applied at two levels to compute inflation. Within an ELI, weighting is performed through the selection of retail outlets and individual products within those outlets. The CPI-RDB provides additional weights for each product-level price that correct sampling error. To aggregate measured inflation from ELIs, we use unpublished weights based on Consumer Expenditure Surveys for each year from 1988–1995, 1999–2004 and 2008-2012. For all other years, we set weights equal to the most recently available year's weights (e.g., assign 1995 weights to 1997).

Trade data. Our main independent variable is the change in import penetration from China over time. In order to make our results comparable with prior work examining the impact of increased import competition with China on employment, we use measures of China import penetration built by Autor et al. (2013) at the level of SIC codes, which we manually match to the ELI categories for which we measure inflation. As a robustness check, we use the import penetration measures available from the U.S. input-output table, which we match to HS-level trade data using the concordance from Pierce and Schott (2012), which allows us to infer the trade share with China.

Instruments for trade with China. To instrument for the patterns of trade with China, we rely on two complementary identification strategies, from Autor et al. (2014) and Pierce and Schott (2016). Autor et al. (2014) instruments changes in China import penetration in the U.S. by changes in China import penetration across industries in developed economies comparable to the US, while

[3]Our price dataset is known as the CPI Research Database (CPI-RDB), which is maintained by the Division of Price and Number Research at the Bureau of Labor Statistics. This is a confidential data set that contains the microdata underlying the non-shelter component of Consumer Price Index (CPI). The CPI-RDB contains all product-level prices on goods and services collected by the BLS for use in the CPI since January 1988. Although the number of individual prices used to construct the CPI has changed over time, the BLS currently collects data on approximately 80,000 products per month from about 23,000 retail outlets across 87 geographical areas in the United States. The sampling frame for the non-shelter component of the CPI represents about 70% of consumer expenditures. We use the CPI-RDB to construct inflation by disaggregated categories called Entry Level Items (ELIs). The BLS defines ELIs for the practical construction of the CPI. There are nearly 360 ELIs between 1988-1998 and 270 ELIs after a 1998 revision of definitions. We collapse the number of ELIs to 250 in order to maintain a consistent definition before and after a 1998 revision to the ELI structure. Examples of ELIs are "Carbonated Drinks," "Washers & Driers," "Woman's Outerwear," and "Funeral Expenses."

Pierce and Schott (2016) use a policy change reducing uncertainty over tariffs with China in different trade industries (the "NTR gap"). These variables are described in detail in Section III, as well as the research designs they make possible. The Pierce and Schott (2016) NTR gap is measured at the level of NAICS6 industries, which we match by hand to the ELI categories for which we observe inflation outcomes.[4]

Industry Characteristics. Finally, we obtain a range of industry characteristics from the 2007 input-output table, as well as from Pierce and Schott (2016). These variables are used to assess to robustness of the estimates to the inclusion of additional controls, as well as to assess heterogeneity in the treatment effect.

II.B Summary Statistics

Table 1 reports the summary statistics from years 1993 to 2007. Panel A consider the full sample. Across ELI categories, inflation was on average 1% per year, but with a large standard deviation of 7 percentage points across industry-years. The change in China import penetration rate (focusing on the change between 1999 and 2011, as in Autor et al. (2013)) features a lot of variation across industries.[5] The average increase in China share was 60 basis points, with a standard deviation a 1.24 percentage points. This panel also shows that the NTR gap (from Pierce and Schott (2016)) and the change in China import penetration in other developed economies (from Autor et al. (2013)) feature substantial variation across industries; they will provide the key source of variation for our research design. Finally, the table report summary statistics for important industry-level controls, such as union membership. Panel B reports similar patterns, focusing on tradable industries.

III Estimating the Impact of Trade with China on U.S. Consumer Prices

In this section, we estimate the effect of trade with China U.S. consumer prices using two complementary identification strategies. After presenting our research design, we report are baseline estimates and document their robustness, as well as heterogeneity in the magnitude of the effect across product categories.

[4]The procedures to build all crosswalks are described in the Online Appendix.

[5]Note that this variable does not change across years, hence the lower number of observations.

III.A Research Design

Estimating the causal effect of trade with China on U.S. consumer prices poses several challenges. To assess the main threats to identification, consider running a simple regression of the change in U.S. consumer prices (inflation) on the change in import penetration from China across U.S. product categories over time. A causal interpretation of the OLS estimate from this specification would be concerning for two main reasons. First, there could be reverse causality: for instance, China may decide to enter product categories where U.S. suppliers are easy to outcompete due to low TFP growth (implying higher U.S. inflation in these product categories and an upward bias of the OLS estimate); or China may decide to enter product categories where U.S. demand is growing (implying higher U.S. inflation if the marginal cost of U.S. producers is upward-sloping, hence another upward bias of the OLS estimate). Second, there may be omitted variable biases given that China has a comparative advantage in specific product categories, which may be on different inflation trends compared with other product categories. For instance, trade with China is primarily occuring in manufacturing rather than in services; since services tend to have higher inflation on average, the OLS coefficient would be biased downward. Likewise, within manufacturing trade with China is concentrated in specific product categories that may be on different inflation trends, such as computers and electronics, a product category characterized by high levels of innovation and low inflation (implying another downward bias for the OLS estimate).

Given these identification challenges, we use two complementary research designs borrowed from recent work by Pierce and Schott (2016) and Autor et al. (2014), who study the consequences of trade with China on employment across U.S. industries. The empirical strategy of Pierce and Schott (2016) exploits a policy change that reduced uncertainty over U.S. import tariffs on Chinese goods and consequently boosted trade with China. The advantage of this research design is that the policy variation is transparent and lends itself to simple tests for pre-trends, as described below. The main limitation is that using a change in uncertainty over import tariffs as an instrument for trade flows may potentially yield estimates with low external validity, because changes in policy uncertainty may have very different effects from more common permanent changes in tariffs (e.g., Handley and Limão (2017)). To assess the stability and generalizability of our estimates, we also use the empirical strategy of Autor et al. (2014), who instrument for the change in import penetration from China across U.S. industries with changes in import penetration from China across industries in eight comparable developed economies.[6] This research design addresses threats to identification that stem

[6] These countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

from U.S.-specific supply or demand patterns, i.e. changes in U.S. supply or U.S. demand across industries that are not correlated with supply and demand changes in the group of eight comparable economies; the main limitation is that reverse causality or omitted variable bias could potentially stem from supply and demand changes that are in fact common to both the U.S. and the eight other developed economies. For instance, services are more income-elastic than manufacturing, implying that relative demand for services should increase in both the U.S. and the group of comparable economies as these countries get richer. In sum, our approach is to compare the results obtained by following the approaches of both Pierce and Schott (2016) and Autor et al. (2014) to assess whether the paint a consistent picture of the effect of trade with China and U.S. consumer prices, both qualitatively and quantitatively. We describe these research designs formally in the rest of this subsection.

Research Design #1. Pierce and Schott (2016) focus on a specific change in U.S. trade policy passed by Congress in October 2000, which eliminated potential tariff increases on Chinese imports.[7] This policy change is known as the granting of "Permanent Normal Trade Relations" (PNTR) to China: although it did not change the import tariff rates the U.S. actually applied to Chinese goods, it reduced the uncertainty over these tariffs. Indeed, before China was granted PNTR, U.S. import tariffs on Chinese goods needed to be renewed by Congress; as explained by Pierce and Schott (2016), without renewal U.S. import tariffs on Chinese goods would have jumped back to high non-NTR tariffs rates assigned to non-market economies (which were originally established under the Smoot-Hawley Tariff Act of 1930).

To assess the reduced-form impact of the granting of PNTR to China, we follow Pierce and Schott (2016) and run specifications of the form:

$$\pi_{it} = \beta PostPNTR_t \times NTR\,Gap_i + \alpha PostPNTR_t \times X_i + \nu X_{it} + \delta_t + \delta_i + \epsilon_{it} \tag{1}$$

where i indexes U.S. indutries, t indexes years, $PostPNTR_t$ is an indicator for the post-PNTR periods (after 2001), $NTRGap_i$ is the difference between the actual import tariffs on Chinese goods and non-NTR tariffs, X_{it} is a vector of time-varying controls and δ_t and δ_i are time and industry fixed effects. The interacted regressor $PostPNTR_t \times X_i$ allows for the effect of time-invariant industry characteristics X_i on inflation to change in the post-PNTR period. Note that this difference-in-differences specification helps address the potential concerns over reverse causality and omitted variables by using variation in NTR gaps across industries but also by including industry fixed

[7] The change became effective when China joined the World Trade Organization at the end of 2001.

effects and time-varying controls.

In addition, we run a specification analogous to (1) but interacting the NTR gaps over more periods, in order to assess whether the effect on inflation indeed manifests itself exactly when the policy change is introduced. This test for pre-trend is a direct way of assessing the plausibility of the assumption underlying this difference-in-differences specification.

