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

Xavier Jaravel, London School of Economics
Erick Sager, Bureau of Labor Statistics

July 2018

Abstract

We estimate the impact of trade with China on U.S. consumer prices and use this evidence to discipline quantitative trade models. Using comprehensive price data from the U.S. Bureau of Labor Statistics and two complementary identification strategies from Pierce and Schott (2016) and Autor et al. (2014), 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; abstracting from GE effects and 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. These price effects are one order of magnitude larger than in the class of trade models nested by Arkolakis et al. (2012). In contrast with these models, we find that (i) the price response of pre-existing domestic products drives the overall price effects; (ii) market concentration is a key predictor of the magnitude of the price response. Using a simple model, we show that these patterns can be explained by a fall in markups in response to increased import competition. These results indicate that the pro-competitive effects of trade have important implications for inflation and consumer welfare.

JEL codes: F10, F13, F14

*For thoughtful discussions and comments, we thank our discussants, Amit Khandelwal and Teresa Fort, as well as Pol Antras, David Atkin, David Autor, Andrew Bernard, Arnaud Costinot, Kirill Borusyak, Thomas Chaney, Swati Dhingra, David Dorn, Giammario Impullitti, Oleg Itskhoki, Marc Melitz, Thomas Sampson, Daniel Sturm, Felix Tintelnot, and Jon Vogel. This research was conducted with restricted access to Bureau of Labor Statistics (BLS) data and all results have been reviewed to ensure that no confidential data are disclosed. The views expressed in this paper are those of the authors alone and do not necessarily reflect those of the Bureau of Labor Statistics or the U.S. government. All errors are our own.

I Introduction

How large are the gains from trade and how are they distributed within an economy? Recent research has developed reduced-form empirical strategies to estimate the impact of trade on the labor market: for example, Autor et al. (2013), Autor et al. (2014) and Pierce and Schott (2016) estimate the effects 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 this paper, we use 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. To estimate the causal effect of trade with China on U.S. consumer prices across industries, we use the instrumental variable approaches developed by Autor et al. (2014) and Pierce and Schott (2016). 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 increase 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).

Estimating the causal effect of trade with China on U.S. consumer prices across industries 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

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

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 is likely to 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 a stable and 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 declined in response to increased Chinese import competition. The magnitudes of the estimates are similar in both reseach designs: on average, a one percentage point increase in Chinese import penetration in a given industry leads to a 3 percentage point fall in the Consumer Price Index in that industry. The results are robust to the inclusion of a variety of industry-specific time-varying controls as well as industry fixed effects, which alleviates potential concerns over reverse causality and omitted variable bias. Using the research design of Pierce and Schott (2016), 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 connect our IV estimates to 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-industry model, it is straightforward to derive from the model the cross-industry IV specifications we run in the first part of the paper. 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 trade elasticities. 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.

We examine a series of potential mechanisms and/or confounding factors that could reconcile our estimates with the class of models from Arkolakis et al. (2012). 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. Third, we check the robustness of our 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.

To shed light on the mechanisms that could explain these large price effects, we examine the extent to which the price effects come from new products or continued products, and we investigate whether the effects are very different for domestic goods or imported goods. We document that product turnover strongly increases in response to increased trade with China. But we find that the price response of pre-existing domestic varieties drives the overall price effects, rather than the price response of products made in China or of new products. We obtain this result by identifying products produced in the U.S. and in China within the Consumer Price Index (using "specification checklists" recording information on product origina), as well as by using data from the U.S. Producer Price Index.

What could explain the price response of domestic products? Conceptually, this response could result from two types of effects of increased trade with China: changes in production cost for U.S. producers or changes in markups. There are several reasons why production costs for U.S. producers might change following an increase in trade with China, such as changes in the cost of imported intermediate inputs, changes in wages or changes in productivity. Given auxiliary results suggesting that the wage and productivity channels are unlikely to play a large role,[2] we focus on documenting the role of intermediate inputs. We implement our IV strategy while also taking into account upstream and downstream exposure to Chinese import competition. We find that accounting for upstream and downstream exposure leaves unaffected our main IV coefficient (for direct import competition); one cannot explain its magnitude by a fall in the cost of imported intermediate inputs.

Having shown that changes in the cost of intermediate inputs do not explain the large price

[2]Using public data from QCEW to measure wages and the NBER CES database to measure changes in TFP, we find no statistically significant relationship between the increase in Chinese import penetration and the average wage or TFP. Futhermore, Autor et al. (2016) find that patents from U.S. manufacturers decline in response to increase Chinese import penetration, which also suggests that cost-cutting innovations are unlikely to drive the price response we observe.

response for domestic products, we examine the possible role of markups. We start with a simple theoretical exercise: could changes in markups plausibly explain the observed domestic price response, or are the observed price effects too large? Using a simple but flexible model following Amiti et al. (2018), we find that the magnitude of our baseline IV estimates can be rationalized by changes in markups. Second, we use the model to derive simple tests of the markup channel based on heterogeneity in the IV estimate across industries. We find the magnitude of our IV estimates varies substantially across industries depending on market structure, in ways that are consistent with the markup channel. We use Herfindahl indices and the initial Chinese import penetration rate to conduct this heterogeneity analysis. We find that for industries in which $10,000/Herfindahl > 10$, i.e. the implied number of "equally-sized firms" in the industry is above 10, the price response is 80.27% smaller than in more concentrated industries. Likewise, for industries in which the 1999 Chinese import penetration rate is above 5, the effect is 80.34% smaller than in industries for which it is below 5. These strong non-linear heterogeneity patterns are consistent with the predictions of our simple model, which brings support to the markup channel.

This paper builds on 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 benchmark our empirical estimates against the predictions of the quantitative trade models nested by Arkolakis et al. (2012). We find a much bigger price response to trade across industries and suggest that it can be explain by markup effects, a channel often termed the "pro-competitive effects" of trade. Our paper is thus part of a large literature that has estimated the empirical relationship between international trade and firm-level markups (e.g., Levinsohn (1993), Krishna and Mitra (1998), Feenstra and Weinstein (2017), Arkolakis et al. (2018) and Amiti et al. (2018)) and that has examined the extent to which opening up to trade may reduce markup distortions (e.g., Brander and Krugman (1983), Atkeson and Burstein (2008), Epifani and Gancia (2011), Edmond et al. (2015), Feenstra (2018), and Impullitti and Licandro (2018)).

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 ways. 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: 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). Third, we use our estimates to point out that benchmark 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, while competition dynamics are a likely explanation.[3]

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; Section V documents the mechanisms driving our main resluts; 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 sources: 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.

Consumer Price Index. Our main outcome variable is inflation faced by U.S. consumers across industries. We measure this variable using the micro data underlying the Consumer Price Index from the Bureau of Labor Statistics' internal CPI Research Database (CPI-RDB). Although the

[3] 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.

CPI-RDB contains information on 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 categories 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.[4]

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 weights based on Consumer Expenditure Surveys for each year from 1988–1995, 1999–2004 and 2008-2012.[5] 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 Acemoglu et al. (2016) 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

[4] 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 micro-data 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 207 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."

[5] We follow Bils and Klenow (2004), Klenow and Krystov (2008), Gagnon, Lopez-Salido and Vincent (2012) and Bils, Klenow and Malin (2012) in using weights based on the Consumer Expenditure Survey.

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.[6]

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 considers 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.[7] 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.

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

[7]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.[8] This research design addresses threats to identification that stem

[8]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 they 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.[9] 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

[9] 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:

$$\begin{aligned} \pi_i &= \alpha + \beta \Delta ChinaIP_i + \nu X_i + \epsilon_i \qquad (2) \\ \Delta ChinaIP_i &= \widetilde{\alpha} + \gamma NTR\, Gap_i + \widetilde{\nu} X_i + \eta_i \end{aligned}$$

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:

$$\begin{aligned} \pi_i &= \alpha + \beta \Delta ChinaIP_i + \nu X_i + \epsilon_i \qquad (3) \\ \Delta ChinaIP_i &= \widetilde{\alpha} + \gamma \Delta ChinaIP_{i,Other} + \widetilde{\nu} X_i + \eta_i \end{aligned}$$

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) directly 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 estimates 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 effects, 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.[10] 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 2004-2007, 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

[10] 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

The previous analysis was conducted at the level of ELIs, the most disaggregated product category in the price data of the Bureau of Labor Statistics. It could be that the large 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).

A remaining potential concern is that trade flows may be mismeasured at the level of ELIs. As a robustness check, we repeat the analysis by aggregating the data at the level of 6-digit industries in the Input-Output table, reporting the results in Tables 4 and 5.

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.

Conducting the analysis at the level of 6-digit IO industries has the added benefit that various precisely-measured industry covariates are available at this level of aggregation, which we use to document heterogeneity in the treatment effect. Online Appendix Table A1 documents how the magnitude of the price effects depends on skill intensity (Panel A) and the level of inflation in the previous decade (Panel B). Panel A reports 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 becomes very imprecisely estimated, indicating that the excluded categories play a key role for the estimates in the full sample.