The previous steps can establish the plausibility of the research design by documenting the dynamics of the effect of NTR gaps, but they do not yield properly scaled estimates of the impact of trade with China on U.S. consumer prices. Accordingly, in a final step we use NTR gaps as an instrument for trade with China, in order to obtain estimates of the impact of trade with China on U.S. consumer prices. To do so, we focus on the post-PNTR sample from 2001 until 2007 and we average all variables at the industry level. We run the following 2SLS specification:

$$\begin{aligned} \pi_i &= \alpha + \beta \Delta ChinaIP_i + \nu X_i + \epsilon_{it} \\ \Delta ChinaIP_i &= \widetilde{\alpha} + \gamma NTR\, Gap_i + \widetilde{\nu} X_i + \eta_{it} \end{aligned} \tag{2}$$

where $\Delta ChinaIP_i$ is the change in import penetration from China post-PNTR. The coefficient β gives the impact of a 1 percentage point increase in trade share with China in an industry on the level of inflation faced by U.S. consumers in that industry.

Research Design #2. Our second identification approach closely follows Autor et al. (2014). The 2SLS specification is very similar to (2) and is written as follows:

$$\begin{aligned} \pi_i &= \alpha + \beta \Delta ChinaIP_i + \nu X_i + \epsilon_{it} \\ \Delta ChinaIP_i &= \widetilde{\alpha} + \gamma \Delta ChinaIP_{i,Other} + \widetilde{\nu} X_i + \eta_{it} \end{aligned} \tag{3}$$

where $\Delta ChinaIP_{i,Other}$ is the change in import penetration from China in the eight other developed economies. Intuitively, if import penetration from China increases in a given industry i in many developed economies, this IV strategy assumes that this is due to a productivity shock in China (not to common shocks in all developed economies, including the U.S.), which yields identification of the coefficient of interest, β. As previously, the data is collapsed at the level of industries from 2001 until 2007.

Aggregation and robustness. When running the various specification above, the level at which we define an "industry" may matter for the magnitude of the estimates. On the one hand, if we consider coarse industry categories, the elasticity of substitution between domestic goods and Chinese goods may be artificially low because we are effectively lumping together very different goods. On the other hand, if we consider extremely detailed categories, it becomes difficult to accurately measure trade flows, generating attenuation bias. As a result, we assess the robustness of our results to different aggregation choices, first by reporting results at the level of detailed ELIs, second by estimating similar equation at the level of coarser industries as defined in the input-output table.

We also check stability of the estimates by varying the sets of controls included in the specifications and by considering different samples. The main potential concern is that China is active in product categories that have always had lower inflation. Specification (1) direclty addresses this concern with the inclusion of product category fixed effects; we check the robustness of the IV specifications with a series of controls: inflation in the 1990s, use of "advanced technologies", and product group fixed effects.

III.B Baseline Estimates

Table 2 reports our main estimats of the response of U.S. consumer prices to the granting of permanent normal trade relations to China. Panel A reports the results of specifications similar to (1). Across all specificaitons, we systematically find that a larger NTR gap (inducing more trade with China via a fall in uncertainty over tariffs) leads to lower inflation. Standard errors are clustered by ELIs over the full length of the panel and show strong statistical significance. The magnitudes of the effects are large: a one standard-deviation change in NTR gap (approximately 0.2 percentage points, cf. Table 1) leads to a fall in inflation between 50 basis points and 1 percentage point across specifications.

The comparison of the magnitude of the effect across specifications is instructive. All specifications include ELI and year fixed effetcs, but the sample and set of controls differ across specifications. Column (1) is the simplest specification, keeping the full sample of ELIs over the entire panel and yields the largest estimates (in absolute value). The point estimate goes from -4.77 to -4.09 when we restrict attention to tradables only in Column (2). In Column (3), the point estimate becomes -3.08 when we include time varying controls in the full sample: specifically, we control for changes in inflation trends in industries using advanced technology after 2000, exposure of the industry to the expiration of the global Multi-Fiber Arrangement (MFA), the initial NTR gap and union membership. These controls were all emphasized as potentially important confounding factors by Pierce and Schott (2016). Once these controls are included, we see that the point estimates remain stable as we restrict attention to tradables only in Column (4). Finally, Column (5) shows that the point estimate remains very similar (statistically indistinguishable) when we exclude product categories that have particularly low levels of inflation, below the 5th percentile of average inflation during the sample (including electronics, etc.). This finding indicates that the result is not driven by a small number of categories which may have persistently low inflation. Overall, these results show a robust large effect across specifications.

A potential worry with the results in Panel A of Table 2 is that the industries that are more exposed to NTR gaps may happen to be on a different inflation trend. To test for pre-trends and gain insights into the dynamics of the effect, we run specification (1) allowing for leads and lags around the policy change. Specifically, we consider four sub-periods: 1991-1994, 1995-1999, 2000-2003 and 2004-2007.[8] Panel A of Figure 1 shows that the effect appears precisely when the policy change is introduced. There is no pre-trend: the point estimate for the period 1991-1994 is indistinguishable from zero (where we have normalized the point estimate for 1995-1999 to be zero). In constrast, there is a large effect in 2000-2003, right after the introduction of the policy. The effect appears to diminish 204-2007, but we obtain relatively imprecise estimates. Panel B of Figure 1 shows that the results are very similar when excluding product categories with an average level of inflation below the 5th percentile, which confirms that the results are not driven by a small number of deflationary categories.

Having established the robustness of the results and the absence of pre-trends, we can now turn to the IV specification (2) to get properly scaled estimates of the impact of trade with China on U.S. consumer prices. Figure 2 shows a strong first-stage relationship between the NTR gap and the change in import penetration rate from China (Panel A), as well as a clear reduced-form relationship between NTR gap and U.S. inflation (Panel B) across industries. Judging from these graphs, summarizing the effect with a linear specification appears to be appropriate. The magnitudes of the estimates from various specifications are reported in Panel B of Table 2. For all specifications, we get large IV estimates for the impact of trade with China on U.S. inflation across industries, which tend to be larger (in absolute value) than the OLS estimates. The first stage is strong in all IV specifications, as shown by the Cragg-Donald and Kleibergen-Paap F statistics. Column (1) reports an OLS coefficient of -2.34 in the full sample, compared with an IV coefficient of -4.44 in Column (2). Columns (3) and (4) show that the OLS and IV coefficients are very similar when considering only tradable goods. Columns (5), (6) and (7) examine the robustness of the IV estimate when slightly changing the sample. In Column (5), the IV coefficient becomes -3.14 when considering only tradable and dropping ELIs with a level of average inflation in the

[8] The results are robust to considering other periods (not reported).

contemporaneous period (2001-2007) below the 5th percentile. The coefficient remains stable in Column (6), dropping ELIs with a level of average inflation in the 1990s below the 5th percentile. Column (7) also reports a similar IV coefficient of 2.71 when controlling for average inflation in the 1990s. Therefore, Panel B of Table 2 shows a robust finding of a very large inflation response to trade with China: a 1 percentage point increase in the spending share on Chinese imports implies a 3 percentage point fall in the rate of inflation. As discussed in the introduction, this estimate is one order of magnitude larger than what one would expect in light of the sufficient statistic formula of Arkolakis et al. (2012) and standard estimates of the trade elasticity (e.g., Simonovska and Waugh (2014)).

To assess whether these large estimates are peculiar to the source of variation from Pierce and Schott (2016), which is ultimately about policy uncertainty, we follow Autor et al. (2014) and instrument changes in China import penetration in the U.S. with changes in China import penetration in eight other developed countries, as in specification (3). Panel A of Table 3 shows that the first-stage is strong (Column (1)) and that there is a clear reduced-form relationship (Columns (2)), even when excluding categories with particularly low inflation rates (Column (3)). Figure 3 shows graphically that these patterns are robust and that the linear approximation to the underlying data is appropriate. Panel B of Table 3 reports the IV estimates. Columns (1) and (2) show that the IV estimate is larger than OLS (in absolute value), with magnitudes similar to Table 2. Columns (3) and (4) show that the points estimates decline for both OLS and IV when we exclude product categories with particularly low inflation rates, but the magnitude of the estimates remain large, much larger than what one would expect from Arkolakis et al. (2012).

III.C Robustness Checks and Heterogeneity

The previous analysis was conducted at the level of ELIs, the most disaggregated product category in the confidential price data of the Bureau of Labor Statistics. A potential concern is that trade flows may be mismeasured at this level. As a robustness check, we repeat the analysis by aggregating the data at the level of 6-digit industries in the Input-Output table. Doing so has the added benefit that various precisely-measured industry covariates are available at this level of aggregation, which we can use to investigate heterogeneity in the treatment effect.

Table 4 shows that the results following the identification strategy of Pierce and Schott (2016) are very similar when the analysis is conducted at the level of 6-digit Input-Output industries. The first stage (Panel A), reduced-form (Panel B) and IV specifications (Panel C) are all strong and robust across samples; they also remain stable depending on the set of controls or industry fixed effects that are included. Similarly, Table 5 shows that the results from the approach of Autor et al. (2014) are very similar at this higher level of aggregation. For both research designs, the IV estimates are consistently above 3 and are precisley estimated. Figure 4 shows graphically the robustness of these findings.

Next, we investigate heterogeneity in the treatment effect. Table 6 reports the magnitude of the estimates depending on consumer income (Panel A), skill intensity (Panel B) and the level of inflation in the previous decade (Panel C). To investigate whether the magnitude of the inflation response to a given trade shock substantially varies with consumer income, we run reduced-form specification interacting the trade shock with the spending share from college graduate in the product category. The spending shares are built using CEX data matched to the intput-output table as in Borusyak and Jaravel (2017). All specifications in Panel A of Table 6 deliver a consistent message: the impact of a given trade shock on U.S. inflation is higher in product categories that cater more to higher-income (college-educated) households. Specifically, Column (1) reports the results regressing the U.S. annual inflation on the NTR gap and the NTR gap interacted with the spending share from college graduates, standardized by its standard deviation (which is effectively the reduced-form for the IV specification shown in (2), with an interaction term). The estimates show that when the spending share from college graduates increase by one standard deviation, the fall in inflation is 35% (= 4.11/11.55) larger. This substantial effect is confirmed in Column (2), which conducts a similar exercise but using the instrument from Autor et al. (2014). The estimates show that the fall in inflation is 38% (= 1.97/5.12) larger in product categories with a one standard deviation higher spending share from college graduates. Columns (3) and (4) report similar effects when excluding from the sample product categories with particularly low inflation rates, below the 5th percentile of the distribution.

Panels B Table 6 report heterogeneity by skill intensity, interacting the instruments for trade with China with the payroll share to college graduates (which is taken from Borusyak and Jaravel (2017)). We consistently find that the effect is stronger in product categories that are more skill intensive, i.e. that devote a higher share of payroll to college graduates. Columns (3) and (4) show that statistical significant for the interaction term is lost when we exclude deflationary categories: the point estimate for the interaction then become very imprecisely estimated, indicating that the excluded categories play a key role for the estimates in the full sample.

Panel C of Table 6 shows that the price response to trade shock is substantially larger in product categories that in general have a lower level of inflation. The interacted regressor, "prior inflation", measures the average level of inflation for each product category in the 1990s and is standardized by its standard deviation. Thus, Column (1) indicates that when average (prior) inflation is one standard deviation higher, the effect of granting permanent normal trade relation to China is 20% lower ($= 1 - \frac{-3.758+0.703}{-3.758}$) in this product category. Columns (2), (3) and (4) show that this result is robust to changes in the sample, considering alternatively only tradables or dropping product categories featuring particularly low inflation (either in contemporaneous sample or in the previous decade).[9]

Overall, a consistent picture emerges across all empirical specifications: trade with China, whether it is instrumented by falling policy uncertainty or by trade between Europe and China, leads to a large fall in inflation for U.S. consumers; this fall in inflation is larger in product categories that cater to college-educated households, that have a higher skill intensity, and that are on a trend of lower inflation. We now turn to a discussion of the implication of these findings.

IV Implications

In this section, we discuss the implications of the estimates from Section III for the average gains from trade, the distributional effects from trade, and for quantitative trade models.

IV.A Magnitudes of Average Gains and Distributional Effects from Trade with China

To assess the overall impact of increased trade with China on the U.S. Consumer Price Index, we start by conducting a simple benchmarking exercise in the spirit of Autor et al. (2013) and Autor et al. (2014). Under two strong assumptions, we can benchmark the labor market effects of trade with China documented in these papers with the gains to U.S. consumers we estimated. First, we assume that increased exposure to Chinese imports affects the absolute level of inflation in the U.S. and not just relative inflation across industries; second, we assume that the total change in Chinese import penetration in the U.S. during the period of interest is driven by supply shocks in China (rather than by reverse causality from changes in demand factors or supply factors in the U.S.).

Under similar assumptions applied to the context of the labor market, Autor et al. (2013) find that rising Chinese import exposure between 2000 and 2007 reduced U.S. manufacturing employment by 1.10 percentage points, explaining 55 percent of the decline in manufacturing employment

[9] Note that in contrast with panels A and B, which conduct the analysis at the level of 6-digit Input-Output industries, panel C uses the ELI sample.

during this period. Between 2000 and 2007, the average increase in China import penetration across all product categories (including "non-traded" categories like services) was 0.73 percentage points; we use this number to scale our preferred estimate of the impact of trade with China on U.S. consumer prices (Column (7) of Panel B of Table 2), which implies that the overall impact of increased trade with China during this period was a fall of 1.97 percentage points ($= 0.73 \times (-2.71)$) in the U.S. Consumer Price Index. This number is relatively large but not implausible, as can be seen by comparing it to the number of manufacturing jobs lost due to increased import competition with China. Given that U.S. nominal GDP was \$10.3 trillion in 2000, according to our estimate increased trade with China induced a gain of \$202.5 billion for U.S. consumers through lower prices. At the same time, China caused a loss of approximately 2 million manufacturing jobs according to Autor et al. (2013). Therefore, the implied gains to U.S. consumers per lost manufacturing job is about \$100,000 ($\frac{\$202.5bn}{2m\ lost\ jobs} = \$101,250\, per\ job$). In other words, these estimates imply that the amount of consumer surplus through lower inflation created by increased trade with China would be sufficient to compensate each U.S. manufacturing worker losing their job by close to \$100,000. Although this number is quite large, it remains plausible at an intuitive level. In contrast, this estimate is very difficult to reconcile with benchmark quantitative trade models, which all suggest that the gains from trade should be much smaller.

Moreover, our estimates have implications for the distributional effects from trade. Recent work has pointed out that high- and low-income households have similar spending shares on imports, in general but also from China specifically (e.g., Borusyak and Jaravel (2017) and Hottman and Monarch (2018)). These patterns suggest that the "expenditure channel" of trade may be distributionally neutral. In contrast, our estimates imply that for a given trade shock, the price response is substantially larger for product categories that cater to higher income households (Panel A of Table 6). Therefore the expenditure channel may in fact have significant distributional effects, in favor of higher-income or more educated households.

IV.B Implications for Quantitative Trade Models

Connection between our empirical estimates and quantitative trade models. Arkolakis et al. (2012) show that in a wide range of trade models, the gains from trade can be expressed as a simple function of two sufficient statistics: the change in the spending share on domestic goods and the trade elasticity. Perhaps the simplest case to consider is a one-sector Armington model where $1 - \sigma < 0$ is the elasticity of relative imports with respect to variables trade costs. Assumig trade balance, it can be shown that:

$$\Delta ln(W_j) = \frac{1}{1-\sigma} \Delta ln(\lambda_{jj}) \tag{4}$$

where $\Delta ln(W_j)$ is the change in welfare in the U.S. and $\Delta ln(\lambda_{jj})$ is the change in U.S. spending share on U.S. goods/services.

Our empirical exercise departs from the baseline model of Arkolakis et al. (2012) because we are running a regression across sectors, while equation (4) makes a statement about the entire (one-sector) economy. However, it is straightforward to show that the cross-industry IV specifications we run to uncover the relationship between change in China import competition and inflation in the U.S. do identify a parameter analogous to $\frac{1}{1-\sigma}$ in Arkolakis et al. (2012). In Online Appendix A we show how our IV specification (1) and (2) can be derived from a multi-sector model similar to Arkolakis et al. (2012), with $\beta = \frac{1}{1-\sigma}$. When the trade elasticity σ is allowed to vary across sectors, then our IV estimator recovers a weighted average of these elasticities across sectors.

While the formula from Arkolakis et al. (2012) nests a variety of trade models, it is well understood that different quantitative trade models imply different estimation strategy for the elasticity of substitution (e.g., Melitz and Redding (2015)). However, these estimation strategies tend to yield relatively similar elasticity estimates around a value of 4 (e.g., Simonovska and Waugh (2014)). As a result, $\frac{1}{1-\sigma} \approx -0.3$, while IV our estimates imply a value at least one order of magnitude larger, close to -3 (cf. Tables 2, 3, 4 and 5). The implied value for σ according to our IV strategy is about 1.3, which is implausibly low. In this sense, our results challenge benchmark quantitative trade models.

Are the empirical estimates really "too large" relative to benchmark quantitative trade models? There are a variety of potential reasons why our IV estimates may in fact be consistent with quantitative trade model. First, if the sectors are sufficiently aggregated, then the elasticity of substitution between domestic and foreign varieties may be much lower than common estimates, which are based on more detailed sector. To alleviate this concern, we have work with detailed sectors (based on the BLS official classification of products into ELI categories) and we have checked that the results across different definition of sectors (working with 6-digit intput-ouput industries as a robustness check, cf. Tables 4 and 5).