Panel B of Table A1 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).[11]

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,

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

leads to a large fall in inflation for U.S. consumers; this fall in inflation is larger in product categories that have a higher skill intensity and that are on a trend of lower inflation. We now turn to a discussion of the mechanisms that could explain these findings.

IV Discussion of Baseline Estimates

In this section, we use two benchmarks to discuss the magnitude of our baseline estimates of the price effects of trade with China (from Section III). We first compare the price effects to the employment effects of trade with China. Then we benchmark our estimates against the predictions of one influential class of quantitative trade models. Finally, we examine the implications of our estimates for the distributional effects from trade.

IV.A Price Effects vs. Employment Effects of Trade across Industries

We start by conducting a simple benchmarking exercise in the spirit of Autor et al. (2013) and Autor et al. (2014), which lets us assess the overall impact of increased trade with China on the U.S. Consumer Price Index and compare it with its employment effects.

Under two strong assumptions, we can benchmark the labor market effects of trade with China documented in Autor et al. (2013) and Autor et al. (2014) with the gains to U.S. consumers (through lower prices) 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 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 difficult to reconcile with benchmark quantitative trade models, which all suggest that the gains from trade should be much smaller.

IV.B Connecting our IV Estimates to Quantitative Trade Models

In an influential paper, 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. Assuming 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 and 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.

There are several potential reasons why our IV estimates may in fact be consistent with this class of quantitative trade 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 sector. To alleviate this concern, we have worked with detailed sectors (based on the BLS official classification of products into ELI categories) and checked that the results are robust across different definition of sectors (working with 6-digit intput-ouput industries as a robustness check, cf. Tables 4 and 5). Second, there is a variety of statistical concerns related to a potential bias in the IV estimates. We have shown in Section III that our results are in fact robust to many sample restrictions, are not driven by a small number of industries, and are very similar regardless of whether we use the identification strategies from Autor et al. (2014) or Pierce and Schott (2016).

The large magnitude of the response of U.S. consumer prices to trade with China is a robust feature of the data. As shown in Table 7 and 8, much of the effect comes from lower inflation for pre-existing domestic products. In other words, exposure to rising Chinese import competition forces domestic U.S. product to lower their prices. The models nested by Arkolakis et al. (2012) 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. We investigate this hypothesis in Section V by studying the role of domestic goods in the observed price effects and by examining heterogeneity in the size of the price response depending on market structure.

IV.C Implications for the Distributional Effects from Trade via the Expenditure Channel

A growing literature studies the distributional effects from trade via the "expenditure channel", i.e. distributional effects induced by price changes (e.g., Fajgelbaum and Khandelwal (2016)). 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)). We provide complementary information by examining whether the magnitude of the price response to a given trade shock (from China) systematically differs across product categories depending on the income level of consumers. Concretely, we repeat our main specifications with an interaction term capturing the income level of consumers across industries.

As our main proxy for consumer income in an industry, we use the spending share from households earning above $60,000 a year. We obtain the spending shares at the level of detailed product categories in the CEX following Borusyak and Jaravel (2017), which we match to ELIs. This variable is standardized by its standard deviation across industries and interacted with the instruments from Pierce and Schott (2016) and Autor et al. (2014).

Table 6 reports the results. Two patterns stand out. First, in Panel A, we find no heterogeneity in IV estimates by consumer income. This suggests that heterogeneity in price responses does not create important distributional effects.[12] For a given increase in import penetration from China, the price response has a similar magnitude across product categories catering to richer or poorer households. However, Panel B reports more nuanced patterns. This panel documents variation in the strength of the first stage by consumer income. With the instrument from Pierce and Schott (2016), the first stage is much stronger (close to 50% larger) in product categories catering to richer consumers. In other words, the response to changes in policy uncertainty is much stronger in product categories that cater to richer groups. In turn, the overall price effect will be much stronger (scaling the first stage by the IV coefficient, which gives the reduced-form price effect). The stronger response of the Chinese import penetration rate in categories caterering to richer groups could be explained by the fact that returns to investment in such product categories may be higher, given that market size tends to increase faster in product categories selling to richer consumers (e.g., Jaravel (2016)). In contrast, we do not find any heterogeneity in first-stage relationships with the instrument from Autor et al. (2014).

In sum, the results in Table 6 indicate that, for a given increase in the Chinese import penetration rate, there is no significant heterogeneity in price effects across income groups (Panel A); but the extent to which the Chinese import penetration rates changes in response to the underlying shock (e.g., change in policy uncertainty) may differ substantially across income groups (Panel B, Columns (1) and (2)). These findings thus paint a nuanced picture of the implications of price and entry dynamics for the distributional effects of trade via the expenditure channel.

[12] This pattern is robust when considering other simple proxies for consumer income, such as the spending shares from college graduates (not reported). In ongoing work, we investigate whether there is important non-linear heterogeneous effects across more detailed income groups.

V Mechanisms

To investigate potential mechanisms driving the results from Section III.B, we start by examining the impact of trade with China on product turnover and on inflation for continued goods. We then assess the extent to which the results are driven by the price response of domestic (U.S.) goods, rather than by Chinese goods. Finally, we examine the mechanisms that could explain the fall in the price of domestic goods, focusing on the role of imported intermediate inputs and changes in markups.

V.A The Role of Continued Products

Product turnover. Panel A of Table 7 investigates the impact of trade with China on product turnover. Product turnover is measured as the rate of "product substitutions" in the BLS data; product substitutions occur when price collectors can no longer find the product they were pricing in a given store (for instance, this could happen because this product was displaced by foreign competition). Panel A of Table 7 shows that product turnover increases substantially in response to trade with China, consistent with the notion that Chinese products displace domestic varieties.

Inflation for continued goods. Panel B of Table 7 documents the impact of trade with China on "inflation for continued products", which is defined as inflation for the set of products which are available across consecutive periods. Continued products inflation excludes product substitutions from the computation of inflation. Therefore it allows us to test whether the overall price response to trade stems from the fact that new products have a lower price (which would occur via product substitutions) or from the fact that pre-existing varieties may decrease their prices (continued products inflation). Across all specifications, we find a robust pattern of lower inflation for continued products in response to increased trade with China. Columns (1) and (2) consider the full set of goods and document a large fall in continued products inflation when using either of our two research designs.

Columns (3) and (4) repeat the analysis but focus on goods that existed in 2000. In other words, we only include in the sample a set of goods that existed prior to the "China shock" (specifically, in 2000). We still find a large response of continued products inflation, which shows that pre-existing varieties are affected by Chinese import competition. This result shows that the patterns of lower continued products inflation in Columns (1) and (2) are not due to goods that were introduced after the China shock, implying that "reallocation effects" do not drive the overall price response. A potential concern is that these estimates are based on a set of goods that existed in 2000 and were also available much earlier or later in the sample (potentially as early as 1990 or as late as 2007). To address the possibility that selection effects (inherent in such an unbalanced panel) may be driving the patterns we document, we repeat the exercise after restricting the number of years we consider. In Columns (5) and (6), we consider goods that existed in 2000 and track them between 1998 and 2002 only. The stability of the estimates in Columns (5) and (6) relative to Columns (3) and (4) indicates that the results are not sensitive to potential selection effects.

In sum, the large response of continued products inflation is a robust feature of the data. This result can help discipline quantitative trade models, because it shows that "reallocation effects" (entry or exit of more/less productive products of firms in response to trade shocks) are not the leading force in the data. Instead, there is a large response of pre-existing varieties (continued products inflation).[13]

V.B The Role of Domestic Products

Having established that continued product play an important role, we now examine the contribution of domestic products. We do so using two complementary datasets, the Producer Price Index data and a subset of products within the Consumer Price Index.

Producer Price Index. We repeat the main analysis using an outcome variable that measures the average change over time in the prices received by domestic producers of goods and services. We measure this variable using micro data underlying the Producer Price Index from the Bureau of Labor Statistics. Following PPI methodology, we aggregate price change from the product level to 6-digit NAICS using weights derived from the Census' value of shipments data. We can then directly match producer price inflation to independent variables at the 6-digit NAICS level. Online Appendix Table A4 reports summary statistics for our PPI sample. See Nakamura and Steinsson (2008) and Goldberg and Hellerstein (2011) for more information about using the PPI for measuring inflation.

Panel A of Table 8 documents the response of prices to trade with China using data from the Producer Price Index. The Producer Price Index only takes into account price changes for products manufactured in the U.S., therefore it is an ideal dataset to test whether the price effects we document are driven by U.S. products. The table reports estimates that are very similar to

[13] Technically speaking, the results on continued products inflation discussed above only show that the response is as large for domestic products as in the full sample, but they do not rigorously establish that the domestic price response accounts for most of the effect. Online Appendix Table A3 provides a formal decomposition of the full sample IV estimate into the contribution of inflation for continued products and inflation for substitutions. The results show that domestic products are driving the price response.

those obtained in the full sample, whether we use the source of variation from Autor et al. (2014) or Pierce and Schott (2016). Columns (1) to (4) report the results for the overall PPI inflation. A 1 percentage point increase in the Chinese import penetration rate leads to a fall in inflation between -2.97 and -4.06 percentage points. Columns (5), (6) and (7) show that the results are similar when computing inflation for continued products in the PPI sample. The IV estimates are between 1.85 and 3.80. In all samples and specifications, the IV estimates are statistically significant at the 5% level and the instruments are strong.