Second, it could be that changes in import penetration from China are correlated with changes in the cost of product across U.S. indutries. For instance, a fall in the cost of intermediate inputs implies a fall in the cost of production in the U.S., hence falling prices and low inflation. To examine the importance of such effects, we repeat our IV exercise while controlling for other trade shocks that could be correlated with increasing import penetration from China and directly affect U.S. prices. Specifically, using data from the 2007 input-output table, we control for the following variables at the level of 6-digit industries: direct imports of intermediate inputs from China and/or from the rest of the world; direct and indirect imports of intermediate inputs from China and/or from the rest of the world (where indirect imports take into account input-output linkages across sectors); exports as a share of domestic production. Panel A of Table 7 repeats the IV specification using the granting of permanent trade relation to China as an instrument for trade with China. The various columns show that across specifications and sets of controls, the IV estimates remain very large. Panel B of Table 7 shows that similar results hold when instrument by other countries' trade with China. Therefore the IV estimates continued to be "too large" relative to benchmark quantitative trade models when accounting for intermediate inputs and other trade-related variable that can affect marginal costs across U.S. industries. In addition, we have checked that the point estimates remain stable when controlling for changes in wages across domestic U.S. industries (not reported in this draft). Online Appendix Table A1 shows that the patterns are similar when considering a restricted sample excluding product categories with particularly low average inflation.

Finally, it could be that the IV estimates are driven by a few outlier industries. However, we have checked that the estimates are stable across samples (in particular, when excluding categories with large deflation) and the various binned scatter plots show that the linear specification is a good approximation to the underlying data: the patterns are not driven by outliers (cf. Figures 2, 3 and 4).

What could explain the magnitude of the empirical estimates? The large magnitude of the response of U.S. consumer prices to trade with China is a robust feature of the data. To examine where it comes from, in ongoing work we conduct the following decompositions:

(1) we examine the extent to which the fall of U.S. consumer prices results from a fall in the price of products manufactured in the U.S., in China or in the rest of the world. We obtain this information by leveraging new data from "specification checklists" filled by BLS data collectors, which keep track of product origin.

(2) focusing on goods produced in the U.S., which we identify in the CPI data but also using a sample from confidential PPI data at the product level, we estimate the extent to which the fall in U.S. consumer prices results from falling prices holding the composition of U.S. products constant, or from a change in the composition of U.S. product (i.e., selection effects).

In ongoing work, using these two decomposition as well as complementary data on TFP at the sector level from the NBER CES data and public-use PPI data at the sector level, we find that the pattern of U.S. inflation in response to increased with China are primarily explained by the response of domestic U.S. prices (not reported in this draft). Our result are consistent with both falling markups or increasing productivity at the level of U.S. products. The key result is that these changes occur in a way that is not consistent with the benchmark trade models nested by Arkolakis et al. (2012). Intuitively, these models require that a fall in U.S. domestic prices can occur only if domestic consumers substitute toward foreign goods (e.g., from China). A simple failure of these models would be the case of endogenous markups *a la* Betrand: because of the threat of Chinese competition, U.S. producers endogenously lower their markups, but there is no substitution toward Chinese goods in equilibrium.

V Conclusion

This estimated the effect of trade with China on U.S. consumer prices across industries. A robust finding emerged: the price response is very large. Across specifications and using different instruments (following either Pierce and Schott (2016) or Autor et al. (2014)), the estimates indicate that a 1 percentage point increase in the share of imports from China leads to at least a 3% fall in U.S. consumer prices. We also document that these effects are substantially larger in product categories that cater to higher-income or more educated households.

Although the response of U.S. prices to trade with China is large, it is not implausible in light of the large impact of Chinese import competition on U.S. manufacturing employment. In a simple benchmark exercise, which makes our inflation estimates comparable to the "lost manufacturing jobs" estimates of Autor et al. (2013), we find that the implied gains through lower prices for U.S. consumers through are approximately $100,000 per lost manufacturing job.

Our estimates of the U.S. price response to increased trade with China are much larger than what is implied by the quantitative trade models nested by Arkolakis et al. (2012). Empirically, deviations from these models appear to be explained by the strong response of U.S. producers; for instance, the may lower their markups or increase their productivity due to the threat of competition with China, even though the actual degree of product substitution of U.S. consumers toward Chinese products is modest. Overall, our estimates suggest that the gains from trade might be much larger than previously thought, and that they might be skewed toward higher-income groups through differential price responses across product categories.

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Table 1: Summary Statistics

Panel A: Full Sample

	Mean	Std. Dev.	Observations
U.S. Inflation Rate	0.98168	7.1185	3,689
Change in China Import Penetration Rate in the U.S., 1999-2011	0.60936	1.2448	207
NTR Gap	0.1907	0.2005	3,689
Change in China Import Penetration Rate in Other Developed Economies, 1999-2011	0.66228	1.16988	207
Advanced Technology	0.0717	0.2548	3,689
Union Membership	10.0660	11.1892	3,689

Panel B: Tradables Only

	Mean	Std. Dev.	Observations
BLS Inflation Rate	-0.4408	7.4890	2,703
Change in China Import Penetration Rate in the U.S., 1999-2011	0.86647	1.4107	150
NTR Gap	0.28685	0.1907	2,703
Change in China Import Penetration Rate in Other Developed Economies, 1999-2011	0.86228	1.2698	150
Advanced Technology	0.10730	0.3063	2,703
Union Membership	15.1292	10.6281	2,703

Notes: This table presents summary statistics for the main variables used in the analysis, which are described in Section II. Panel A considers the full sample, while Panel focuses on tradable goods only.

Table 2: The Response of U.S. Consumer Prices to Granting Permanent Normal Trade Relations to China

Panel A: Dynamic Reduced-Form Specifications (Full Panel of Industries, 1993-2007)

	Annual U.S. Inflation Rate				
	(1)	(2)	(3)	(4)	(5)
NTR Gap × Post 2000	-4.77***	-4.09***	-3.0864***	-2.8097**	-2.5942**
	(1.14)	(1.60)	(1.133)	(1.4645)	(1.3558)
Advanced Tech. × Post 2000			-1.845299	-1.879*	-1.51466
			(1.130)	(1.133)	(1.1484)
MFA exposure			-9897.122**	-11747.4**	-11406.3**
			(4651.47)	(4656.85)	(5014.95)
NTR gap			4.49	4.575	3.374
			(6.62)	(6.508)	(5.801)
Union membership			0.0829*	0.07714	0.06287
			(0.0440)	(0.045)	(0.04582)
ELI Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	3,689	2,703	3,689	2,703	2,550
Sample	Full	Tradables Only	Full	Tradables Only	Tradables Only & Inflation > p5

Panel B: Instrumental Variables Specifications (Cross-Industry Sample After Granting of Permanent Normal Trade Relations, 2001-2007)

	Annual U.S. Inflation Rate						
	OLS	IV	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in China Import	-2.34***	-4.44***	-2.25***	-4.48***	-3.14***	-3.11***	-2.71**
Penetration (1999-2011)	(0.3268)	(1.038)	(0.356)	(1.062)	(1.121)	(1.00)	(1.326)
Tradable	-3.58***	-2.05***					
	(0.5502)	(0.787)					
Average Inflation in 1990s							0.58***
							(0.2139)
Cragg-Donald F		24.77		19.479	19.774	25.544	7.635
Kleibergen-Paap F		19.77		19.280	15.663	17.384	8.939
Observations	207	207	150	150	136	136	150
Sample	Full		Tradables Only		Tradables Only & Inflation > p5	Tradables Only & 1990s Inflation > p5	Tradables Only

Notes: In Panel A, the data extends from 1993 to 2007. See specification (1) in the main text. The specification uses square-root ELI weights and ELI fixed effects. Year fixed effects are included. In Column (5), ELIs-years below the fifth percentile in the inflation distribution are dropped. In Panel B, the level of observation is an ELI: the data is collapsed at the ELI level after 2000. Square-root ELI weights are used. Heteroskedasticity-robust standard errors are reported. Standard errors are clustered by ELIs. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: The Response of U.S. Consumer Prices to Trade with China, Instrumented by Other Developed Countries' Trade with China

Panel A: First-stage and Reduced-Form Specifications

	Change in China Import Penetration in U.S. (1999-2011)	Annual U.S. Inflation Rate	
	(1)	(2)	(3)
Change in China Import Penetration in Other Developed Countries (1999-2011)	0.9315***		
	(0.1045)		
Change in China Import Penetration in the U.S. (1999-2011)		-2.5275***	-1.7383***
		(0.4014)	(0.39607)
Observations	153	153	139
Sample	Manufacturing Only	Manufacturing Only	Manufacturing Only & Inflation > p5