U.S. Goods Identified in Specification Checklists. A limitation of using the Producer Price Index data to assess the contribution of domestic products is that the sample is different from the Consumer Price Index. For instance, the PPI takes into account intermediate goods while the Consumer Price Index only accounts for inflation for final goods. To assess more specifically whether our estimates from Section II are driven by U.S. goods as opposed to foreign (Chinese) goods, we identify U.S. goods in the CPI using specification checklists.

For each product in the CPI, characteristics are recorded in specification checklist files. We use the specification checklists to gather information on the country of origin for each product and then repeat each estimation exercise on subsamples of U.S. products. While checklists for some categories of items explicitly gather country of origin information (e.g., "Was the product made in the United States; Yes or No?" or "Write in the country in which the product was made."), other categories only leave an "Other Information" entry that is populated with text. When this text contains information about country of origin (e.g., "Made in China") we record the country name. For products that have low import penetration and do not have an explicit country of origin checkbox (such as most product categories within services), we assume a lack of information about country of origin indicates a U.S. produced good. Online Appendix Table A5 reports summary statistics on the number of product categories that gather country of origin information.

Panel B of Table 8 documents the response of prices to trade with China in the Consumer Price Index when only taking into account U.S. goods. Consistent with our results using the Producer Price Index data, we obtain estimates that are very similar to those obtained in the full sample, with both identification strategies from Autor et al. (2014) or Pierce and Schott (2016). Columns (1) to (5) report the results with the full CPI inflation as the outcome. As in the main sample, the IV estimates tend to decrease when highly deflationary categories are excluded, but they remain large, equal to -3.71 when following Pierce and Schott (2016) in Column (3) and -1.97 when following Autor et al. (2014) in Column (6). Colums (5) and (6) show that the effects remain significant and similar in magnitude when focusing on continued U.S. goods. The instruments are strong across all specifications.[14]

Discussion: what could explain the price response of domestic products? The results in Table 8 show that there is a large response of domestic prices to trade with China. Conceptually, this response could result from two types of effects of increased trade with China: changes in production cost for U.S. producers or changes in markups.

There are several reasons why production costs for U.S. producers might change following an increase in trade with China. First, it could be the case that U.S. producers benefit from cheaper intermediate inputs. We examine the importance of such effects in Subsection V.C. Second, it could be that labor cost falls or that productivity increases, as increased import competition may lead to a fall in domestic wages or may spur cost-reducing innovations. Using public data from QCEW to measure wages and the NBER CES database to measure changes in TFP, we find that there is no statistically significant relationship between the increase in Chinese import penetration and the average wage or TFP (not reported in the manuscript). These results suggest that the wage and innovation channels are unlikely to play a large role. Autor et al. (2016) find that patents from U.S. manufacturers decline in response to increase Chinese import penetration, which also suggests that cost-cutting innovations are unlikely to drive the price response we observe. We proceed by first examining the role of intermediate inputs, before turning to markups.

V.C The Role of Intermediate Inputs

The measure of Chinese import penetration we have used so far is meant to reflect exposure to import competition, not to imported intermediate inputs. But it could be the case that changes in import penetration from China ("direct exposure") in an industry happens to be correlated with changes in the degree of import competition with China faced by the suppliers of that industry ("indirect exposure").

To examine the importance of such effects, we first repeat our IV exercise while controlling for other trade patterns that could be correlated with increasing import penetration from China and affect U.S. prices through channels other than increased import competition. 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

[14]Online Appendix Table A3 provides the results of a formal decomposition showing that inflation for U.S. goods accounts for most of the price response to trade with China.

take into account input-output linkages across sectors); exports as a share of domestic production. The various columns of Panel A of Table 9 show that, across specifications and sets of controls, the IV estimates remain very large. Online Appendix Table A2 shows that the patterns are similar when considering a restricted sample excluding product categories with particularly low average inflation.

As another test for the role of intermediate inputs in explaining our results, we implement our IV strategies accounting for input-output linkages. In Panel B of Table 9, we have three endogenous variables: the change in Chinese import penetration (as previously), but also the change in Chinese import penetration in upstream industry and the change in Chinese import penetration in downstream industries. Following Acemoglu et al. (2016) and Pierce and Schott (2016), we build "downstream" and "upstream" versions of the instrument so that we can run the IV specifications with the three endogenous variables. Downstream and upstream exposure reflect the changes in import competition affecting an industry's suppliers and customers, taking into account input-output linkages.

The results reported in Panel B of Table 9 are very similar to our baseline estimates, indicating that price effects via intermediate inputs cannot explain our results. In Columns (1) to (3), with the IV strategy Pierce and Schott (2016), the IV estimate for the effect of Chinese import competition on prices hover between -2.36 and -2.14. The IV estimates for upstream and downstream effects are imprecisely estimated and not statistically distinguishable from zero. In Columns (4) and (5), using the IV strategy of Autor et al. (2014), the IV estimate for direct import competition remains similar but we also find that an increase in "downstream" Chinese import competition leads to substantial price declines.[15] This result means that if China gains market shares in industries that are the downstream customers of a given U.S. industry, then inflation falls in that industry. This pattern is consistent with the notion that competition dynamics are a first-order determinant of the price effects of trade. We also find significant price effects of upstream exposure. These results indicate that input-output linkages are important for understanding the overall price effects of China. But upstream and downstream exposure leave unaffected our main IV coefficient (for direct import competition); they cannot help explain its magnitude by a fall in the cost of imported intermediate inputs.

[15] The instrument from Pierce and Schott (2016) appears to be under-powered to examine the impact of intermediate inputs. But using the instrument from Autor et al. (2014) we get a strong first stage for both upstream and downstream effects, as reported in Figure 5 (which also reports strong reduced-form relationships).

V.D The Role of Markups

Having shown that changes in the cost of intermediate inputs do not explain the large price response for domestic products, we now examine the possible role of markups. We start with a simple theoretical exercise: could changes in markups plausibly explain the observed domestic price response, or are the observed price effects too large? Using a simple but flexible model following Amiti et al. (2018),[16] we find that our baseline IV estimates can be rationalized by changes in markups. Second, we use the model to derive simple tests of the markup channel based on heterogeneity in the IV estimate across industries. We find the magnitude of our IV estimates varies substantially across industries depending on market structure, in ways that are consistent with the markup channel.

Could the magnitude of the markup response explain the observed price effects? In this subsection, we show that the magnitude of the IV estimate can plausibly be explained by changes in markups of domestic producers in response to increased competition with China. To illustrate the mechanisms at play in the simplest possible way, we start with a setting with one U.S. producer one Chinese producer in each industry; price dynamics depend on their strategic interaction. We then generalize our formula to accommodate multiple producers and discuss testable implications.

Consider two producers in a given industry offering differentiated goods with elasticity of substitution σ. One producer is based in the U.S., the other in China. They respectively charge prices p^{Chn} and p^{US}, have market shares S and $1 - S$, marginal costs of production c^{US} and c^{Chn}, and markups μ^{US} and μ^{Chn}. Denote by p the industry price index. Amiti et al. (2018) show that under very mild regularity conditions (namely, an invertible demand system and any given competition structure), each firm's profit-maximizing price can be expressed as the solution to a fixed point equation: $p^i = c^i + \mu^i(p^i, p^{-i})$. From there, one can define the "own-price markup elasticity" as $\Gamma^i \equiv -\frac{\partial \mu^i}{\partial p^i}$ and the "competitor price elasticity" as $\Gamma^{-i} \equiv \frac{\partial \mu^i}{\partial p^{-i}}$. Under relatively mild regularity conditions, Amiti et al. (2018) shows that $\Gamma^i = \Gamma^{-i}$.[17] With constant markup pricing, $\Gamma^i = \Gamma^{-i} = 0$. With oligopolistic competition (e.g., Krugman (1979) and Atkeson and Burstein (2008)), Γ^i and Γ^{-i} are increasing in the firm's market share. Empirically, Amiti et al. (2018) cannot reject $\Gamma^i = \Gamma^{-i}$ and their findings suggest that the average markup elasticity Γ is in the range 0.6 to 1.

Let's now consider the impact of a change in trade on the industry price index. A first-order

[16] We are indebted to Oleg Itskhoki for very insightful comments and suggestions.