Panel B: Instrumental Variables Specifications

	Annual U.S. Inflation Rate			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Change in China Import Penetration (1999-2011)	-2.345***	-2.71***	-1.592***	-1.894***
	(0.3299)	(0.3869)	(0.2075)	(0.4180)
Cragg-Donald		316.12		253.61
Kleibergen-Paap F		79.36		119.56
Observations	153	153	139	139
Sample	Manufacturing Only		Manufacturing Only & Inflation > p5	

Notes: The level of observation is an ELI: the data is collapsed at the ELI level after 2000. Square-root ELI weights are used. Heteroskedasticity-robust standard errors are reported. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Estimating the Response of U.S. Consumer Prices to Granting Permanent Normal Trade Relations to China at the level of 6-digit Input-Output Industries

Panel A: First-Stage Specifications

	Change in China Import Penetration in the U.S. (1999-2011)			
	(1)	(2)	(3)	(4)
NTR Gap	2.5066***	2.01138**	2.8464***	1.466***
	(0.8008)	(0.83229)	(1.0798)	(0.57741)
Manufacturing		0.29088		
		(0.18849)		
Observations	91	91	58	51
Sample	Full	Full	Tradables	Tradables & Inflation > p5

Panel B: Reduced-Form Specifications

	Annual U.S. Inflation Rate			
	(1)	(2)	(3)	(4)
NTR Gap	-14.589***	-12.523***	-11.755***	-6.4129*
	(3.250)	(4.0462)	(4.5032)	(3.321)
Tradables		-1.3080		
		(1.2150)		
Observations	91	91	58	51
Sample	Full		Tradables	Tradables & Inflation > p5

Panel C: Instrumental Variables Specifications

	Annual U.S. Inflation Rate						
	OLS (1)	IV (2)	IV (3)	OLS (4)	IV (5)	IV (6)	IV (7)
Change in China Import	-2.9580***	-5.996***	-5.4038***	-2.95***	-4.130***	-4.23***	-4.3727**
Penetration (1999-2011)	(0.3602)	(0.69205)	(1.5309)	(0.3605)	(1.0481)	(1.205)	(2.0633)
Tradable	-1.8609***	0.28009	-3.8438***				
	(0.81968)	(1.8464)	(0.7951)				
IO2 Fixed Effects			Yes			Yes	
Cragg-Donald F		9.093	8.010		8.194	7.081	8.721
Kleibergen-Paap F		6.576	5.880		6.948	6.087	6.451
Observations	91	91	91	58	58	58	51
Sample		Full			Tradables		Tradables & Inflation > p5

Notes: The level of observation is an IO6 category: the data is collapsed at the IO6 level after 2000. Square-root IO final consumption spending weights are used. Heteroskedasticity-robust standard errors are reported. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: The Response of U.S. Consumer Prices to Trade with China at the level of 6-digt Input-Output Industries, Instrumenting by Other Developed Countries' Trade with China

Panel A: First-Stage Specifications

	Change in China Import Penetration in the U.S. (1999-2011)			
	(1)	(2)	(3)	(4)
Change in China Import Penetration in	1.2913***	1.30***	1.30***	0.9943***
Other Developed Economies (1999-2011)	(0.3595)	(0.38852)	(0.3888)	(0.18722)
Manufacturing		-0.0366		
		(0.0981)		
Observations	91	91	58	51
Sample	Full	Full	Manufacturing	Manufacturing
				& Inflation > p5

Panel B: Reduced-Form Specifications

	Annual U.S. Inflation Rate		
	(1)	(2)	(3)
Change in China Import Penetration	-4.9813***	-4.59341***	-2.4043***
in the U.S. (1999-2011)	(0.9646)	(1.0403)	(0.58411)
Manufacturing			
Observations	91	58	51
Sample	Full	Manufacturing	Manufacturing
			& Inflation > p5

Panel C: Instrumental Variables Specifications

	Annual U.S. Inflation Rate			
	(1)	(3)	(4)	(5)
Change in China Import Penetration	-3.7313***	-3.107***	-3.5313***	-2.428***
in the U.S. (1999-2011)	(0.791)	(0.45823)	(0.692053)	(0.54708)
Manufacturing	-1.3661			
	(0.8257)			
IO2 Fixed Effects				
Cragg-Donald F	171.62	322.77	101.416	148.032
Kleibergen-Paap F	11.018	31.96	10.972	27.613
Observations	91	83	54	47
Sample	Full	Full	Manufacturing	Manufacturing
		& Inflation > p5		& Inflation > p5

Notes: The level of observation is an IO6 category: the data is collapsed at the IO6 level after 2000. Square-root IO final consumption spending weights are used. Heteroskedasticity-robust standard errors are reported. $*p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$.

Table 6: Heterogeneity in U.S. Consumer Price Response to Trade with China

Panel A: By Consumer Income

	Annual U.S. Inflation Rate			
	(1)	(2)	(3)	(4)
NTR Gap	-11.55***		-6.37**	
	(4.412)		(3.19)	
NTR Gap × Spending Share from College Grads/SD	-4.11**		-2.64**	
	(1.9260)		(1.092)	
Change in China Import Penetration in Other Developed Economies (1999-2011)		-5.12***		-3.267***
		(1.07)		(0.9163)
Change in China Import Penetration in Other Developed Economies (1999-2011) × Spending Share from College Grads/SD		-1.972***		-1.0801**
		(0.677)		(0.52599)
Observations	56	56	50	50
Sample	Tradables Only		Tradables Only Inflation > p5	

Panel B: By Skill Intensity

	Annual U.S. Inflation Rate			
	(1)	(2)	(3)	(4)
NTR Gap	-11.59**		-6.3987**	
	(4.769)		(3.270)	
NTR Gap ×Payroll Share to College Grads/SD	-15.064***		-3.283	
	(4.404)		(3.429)	
Change in China Import Penetration in Other Developed Economies (1999-2011)		-3.637***		-2.6361***
		(0.5915)		(0.6247)
Change in China Import Penetration in Other Developed Economies (1999-2011) × Payroll Share to College Grads/SD		-1.64946***		-2.3489
		(0.35816)		(2.542)
Observations	58	58	51	51
Sample	Tradables Only		Tradables Only Inflation > p5	

Panel C: By Average Inflation in 1990s

	Annual U.S. Inflation Rate			
	(1)	(2)	(3)	(4)
NTR Gap	-3.758***	-3.843***	-4.173***	-4.866***
	(1.467)	(1.437)	(1.4429)	(1.525)
NTR Gap×Prior Inflation	0.70386***	1.2112**	1.5813***	2.0495***
	(0.3536)	(0.55008)	(0.5578)	(0.65901)
Prior Inflation	0.72646***	0.5060**	0.06560	0.05107
	(0.1543)	(0.24919)	(0.25713)	(0.30427)
Tradable	-1.1619			
	(0.7374)			
Observations	207	150	136	136
Sample	Full	Tradables Only	Tradables Only Inflation > p5	Tradables Only 1990s inflation > p5

Notes: The level of observation is an IO6 category: the data is collapsed at the IO6 level after 2000. Square-root IO final consumption spending weights are used. Heteroskedasticity-robust standard errors are reported. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Controlling for Potential Confounding Factors

Panel A: Response of U.S. Consumer Prices to
Granting Permanent Trade Relation to China (IV Specifications)

	Annual U.S. Inflation Rate				
	(1)	(2)	(3)	(4)	(5)
Change in China Import	-3.217	-3.1541	-3.996***	-3.8919***	-2.981**
Penetration (1999-2011)	(2.9538)	(2.4375)	(0.73600)	(0.7084)	(1.477)
Direct Imports of Intermediate Inputs	-68.771				
from China	(177.79)				
Direct and Indirect Imports		-70.15			
of Intermediate Inputs from China		(136.96)			
All Direct Imports of Intermediate Inputs			10.669		
			(7.688)		
All Direct and Indirect Imports				10.054	
of Intermediate Inputs				(8.156)	
Export Share					-10.3929
					(9.3471)
Cragg-Donald F	1.529	1.761	9.625	10.341	3.907
Kleibergen-PaapF	1.794	1.877	7.340	7.986	3.457
Observations	58	58	58	58	58
Sample			Tradables		

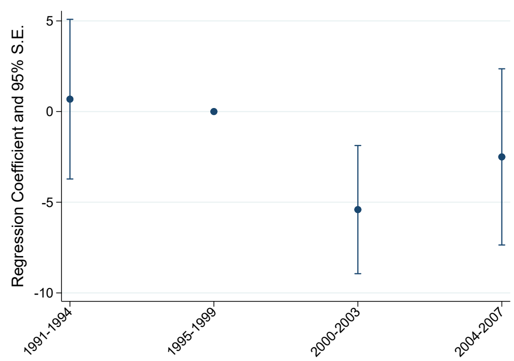
Panel B: Response of U.S. Consumer Prices to Trade with China,
Instrumented by Other Countries' Trade with China (IV Specifications)

	Annual U.S. Inflation Rate				
	(1)	(2)	(3)	(4)	(5)
Change in China Import	-1.014*	-1.2018***	-3.707***	-3.6690***	-2.996***
Penetration (1999-2011)	(0.5563)	(0.5553)	(0.72158)	(0.7146)	(0.4974)
Direct Imports of Intermediate Inputs	-187.65***				
from China	(42.071)				
Direct and Indirect Imports		-168.21***			
of Intermediate Inputs from China		(42.55)			
All Direct Imports of Intermediate Inputs			9.943		
			(7.3463)		
All Direct and Indirect Imports				9.945	
of Intermediate Inputs from China				(8.0025)	
Export Share					-10.484
					(6.82)
Cragg-Donald F	23.880	27.256	92.803	94.874	85.32
Kleibergen-Paap F	10.52	11.27	10.857	10.77	7.855
Observations	54	54	54	54	54
Sample			Manufacturing		

Notes: The level of observation is an IO6 category: the data is collapsed at the IO6 level after 2000. Square-root IO final consumption spending weights are used. Heteroskedasticity-robust standard errors are reported. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Dynamic Response of U.S. Consumer Prices to Granting Permanent Normal Trade Relations to China

Panel A: Full Sample



Panel B: Excluding Categories with Average Inflation < p5

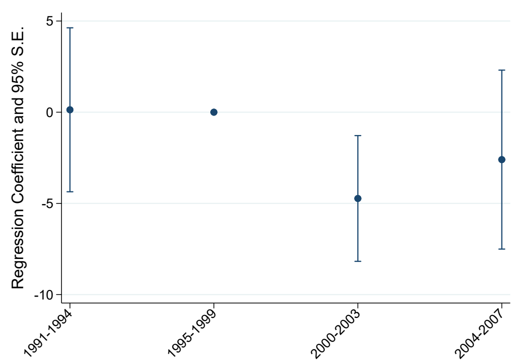
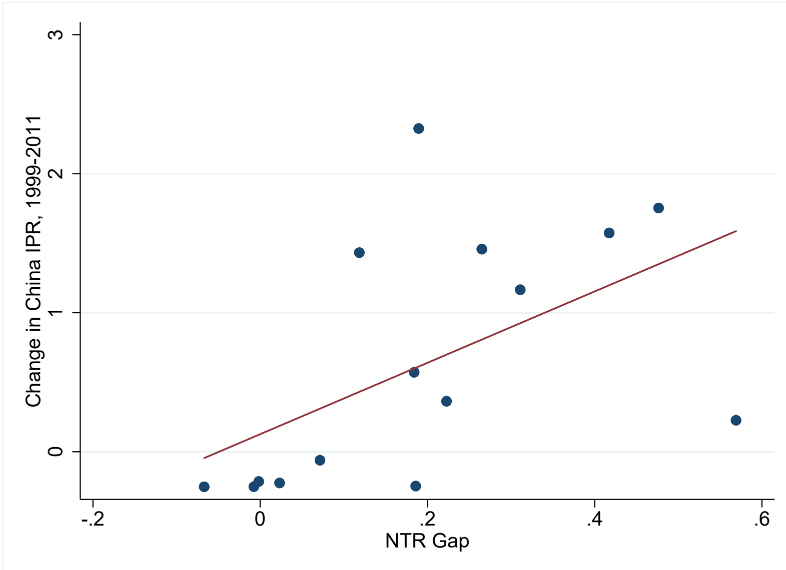


Figure 2: First-Stage and Reduced-Form for the Effect of Trade with China on U.S. Consumer Prices, Instrumenting by U.S. Granting of Permanent Normal Trade Relations to China

Panel A: First Stage



Panel B: Reduced Form

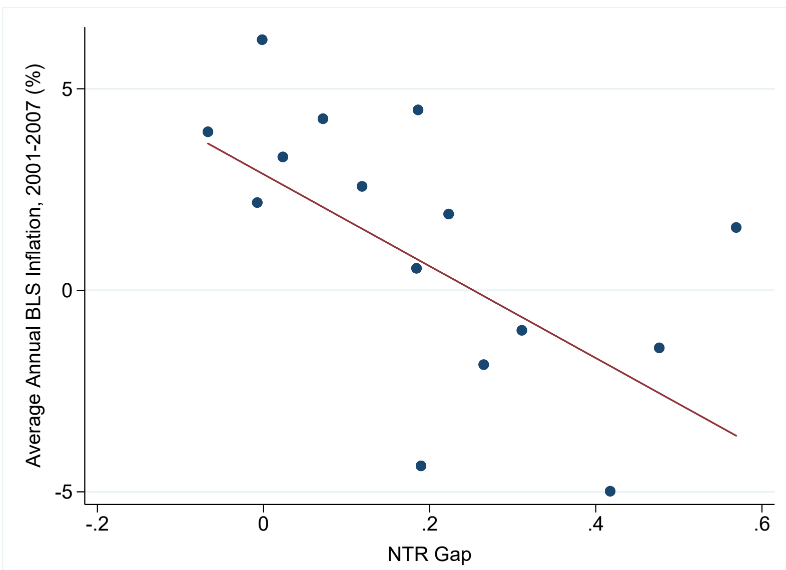
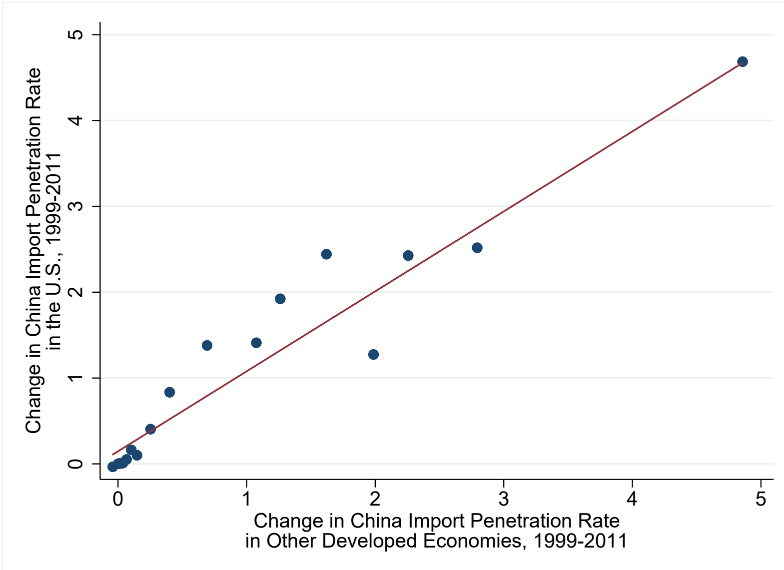


Figure 3: First-Stage and Reduced-Form for the Effect of Trade with China on U.S. Consumer Prices, Instrumenting by Other Developed Countries' Trade with China