[17] This condition is satisfied is the perceived demand elasticity of the firm is a function of the price of the firm relative to the industry expenditure function. Intuitively, this condition is satisfied when the expenditure function in the industry summarized all necessary information contained in all competitor prices. This imposes certain restrictions, such as symmetry in preferences.

approximation yields:

$$
\begin{aligned}
dp &= Sdp^{Chn} + (1-S)dp^{US}, \\
dlogS &= (1-\sigma)(1-S)\left(dp^{Chn} - dp^{US}\right), \\
dp^{US} &= dc^{US} + \Gamma\left(dp^{Chn} - dp^{US}\right), \\
dp^{Chn} &= dc^{Chn} + \Gamma\left(-dp^{Chn} + dp^{US}\right).
\end{aligned}
$$

Suppose that there is no change in production cost in the U.S. while there is one in China, i.e. $dc^{US} = 0$ and $dc^{Chn} \neq 0$. Then we get

$$
\begin{aligned}
dp^{US} &= \frac{\Gamma}{1+\Gamma}dp^{Chn} \\
dp^{Chn} &= \frac{1}{1+\Gamma}dc^{Chn} + \frac{\Gamma}{1+\Gamma}dp^{US}
\end{aligned}
$$

These two equations imply:

$$
\begin{aligned}
dp^{Chn} &= \frac{1+\Gamma}{1+2\Gamma}dc^{Chn} \\
dp^{US} &= \frac{\Gamma}{1+2\Gamma}dc^{Chn}
\end{aligned}
$$

Therefore,

$$
\begin{aligned}
dS &= -(\sigma-1)S(1-S)\frac{dc_1}{1+2\Gamma}, \\
dp &= \frac{S+\Gamma}{1+2\Gamma}dc_1, \\
\frac{dp}{dS} &= -\frac{1+\frac{\Gamma}{S}}{(\sigma-1)(1-S)}, \qquad (5)
\end{aligned}
$$

where dS is the percentage point change in market share while dp is the percentage point change in the industry price index, like in our empirical specifications.

Equation (5) provides a simple expression to assess the strength of the relationship between the change in the import share from China and the industry price index when domestic prices response only due to the markup channel. Setting $\sigma = 5$ from Head and Mayer (2014), $\Gamma = 0.6$ from Amiti et al. (2018) and $S = 0.0452$ (using the import penetration rate in China in 1999 from Acemoglu et al. (2016)), we get:

$$\widehat{\frac{dp}{dS}} = -3.73.$$

The simple two-firm example above shows that is is possible to get a strong relationship between the industry price index and the change in the China share through endogenous markups. Intuitively, when China becomes more productive, it reduces its price, which force the U.S. product to also reduce their price. Because of the U.S. price response, the equilibrium change in the spending share on the Chinese good is lower than it would be absent this price response. In a limit case where the markup elasticity is very high, $\Gamma \to \infty$, China's market share barely changes because $dp^{US} \approx dp^{Chn}$, but both dp^{US} and dp^{Chn} change a lot, and so does dp, so $\frac{dp}{dS} \to \infty$.

In contrast, with constant markups ($\Gamma = 0$), the magnitude of the effect reverts to the case studied by Arkolakis et al. (2012): $\widehat{\frac{dp}{dS}} = -0.26$. With $\Gamma = 0$, obtaining large movements in dp would require an implausibly low elasticity of substitution σ.

Equation (5) also shows that one can (indirectly) tests for the relevance of the markup channel by studying heterogeneity in the IV estimates across subsamples. First, $\frac{dp}{dS}$ is increasing in Γ. In the presence of strategic interactions, the magnitude of the markup elasticity depends on market structure: we expect a stronger response in markets that are more concentrated, because domestic firms with market power get disrupted by productivity increases in China. Moreover, starting from an equilibrium with a small spending share on Chinese goods (as in the data), $\frac{dp}{dS}$ is decreasing in S. If China has a larger initial market share in an industry, by gaining additional market shares in that industry China is not going to disrupt domestic U.S. producers as much as in another industry with a lower initial Chinese import penetration is lower. Intuitively, there is less room for China to be disruptive in an industry where it already has a high initial market share.

Online Appendix A presents a version of the model that accommodates multiple firms. This more general model helps make more precise the comparative statics discussed above. As a proxy for market concentration, we use the Herfindahl index, denoted by H. We compute the number of "equally-sized firms" that would prevail in the market given this Herfindahl index: $N = \frac{10{,}000}{H}$. Then, the response of the industry price index to changes in the Chinese import penetration rate is:

$$\frac{dp}{dS} = -\frac{\left(\frac{S\Lambda-(1-S)}{(1+(N+1)\Gamma)} + \frac{(1-S)(1+\Gamma)}{1+(N+1)\Gamma}\left(\frac{1+(3-N)\Gamma}{1+(2-N)\Gamma}\right)\left(\frac{\Lambda}{(1+(N+1)\Gamma)}\right)\right)}{(\sigma-1)S(1-S)\left(\frac{\Lambda+1}{(1+(N+1)\Gamma)} - \frac{1+\Gamma}{1+(N+1)\Gamma}\left(\frac{1+(3-N)\Gamma}{1+(2-N)\Gamma}\right)\left(\frac{\Lambda}{(1+(N+1)\Gamma)}\right)\right)}, \tag{6}$$

with $\Lambda = \frac{(1+(N+1)\Gamma)(1+(2-N)\Gamma)}{(1+(N+1)\Gamma)(1+(2-N)\Gamma)-N\Gamma(1+(3-N)\Gamma)}$. As discussed in Online Appendix A, the elasticity of markups Γ is itself a function of the Herfindahl index — in our baseline calibration, we compute Γ assuming Bertrand competition, but similar patterns hold with Cournot.

Equation (6) shows that in $\frac{dp}{dS}$ is decreasing in N. The more concentrated the domestic market is, the larger we expect the price response per unit of increase in Chinese import penetration. As before, $\frac{dp}{dS}$ is decreasing in S. Figure 6 illustrates the strength of the predicted heterogeneity in treatment effect. The effects are non-linear: $\frac{dp}{dS}$ is much larger in concentrated domestic market and much larger in industries with an initially low Chinese import penetration rate. Next, we take these predictions to the data and examine whether the observed heterogeneity in the price response to increased Chinese import penetration rate is consistent with the markup channel.

Heterogeneity in price effects depending on market structure. To test whether $\frac{dp}{dS}$ varies in the data in ways that are smilar to the calibration results illustrated in Figure 6, we obtain data on Herfindahl indices by industries from the Census and the 1999 Chinese import penetration rate across industries from Acemoglu et al. (2016). To assess whether there are strong non-linearities, in our baseline specification we create indicator variables for industries with $10,000/Herfindahl > 10$ or with a 1999 Chinese import penetration rate above 5%. We interact these indicator variables with the changes in the Chinese import penetration rate in the U.S. during our sample period (2000—2007) as well as with our two instruments (the NTR gaps and the change in the import penetration rate in Europe). We then compute the IV estimates.

Table 10 reports the results. Columns (1) to (4) report the IV estimates for the full inflation rate. The table shows that domestic market concentration and the 1999 Chinese import penetration rate are strong predictors of heterogeneity in the treatment effect. For industries in which $10,000/Herfindahl > 10$, i.e. the implied number of "equally-sized firms" in the industry is above 10, the price response is 80.27% smaller ($= 1 - \frac{-2.798+2.246}{-2.798}$) than in industries for which it is below 10. Likewise, for industries in which the 1999 Chinese import penetration rate is above 5, the effect is 80.34% smaller ($= 1 - \frac{-2.798+2.246}{-2.798}$) than in industries for which it is below 5.

These magnitudes remain similar when the sample is restricted to tradables only (Column (2)) or when excluding highly deflationary inflation categories (Columns (3) and (4)). The point estimates on the interacted regressors account for between 51% and 88% of the magnitude of the average effect. In all specifications, the IV estimates are significant at the 5% or 1% level and the instruments are relatively strong.

Column (5) of Table10 document heterogeneity in the effect for inflation for continued products, while Column (6) documents the patterns for inflation for U.S. goods. With these outcomes as well, the effect is much larger when the domestic market is more concentrated and when the initial Chinese import penetration rate is small. For continued products, in industries with $10,000/Herfindahl > 10$ the price response is 61.59% smaller ($= 1 - \frac{-5.143+3.168}{-5.143}$). Furthermore, the IV estimate becomes close to 0 in industries whose 1999 Chinese import penetration rate is above 5. For inflation for U.S. products only, the estimate falls by 90% ($= 1 - \frac{-5.19+4.678}{-5.19}$) in industries with $10,000/Herfindahl > 10$ and is close to 0 for industries whose 1999 Chinese import penetration rate is above 5.

Online Appendix Tables A6 and A7 document the robustness of these results. Online Appendix Table A6 uses an alternative threshold to document the heterogeneity in the response of prices to increased import penetration from China. The specifications in these tables use an indicator variables for industries with $10,000/Herfindahl > 16$, instead of 10. The result are similar: across samples, the IV estimate is between 33% and 84% smaller in industries with $10,000/Herfindahl > 16$. Online Appendix Table A7 examines heterogeneity in the effect when using the 1999 Chinese import penetration rate as a linear interaction term, instead of using a threshold. Columns (1) to (4) show that a one standard deviation increase in the 1999 Chinese import penetration rate is associated with a large fall in the magnitude of the IV estimate. Column (5) reports a similar finding when using the average Chinese import penetration rate from 1995 to 1999. Finally, Column (6) uses the 1999 Chinese import penetration rate in developed economies other than the U.S. (from Autor et al. (2014)) as an instrument for the 1999 Chinese import penetration rate in the U.S. With this specification as well, we find that the effect is much smaller in industries that were already significantly exposed to import competition from China.

Overall, these findings are consistent with the notion that markup effects are an important explanatory mechanism. Furthermore, following Autor et al. (2016), using Compustat data we document that the profitability of U.S. firms declines in those industries with increased import penetration from China (not reported). This finding also supports the hypothesis that falling markups are an important channel for the observed price effects.