Panel A: First Stage



Panel B: Reduced Form

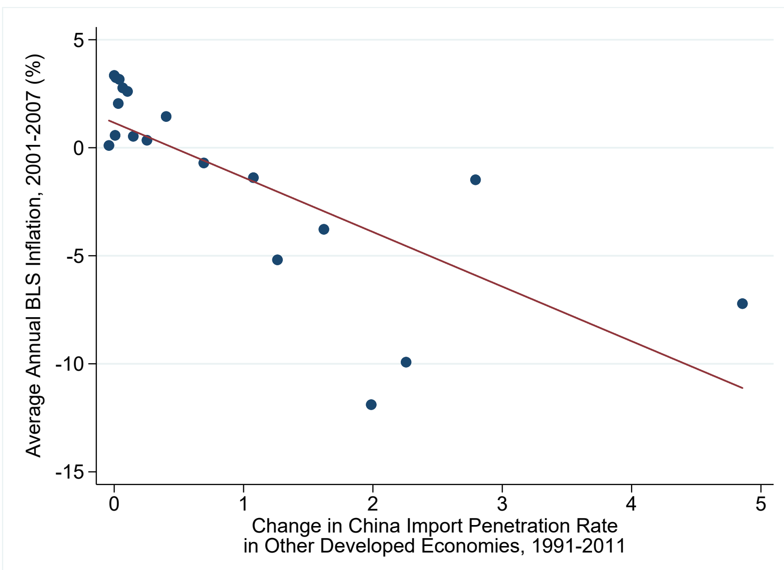
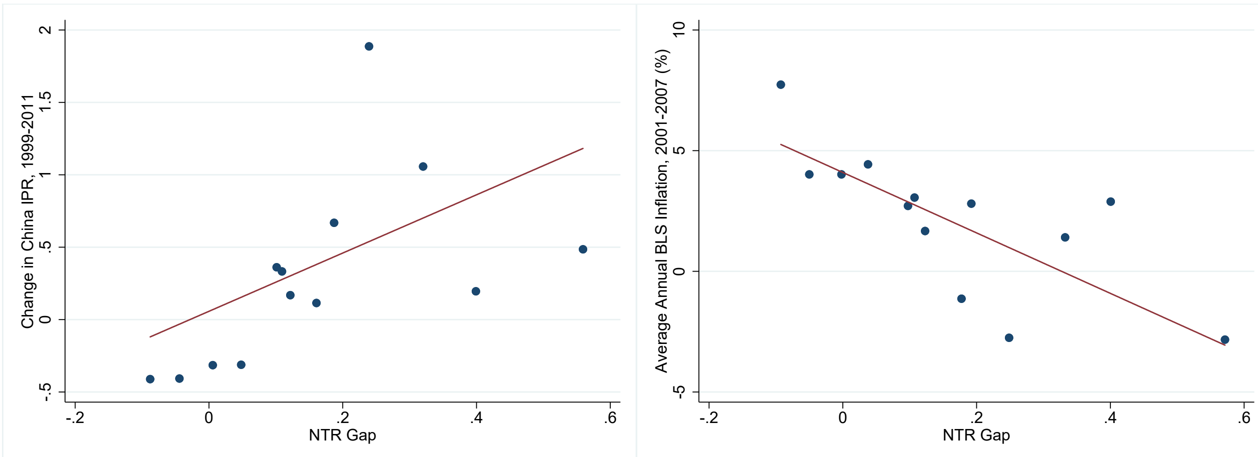
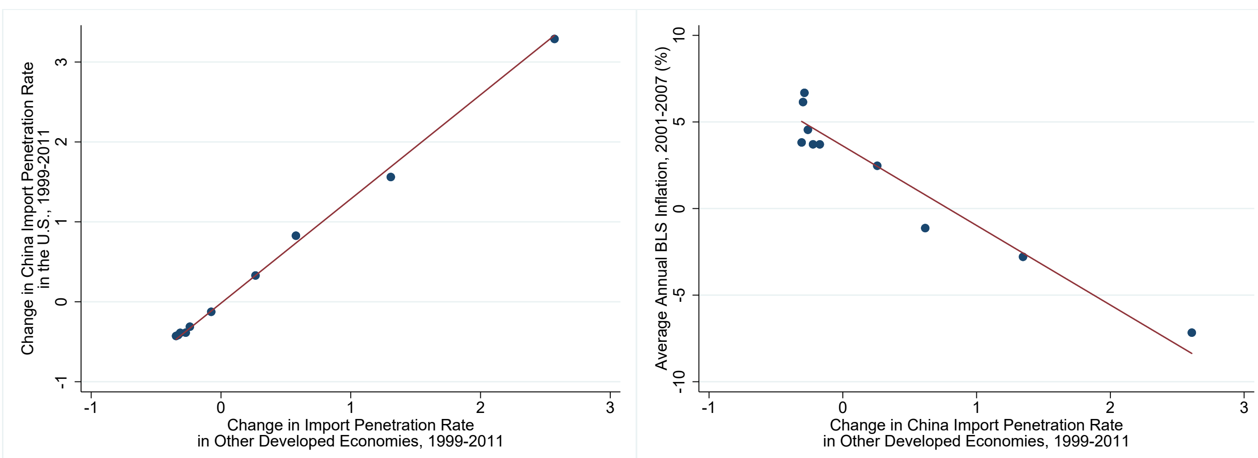


Figure 4: Estimating the Response of U.S. Consumer Prices to Trade with China at the level of 6-digit Input-Output Industries

Panel A: First Stage and Reduced-Form Instrumenting by U.S. Granting of Permanent Normal Trade Relations to China



Panel B: First Stage and Reduced-Form Instrumenting by Other Developed Countries' Trade with China



Online Appendices

A Theory Appendix

In this Appendix, we derive our IV specifications (2) and (3) from a multi-sector version of the baseline trade model in Arkolakis et al. (2012). We start by discussing the case with a single sector, then move to many sectors.

Single sector. Assume that households have CES preferences over domestic and foreign varieties. i indexes countries and j is the home country.

$$U_j = \left(\sum_{i=1}^{n} q_{ij}^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)}$$
$$P_j = \left(\sum_{i=1}^{n} (w_i \tau_{ij})^{1-\sigma} \right)^{1/(1-\sigma)}$$
$$X_{ij} = \left(\frac{w_i \tau_{ij}}{P_j} \right)^{1-\sigma} Y_j$$

where $Y_j = \sum_{i=1}^{n} X_{ij}$ is total expenditures in country j. Notes that $1 - \sigma < 0$ is the elasticity of relative imports with respect to variables trade costs:

$$1 - \sigma = \frac{\partial ln(X_{ij}/X_{jj})}{\partial ln(\tau_{ij})}$$

The four step that follow derive change in "real income", $W_j = Y_j/P_j$, caused by a change in trade costs and labor endowments across the world.

Step 1: Define domestic labor as the numeraire, i.e. the domestic wage is normalized to 1. This implies $dln(Y_j) = 0$ by trade balance ($Y_j = w_j L_j$). So $dln(W_j) == dln(P_j)$.

Step 2: Using the fact that if $z = \sum_i \alpha_i x_i$, then $dln(z) = \sum_i \frac{\alpha_i x_{i0}}{z_0} dln(x_i)$, we get

$$dln(P_j) = \frac{1}{1-\sigma} \sum_i \left[\left(\frac{(w_i \tau_{ij})^{1-\sigma}}{\sum_k (w_k \tau_{kj})^{1-\sigma}} \right) dln\left((w_i \tau_{ij})^{1-\sigma} \right) \right]$$

Now simplify the weights:

$$\frac{(w_i \tau_{ij})^{1-\sigma}}{\sum_k (w_k \tau_{kj})^{1-\sigma}} = \frac{X_{ij} \frac{P_j^{1-\sigma}}{Y_j}}{\sum_i X_{ij} \frac{P_j^{1-\sigma}}{Y_j}} = \frac{X_{ij}}{Y_j}$$

Using $dln\left((w_i\tau_{ij})^{1-\sigma}\right) = (1-\sigma)\left(dln(w_i) + dln(\tau_{ij})\right)$ and the result from step 1, we get:

$$dln(W_j) = \sum_i \frac{X_{ij}}{Y_j}\left(dln(w_i) + dln(\tau_{ij})\right)$$

Step 3: We can now express $dln(w_i) + dln(\tau_{ij})$ in terms of import shares. Intuitively, we can infer the underlying price change from a given change in import shares, using the elasticity of substitution. Since $w_j = 1$ by normalization,

$$(w_i\tau_{ij})^{1-\sigma} = \frac{X_{ij}/Y_j}{X_{jj}/Y_j}$$

so

$$dln(w_i) + dln(\tau_{ij}) = \frac{1}{1-\sigma}\left(dln(\lambda_{ij}) - dln(\lambda_{jj})\right)$$

with $\lambda_{ij} = X_{ij}/Y_j$. So

$$\begin{aligned} dln(W_j) &= \frac{1}{1-\sigma}\sum_i \lambda_{ij}\left(dln(\lambda_{jj}) - dln(\lambda_{ij})\right) \\ &= \frac{1}{1-\sigma} dln(\lambda_{jj}) \underbrace{\sum_i \lambda_{ij}}_{=1} - \frac{1}{1-\sigma} \underbrace{\sum_i \lambda_{ij} dln(\lambda_{ij})}_{=0} \end{aligned}$$

Therefore

$$dln(W_j) = \frac{1}{1-\sigma} dln(\lambda_{jj})$$

Step 4: Finally, we integrate over the infinitesimal logarithmic changes. Since percentage changes are transitive and since the elasticity doesn't change, we can consider large changes and write:

$$\Delta ln(W_j) = \frac{1}{1-\sigma}\Delta ln(\lambda_{jj})$$

Many sectors. We can now turn to the case with many sectors and derive our IV specifications. We have multiple sectors indexed by s. Assume that consumers have Cobb-Douglas preferences over sectors, with expenditure shares η_s. The elasticity of susbtitution in each sector is σ_s. The consumer price index is:

$$P_j = \Pi_{s=1}^{S}\left(P_j^s\right)^{\eta_s}$$

Following the same steps as above, the overall welfare change is given by:

$$\Delta ln(W_j) = \sum_s \left(\frac{\eta_s}{1-\sigma_s}\Delta ln(\lambda_{jj}^s)\right)$$

Note that we can derive the price change in each sector as a function of the change in domestic expenditure shares:

$$\Delta ln(P_j^s) = -\frac{1}{1-\sigma_s}\Delta ln(\lambda_{jj}^s)$$

Introducing common inflation shocks over time across sectors as well as sector-specific inflation shocks, we get:

$$\Delta log(P_j^s) = \alpha - \frac{1}{1-\sigma_s}\Delta ln(\lambda_{jj}^s) + \epsilon_j$$

Note that our IV specifications are of the form:

$$\Delta log(P_j^s) = \alpha + \beta \Delta \lambda_{jCHINA}^s + \epsilon_j$$

where j indexes the home country, i.e. the U.S. This approximation is based on two assumptions:
(A1) we assume that China is the only trade partner of the US, i.e. $\lambda_{jj}^s + \lambda_{jCHINA}^s = 1\ \forall s$.
(A2) we assume that the the initial import share from China is small.
Under these assumptions, we have

$$\begin{aligned}\Delta log(P_j^s) &= \alpha - \frac{1}{1-\sigma_s}\Delta ln(1-\lambda_{jCHINA}^s) + \epsilon_j \\ &\approx \alpha - \frac{1}{1-\sigma_s}\Delta \lambda_{jCHINA}^s + \epsilon_j \end{aligned} \tag{A1}$$

Finally, we run the regression using spending weights so that we should recover the average spending-weighted $\frac{1}{1-\sigma_s}$ if the model is correct. We are relaxing (A1) and (A2) in ongoing work.

B Online Appendix Tables and Figures

Table A1: Controlling for Potential Confounding Factors in Sample Excluding Categories with Lowest Inflation

	Annual BLS Inflation Rate				
	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(5)	(6)
Change in China Import	-1.5835***	-1.5195***	-2.5906***	-2.6149***	-1.739***
Penetration (1999-2011)	(.433924)	(.3500)	(.53492)	(.59934)	(.6013)
Direct Imports of Intermediate Inputs	-100.85*				
from China	(53.41)				
Direct and Indirect Imports		-102.88**			
of Intermediate Inputs from China		(45.483)			
All Direct Imports of Intermediate Inputs			11.43*		
			(6.3176)		
All Direct and Indirect Imports				10.055	
of Intermediate Inputs				(7.70579)	
Export Share					-6.078
					(3.712)
First-stage Cragg-Donald Wald F stat					93.0
First-stage Kleibergen-Paap rk Wald F stat					18.5
Sample	Manufacturing, excluding categories with inflation < p5				
Observations	47				

Notes: The level of observation is an IO6 category: the data is collapsed at the IO6 level after 2000. Square-root IO final consumption spending weights are used. Heteroskedasticity-robust standard errors are reported. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: Distribution of NTR Gaps, Tradables Only

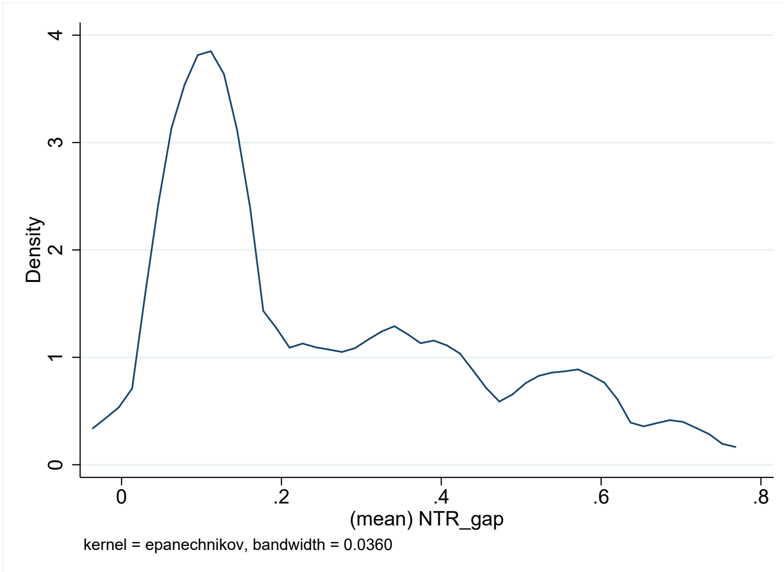


Figure A2: The Response of U.S. Consumer Prices to Granting Permanent Normal Trade Relations to China, Dynamic Effects for Categories with Average Inflation > p10

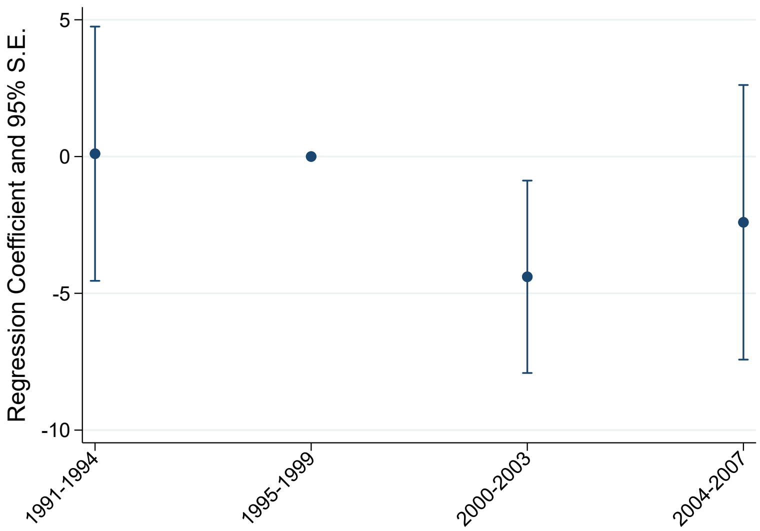
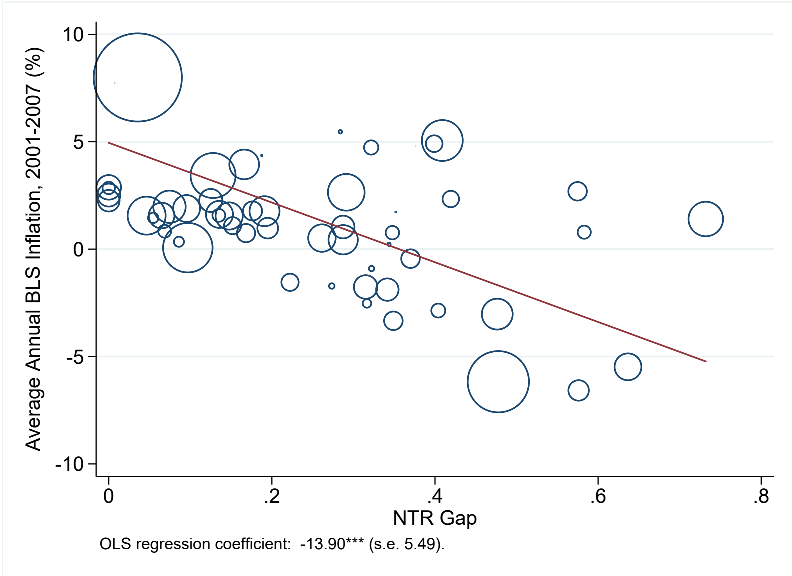
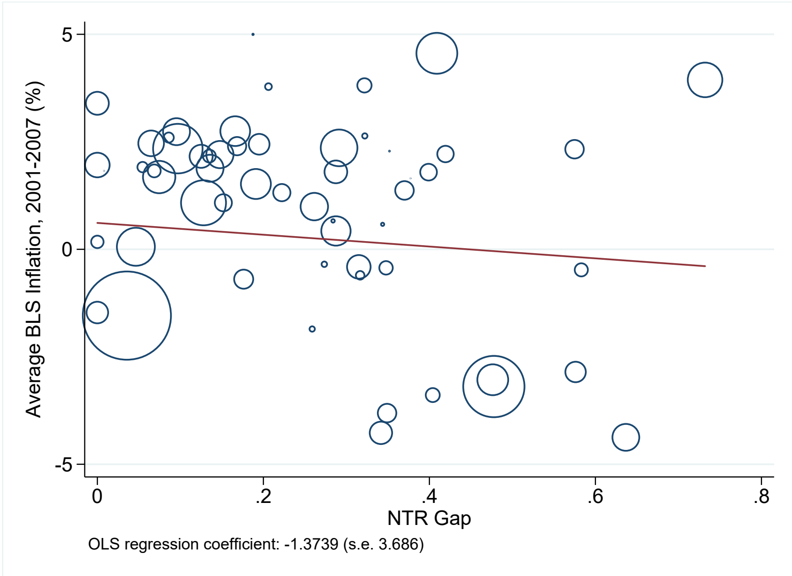


Figure A3: The Relationship between Inflation and NTR Gap across IO6 categories

Panel A: Between 2001 and 2007, Tradable Categories Only



Panel B: Between 1993 and 2000, Tradable Categories Only



Notes: The level of observation is an IO6 category within tradables ($N = 53$). The sample excludes IO6 categories with an average inflation rate below -10% per year. IO-level final consumption weights are used. Heteroskedasticity-robust standard errors are reported.