VI Conclusion

This paper 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.

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. The magnitude of the price effects heavily depend on domestic market concentration and on China's pre-determined import penetration rate. These findings are consistent with the view that falling markups are an important channel. Overall, our estimates suggest that the pro-competitive effects of trade have important implications for inflation and consumer welfare.

References

Acemoglu, Daron, David Autor, David Dorn, Gordon H Hanson, and Brendan Price, "Import competition and the great US employment sag of the 2000s," *Journal of Labor Economics*, 2016, *34* (S1), S141–S198.

Amiti, Mary, Oleg Itskhoki, and Jozef Konings, "International Shocks, Variable Markups and Domestic Prices," *Working Paper*, 2018.

Arkolakis, Costas, Arnaud Costinot, and Andres Rodriguez-Clare, "New trade models, same old gains?," *American Economic Review*, 2012, *102* (1), 94–130.

_ , _ , Dave Donaldson, Andrés Rodríguez-Clare et al., "The elusive pro-competitive effects of trade," Technical Report, Review of Economic Studies 2018.

Atkeson, Andrew and Ariel Burstein, "Pricing-to-market, trade costs, and international relative prices," *American Economic Review*, 2008, *98* (5), 1998–2031.

Autor, David, David Dorn, and Gordon Hanson, "The China syndrome: Local labor market effects of import competition in the United States," *American Economic Review*, 2013, *103* (6), 2121–68.

_ , _ , Gordon H Hanson, Gary P Pisano, and Pian Shu, "Foreign Competition and Domestic Innovation: Evidence from US Patents," 2016.

_ , _ , Gordon Hanson, and Jae Song, "Trade adjustment: Worker-level evidence," *The Quarterly Journal of Economics*, 2014, *129* (4), 1799–1860.

Bai, Liang and Sebastian Stumpner, "Estimating the Price Effects of Globalization: The Case of US Imports from China," *Working Paper*, 2018.

Borusyak, Kirill and Xavier Jaravel, "The Distributional Effects of Trade: Theory and Evidence from the United States," Technical Report, Working Paper 2017.

Brander, James and Paul Krugman, "A reciprocal dumping model of international trade," *Journal of international economics*, 1983, *15* (3-4), 313–321.

Edmond, Chris, Virgiliu Midrigan, and Daniel Yi Xu, "Competition, markups, and the gains from international trade," *American Economic Review*, 2015, *105* (10), 3183–3221.

Epifani, Paolo and Gino Gancia, "Trade, markup heterogeneity and misallocations," *Journal of International Economics*, 2011, *83* (1), 1–13.

Fajgelbaum, Pablo D and Amit K Khandelwal, "Measuring the unequal gains from trade," *The Quarterly Journal of Economics*, 2016, *131* (3), 1113–1180.

Feenstra, Robert C, "Restoring the product variety and pro-competitive gains from trade with heterogeneous firms and bounded productivity," *Journal of International Economics*, 2018, *110*, 16–27.

_ **and David E Weinstein**, "Globalization, markups, and US welfare," *Journal of Political Economy*, 2017, *125* (4), 1040–1074.

Handley, Kyle and Nuno Limão, "Policy uncertainty, trade, and welfare: Theory and evidence for china and the united states," *American Economic Review*, 2017, *107* (9), 2731–83.

Head, Keith and Thierry Mayer, "Gravity equations: Workhorse, toolkit, and cookbook," in "Handbook of international economics," Vol. 4, Elsevier, 2014, pp. 131–195.

Hottman, Colin and Ryan Monarch, "Estimating Unequal Gains across US Consumers with Supplier Trade Data," Technical Report, Working Paper 2018.

Impullitti, Giammario and Omar Licandro, "Trade, firm selection and innovation: The competition channel," *The Economic Journal*, 2018, *128* (608), 189–229.

Jaravel, Xavier, "The unequal gains from product innovations: Evidence from the us retail sector," 2016.

Krishna, Pravin and Devashish Mitra, "Trade liberalization, market discipline and productivity growth: new evidence from India," *Journal of development Economics*, 1998, *56* (2), 447–462.

Krugman, Paul R, "Increasing returns, monopolistic competition, and international trade," *Journal of international Economics*, 1979, *9* (4), 469–479.

Levinsohn, James, "Testing the imports-as-market-discipline hypothesis," *Journal of International Economics*, 1993, *35* (1-2), 1–22.

Melitz, Marc J and Stephen J Redding, "New trade models, new welfare implications," *American Economic Review*, 2015, *105* (3), 1105–46.

Pierce, Justin R and Peter K Schott, "A concordance between ten-digit US Harmonized System Codes and SIC/NAICS product classes and industries," *Journal of Economic and Social Measurement*, 2012, *37* (1, 2), 61–96.

_ **and** _ , "The surprisingly swift decline of US manufacturing employment," *American Economic Review*, 2016, *106* (7), 1632–62.

Simonovska, Ina and Michael E Waugh, "Trade models, trade elasticities, and the gains from trade," Technical Report, National Bureau of Economic Research 2014.

Table 1: Summary Statistics

Panel A: Full Sample

	Mean	Std. Dev.	Observations
CPI 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
"Downstream" Change in China Import Penetration Rate in the U.S., 1999-2011	0.13061	0.12383	211
"Upstream" Change in China Import Penetration Rate in the U.S., 1999-2011	0.07549	0.13904	211
NTR Gap	0.1907	0.2005	3,689
"Downstream" NTR Gap	0.044793	0.04875	2,060
"Upstream" NTR Gap	0.07443	0.06248	2,060
Change in China Import Penetration Rate in Other Developed Economies, 1999-2011	0.66228	1.16988	207
"Downstream" Change in China Import Penetration Rate in Other Developed Economies, 1999-2011	0.1272	0.12192	225
"Upstream" Change in China Import Penetration Rate in Other Developed Economies, 1999-2011	0.07717	0.13523	225
Advanced Technology	0.0717	0.2548	3,689
Union Membership	10.0660	11.1892	3,689

Panel B: Tradables Only

	Mean	Std. Dev.	Observations
CPI 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 B 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*** (0.4014)	-1.7383*** (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 (1)	IV (2)	OLS (3)	IV (4)
Change in China Import Penetration (1999-2011)	-2.345*** (0.3299)	-2.71*** (0.3869)	-1.592*** (0.2075)	-1.894*** (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: Robustness — the Price Effects of 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: Robustness — the Price Effects of 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: Implications for the Distributional Effects of Trade via the Expenditure Channel

Panel A: Heterogeneity in IV Estimates

	Annual U.S. Inflation Rate			
	(1)	(2)	(4)	(5)
Change in China Import Penetration Rate in the U.S., 1999-2011	-2.9440***	-3.775***	-1.5357***	-1.1372***
	(1.039)	(1.393)	(0.4235)	(0.43325)
Change in China Import Penetration Rate in the U.S. (1999-2011) ×Spending Share from HH with Income>$60k	0.14018	2.4853	-0.8264	-0.97956
	(0.94730)	(1.9463)	(0.61880)	(0.74167)
Cragg-Donald F	5.003	3.222	99.58	71.90
Kleibergen-Paap F	1.698	0.861	12.38	9.087
IV Strategy	PS (2016)	PS (2016)	ADH (2014)	ADH (2014)
Controls:				
Spending Share from HH with Income>$60k	✓	✓	✓	✓
Observations	211	151	152	138
Sample	Full	Tradables Only	Tradables Only	Tradables Only & Inlf > p5

Panel B: Heterogeneity in First-Stage Responses

	Change In China Import Penetration Rate			
	(1)	(2)	(3)	(4)
NTR Gap	2.4109***	2.3714***		
	(0.4965)	(0.5110)		
NTR Gap ×Spending Share from HH with Income>$60k	1.2871***	1.2272***		
	(0.2960)	(0.3621)		
Change in China Import Penetration in Other Developed Economies (1999-2011)			0.8796***	0.7685***
			(0.09528)	(0.08894)
Change in China Import Penetration in Other Developed Economies (1999-2011) ×Spending Share from HH with Income>$60k			0.12347	0.009181
			(0.14467)	(0.13941)
Controls:				
Spending Share from HH with Income>$60k	✓	✓	✓	✓
Observations	211	151	152	138
Sample	Full	Tradables Only	Tradables Only	Tradables Only & Infl. > p5

Notes: The level of observation is an ELI. Square-root spending weights are used. Heteroskedasticity-robust standard errors are reported. $^*p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: The Role of Continued Products

Panel A: Product Turnover

	Product Turnover	
	(1)	(2)
Change in China Import	1.7270	1.458779***
Penetration (1999-2011)	(1.533)	(0.403779)
Cragg-Donald	16.58	301.80
Kleibergen-Paap F	16.73	78.035
IV Strategy	PS (2016)	ADH (2014)
Observations	145	149
Sample	Manufacturing, Inflation > p5	

Panel B: Continued Products Inflation

	Continued Products Inflation					
	(1)	(2)	(3)	(4)	(5)	(6)
Change in China Import	-5.5314***	-3.748***	-3.435***	-2.024***	-4.368***	-2.024***
Penetration (1999-2011)	(1.689)	(0.5271)	(1.043)	(0.4157)	(1.494)	(0.4157)
Cragg-Donald	18.497	399.93	28.08	276.1	18.01	276.17
Kleibergen-Paap F	16.379	117.55	17.197	84.7	16.68	84.72
IV Strategy	PS (2016)	ADH (2014)	PS (2016)	ADH (2014)	PS (2016)	ADH (2014)
Observations	134	139	134	138	140	138
Sample	Manufacturing, Inflation > p5					
Sample restriction	All goods		Only goods that existed in 2000		Year 1998 to 2002; only goods that existed in 2000	

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 8: The Role of Domestic Products

Panel A: Response of U.S. Producer Price Index to Trade with China, IV Estimates

	Full PPI Infl.				Continued Products PPI Infl.		
	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in China Import	-3.56**	-3.55**	-4.062**	-2.979**	-1.85**	-1.922**	-3.803**
Penetration (1999-2011)	(1.605)	(1.6049)	(2.047)	(1.493)	(0.4019)	(0.4042)	(1.785)
Tradable	2.83*						
	(1.537)						
Cragg-Donald F	5.948	5.883	5.072	165.71	30.088	30.969	165.71
Kleibergen-Paap F	8.741	8.773	8.260	30.348	36.152	33.906	30.348
IV Strategy	PS (2016)	PS (2016)	PS (2016)	ADH (2014)	PS (2016)	PS (2016)	ADH (2014)
Observations	256	252	243	243	425	414	243
Sample	Full	Tradables Only	Tradables Only & Inflation > p5	Full	Tradables Only	Tradables Only & Inflation > p5	Full

Panel B: Response of CPI Inflation to Trade with China, U.S. Goods Only, IV Estimates

	Full CPI Inflation, U.S. Goods Only					Continued Products CPI Infl., U.S. Goods Only	
	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(5)	(6)
Change in China Import	-6.583***	-6.641***	-3.710***	-3.468**	-1.978***	-5.063***	-3.213***
Penetration (1999-2011)	(1.660)	(1.698)	(2.047)	(0.5813)	(0.473)	(1.632)	(0.477)
Tradable	-2.335*						
	(1.392)						
Cragg-Donald F	26.54	20.11	21.23	319.58	257.71	15.64	367.73
Kleibergen-Paap F	20.08	19.56	16.65	79.37	126.68	14.03	119.13
IV Strategy	PS (2016)	PS (2016)	PS (2016)	ADH (2014)	ADH (2014)	PS (2016)	ADH (2014)
Observations	219	153	136	155	138	137	138
Sample	Full	Tradables Only	Tradables Only & Inflation > p5	Tradables Only	Tradables Only & Inflation > p5	Tradables Only & Inflation > p5	Tradables Only & Inflation > p5

Notes: For Panel A, the level of observation is a consolidated NAICS code; the data is collapsed at the NAICS level after 2000. Square-root NAICS output weights are used. For Panel B, the level of observation is an ELI and square-root spending weights are used. Heteroskedasticity-robust standard errors are reported. $^*p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: The Role of Intermediate Inputs

Panel A: Main IV Specifications Controlling for Intermediates and Exports (IO level)

	Annual U.S. Inflation Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Change in China Import	-3.996***	-3.8919***	-2.981**	-3.707***	-3.6690***	-2.996***
Penetration (1999-2011)	(0.73600)	(0.7084)	(1.477)	(0.72158)	(0.7146)	(0.4974)
Direct Imports of Intermediate	10.669			9.943		
Inputs	(7.688)			(7.3463)		
Direct and Indirect Imports		10.054			9.945	
of Intermediate Inputs		(8.156)			(8.0025)	
Export Share			-10.3929			-10.484
			(9.3471)			(6.82)
Cragg-Donald F	9.625	10.341	3.907	92.803	94.874	85.32
Kleibergen-PaapF	7.340	7.986	3.457	10.857	10.77	7.855
IV Strategy	PS (2016)	PS (2016)	PS (2016)	ADH (2014)	ADH (2014)	ADh (2014)
Observations	58	58	58	54	54	54
Sample	Tradables Only					

Panel B: IV Specifications with Multiple Endogenous Variables (ELI level)

	Annual U.S. Inflation Rate				
	(1)	(2)	(3)	(4)	(5)
Change in China Import	-2.366**	-2.239**	-2.14**	-1.987***	-1.64***
Penetration (1999-2011)	(1.0604)	(1.1474)	(1.0367)	(0.5306)	(0.2755)
"Downstream" Change in China Import	-0.3455	-1.2082	-0.90214	-1.933***	-1.5809***
Penetration (1999-2011), standardized	(1.0452)	(1.1570)	(1.10706)	(0.49307)	(0.4478)
"Upstream" Change in China Import	-1.2148	-0.80005	-0.6942	-6.548***	-2.84**
Penetration (1999-2011), standardized	(1.352)	(1.632)	(1.731)	(1.7670)	(1.165)
Cragg-Donald F	5.597	4.099	4.697	98.333	131.084
Kleibergen-PaapF	4.290	2.703	1.964	21.677	43.576
IV Strategy	PS (2016)	PS (2016)	PS (2016)	ADH (2014)	ADH (2014)
Observations	205	149	135	146	135
Sample	Full	Tradables Only	Tradables Only & Inlf > p5	Tradables Only	Tradables Only & Inlf > p5

Notes: In Panel A, 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. In Panel B, the level of observation is an ELI. Heteroskedasticity-robust standard errors are reported. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

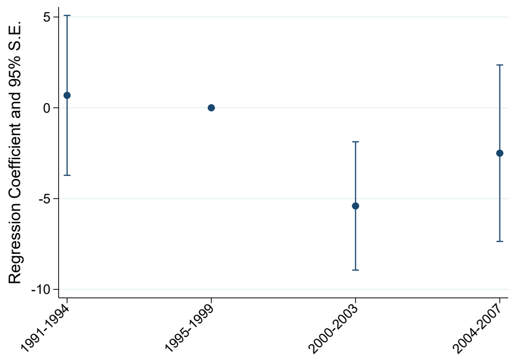
Table 10: Heterogeneity by Market Structure

	Annual U.S. Inflation Rate				Inflation for Continued Products	Inflation for U.S. Products Only
	(1)	(2)	(3)	(4)	(5)	(6)
Change in China Import Penetration Rate	-2.798***	-2.957***	-3.512***	-2.935***	-5.143***	-5.19***
in the U.S., 1999-2011	(0.327)	(0.484)	(0.503)	(0.367)	(1.485)	(1.636)
Change in China Import Penetration Rate	2.246**	2.615***	2.821***	2.726***	3.168*	4.678***
in the U.S. (1999-2011) $\times 1(10,000/Herfindahl > 10)$	(1.032)	(0.812)	(0.860)	(0.990)	(1.669)	(1.70)
Change in China Import Penetration Rate	2.248**	1.513**	2.598**	2.372***	5.979***	5.712**
in the U.S. (1999-2011) $\times 1(1999ChinaShare > 5\%)$	(0.936)	(0.749)	(1.028)	(0.772)	(2.125)	(2.499)
Cragg-Donald F	7.731	9.209	6.421	9.064	6.966	7.736
Kleibergen-Paap F	4.612	5.628	3.778	4.955	6.571	4.615
IV Strategy	PS (2016) & ADH (2014)					
Controls:						
$(1/Herfindahl > 10)$	✓	✓	✓	✓	✓	✓
$1(1999ChinaShare > 5\%)$	✓	✓	✓	✓	✓	✓
Tradable	✓		✓	✓	✓	✓
Observations	135	132	121	132	121	135
Sample	Full	Tradables Only	Infl > p5	Infl > p1	Infl > p5	Full

Notes: The level of observation is an ELI. 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

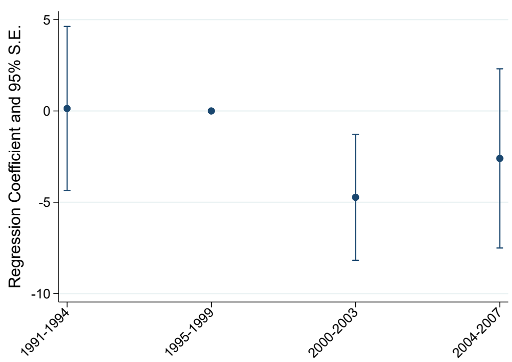
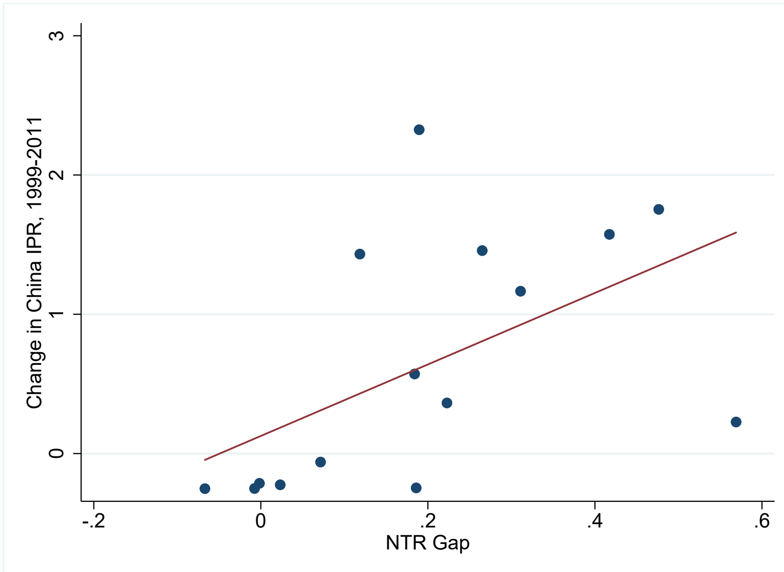


Figure 2: First-Stage and Reduced-Form for the Effect of Trade with China on U.S. Consumer Prices, Instrumenting by U.S. Granting of Permanent Normal Trade Relations to China

Panel A: First Stage



Panel B: Reduced Form

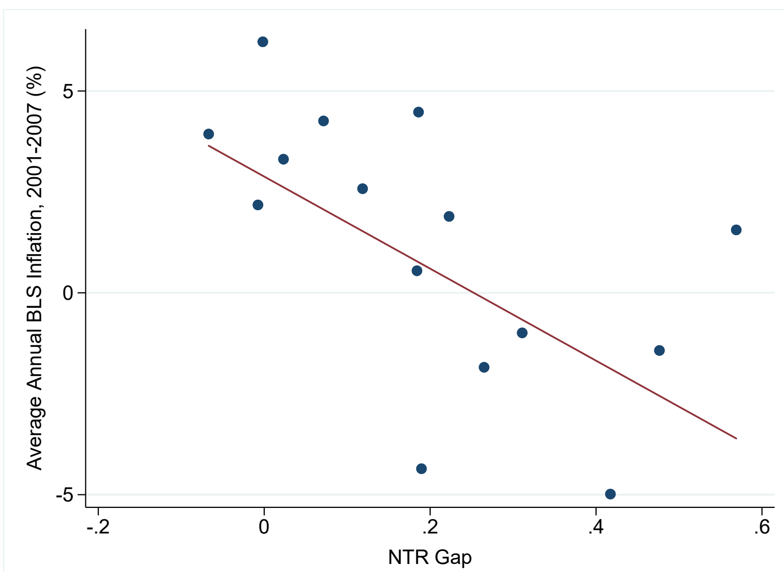
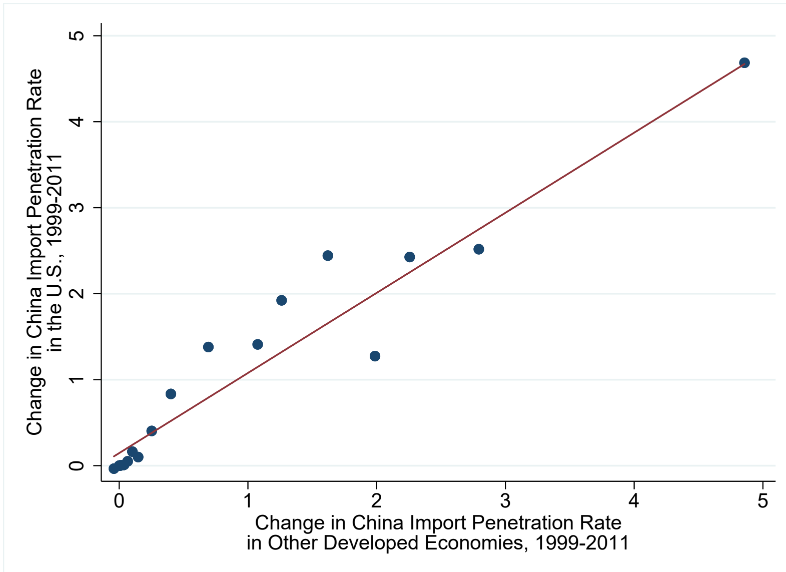


Figure 3: First-Stage and Reduced-Form for the Effect of Trade with China on U.S. Consumer Prices, Instrumenting by Other Developed Countries' Trade with China

Panel A: First Stage



Panel B: Reduced Form

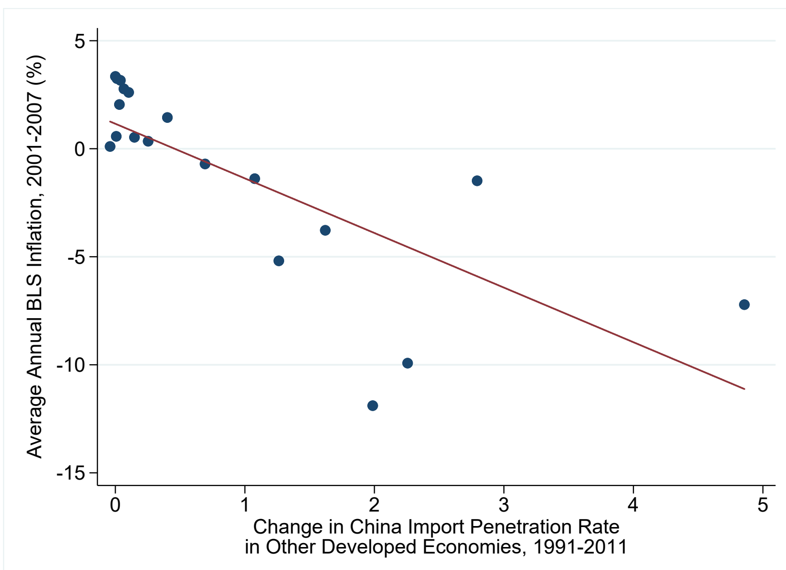
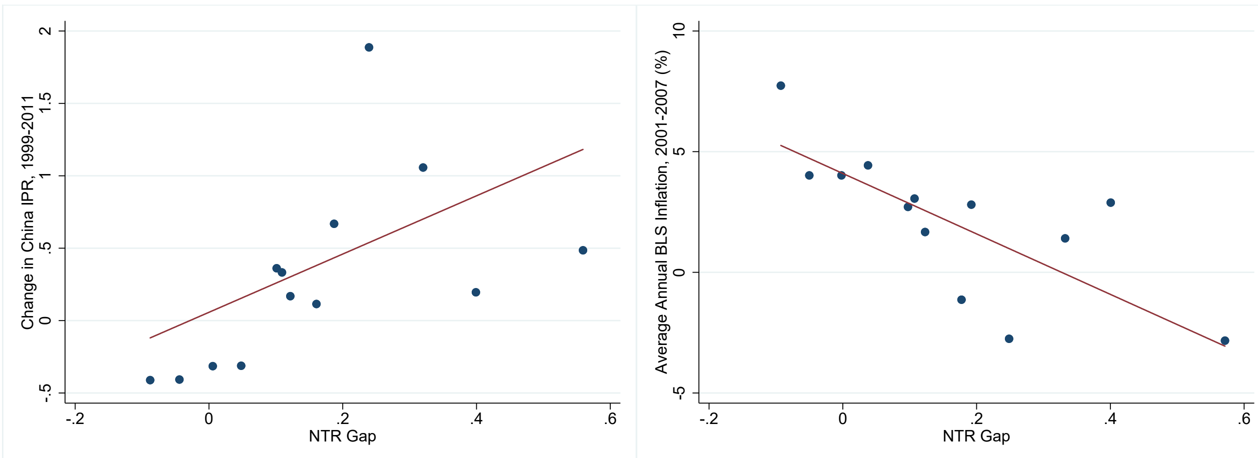


Figure 4: Estimating the Response of U.S. Consumer Prices to Trade with China at the level of 6-digit Input-Output Industries

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

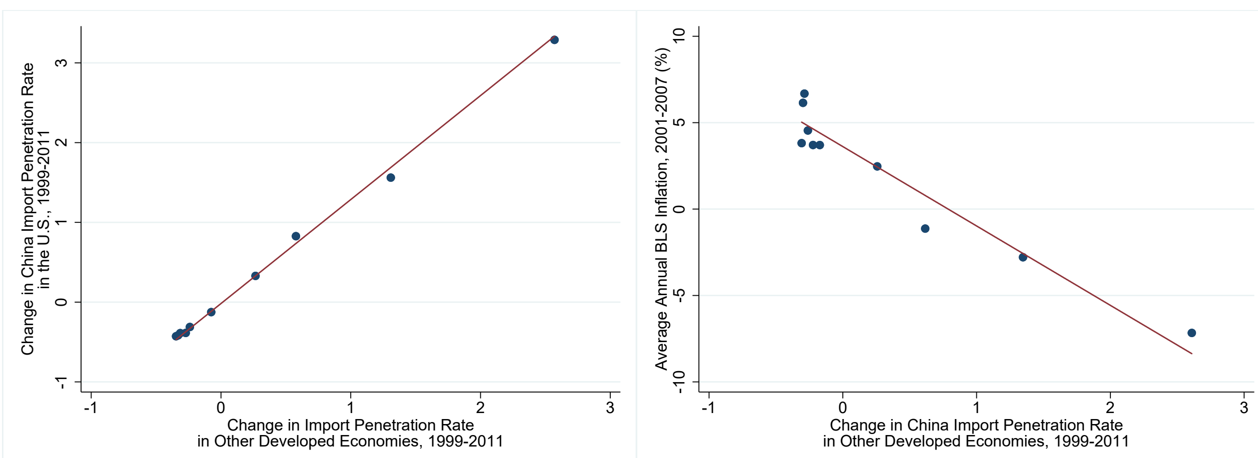
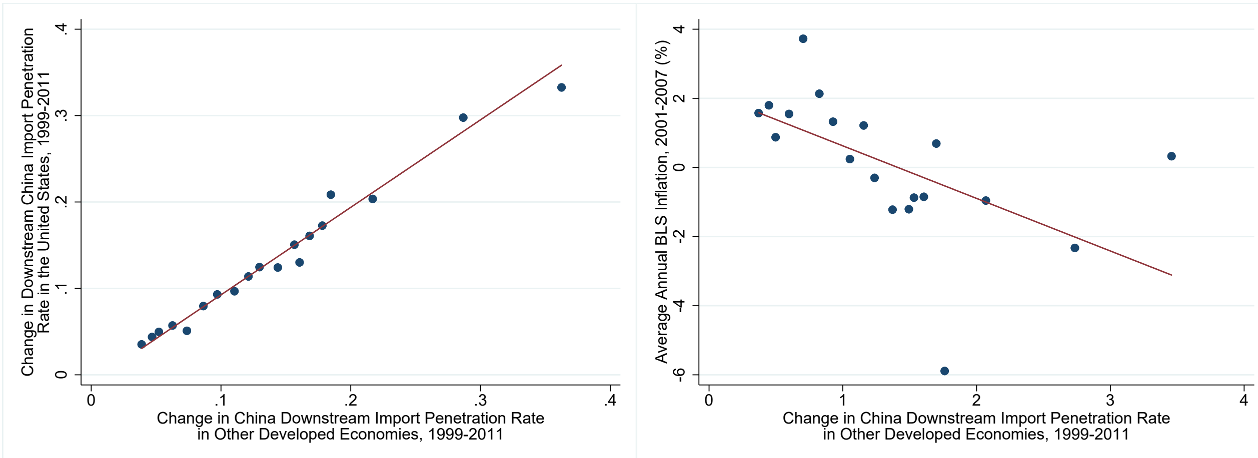


Figure 5: The Role of Intermediate Inputs

Panel A: Downstream Effects



Panel B: Upstream Effects

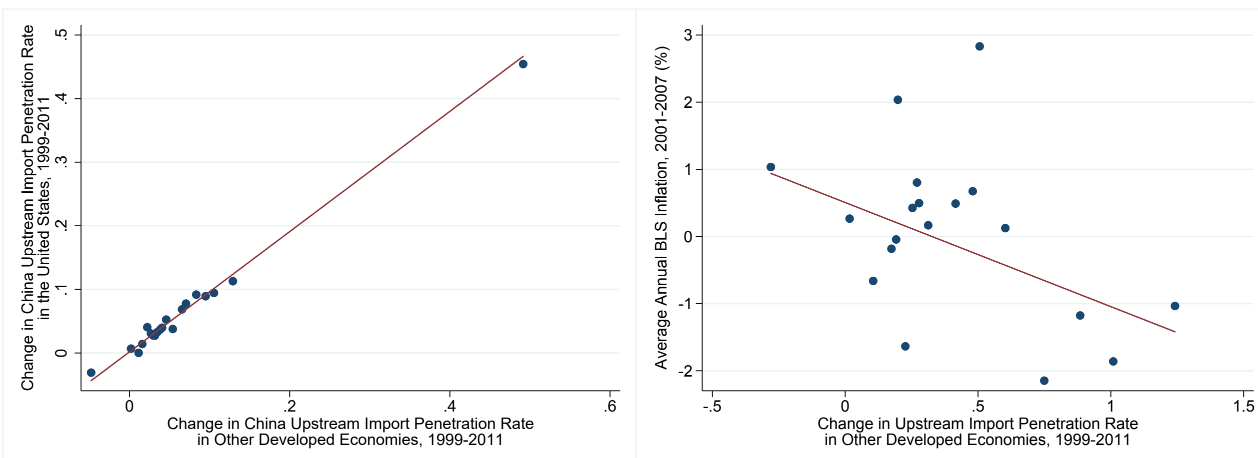
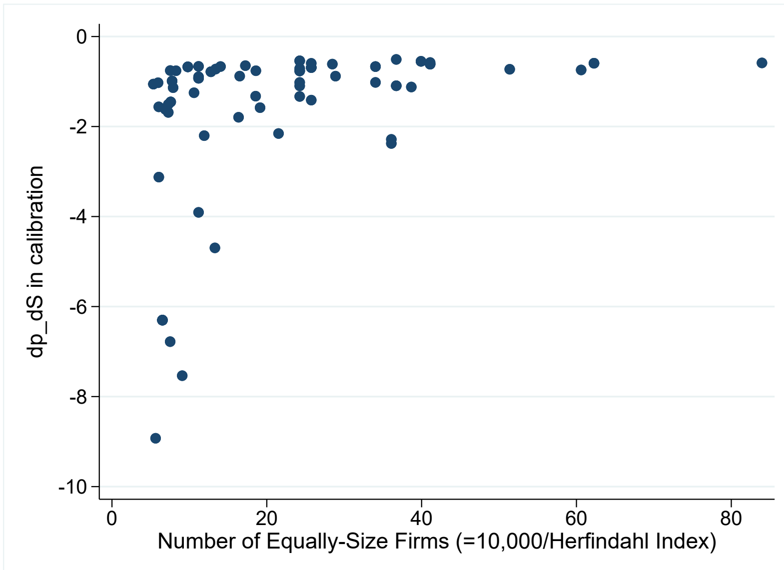
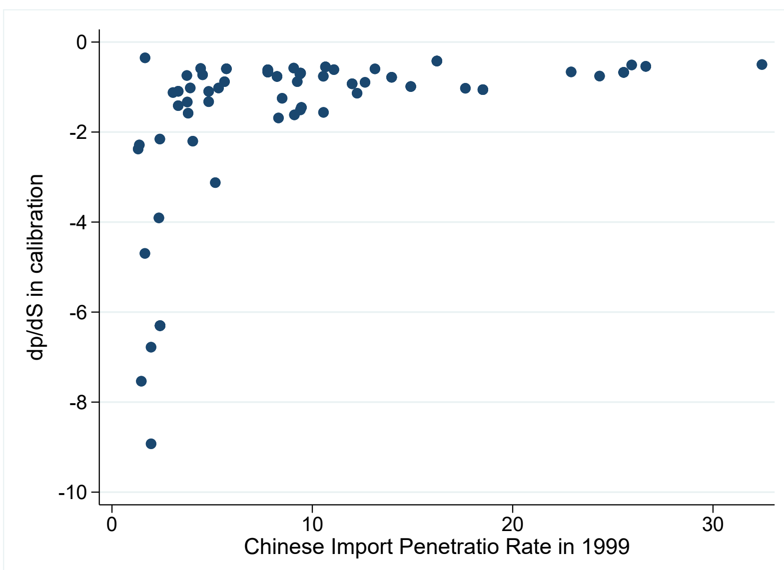


Figure 6: Predicted Heterogeneity in the Response of Prices to Changes in Chinese Import Penetratoin

Panel A: Heterogeneity by Herfindahl index



Panel B: Heterogeneity by 1999 Chinese Import Penetration Rate



Online Appendices

A Theory Appendix

A.A Connecting the IV Specification to Arkolakis et al. (2012)

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

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

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.

A.B Assessing the Importance of Markup Effects

This appendix presents a simple model to assess the importance of markup effects, building on Amiti et al. (2018). We consider a setting with N symmetric U.S. goods and one Chinese goods. Goods can equivalently be viewed as firms. Given symmetry, prices changes can be written as:

$$\begin{aligned}dp_{US} &= dmc_{US} - \Gamma dp_{US} + (N-1)\Gamma dp_{US} + \Gamma dp_{China} \\ dp_{China} &= dmc_{China} - \Gamma dp_{China} + N\Gamma dp_{US}\end{aligned}$$

Therefore,

$$\begin{aligned}dp_{US} &= \frac{1}{1+(2-N)\Gamma}dmc_{US} + \frac{\Gamma}{1+(2-N)\Gamma}dp_{China} \\ dp_{China} &= \frac{1}{1+\Gamma}dmc_{China} + \frac{N\Gamma}{1+\Gamma}dp_{US}\end{aligned}$$

Setting $dmc_{US} = 0$ we obtain:

$$dp_{US} - dp_{China} = \frac{\Gamma}{1+(2-N)\Gamma}dp_{China} - \frac{1}{1+\Gamma}dmc_{China} - \frac{N\Gamma}{1+\Gamma}dp_{US}$$
$$dp_{US} = \frac{1+\Gamma}{1+(N+1)\Gamma}\left(\frac{1+(3-N)\Gamma}{1+(2-N)\Gamma}\right)dp_{China} - \frac{1}{1+(N+1)\Gamma}dmc_{China}$$

We can now solve for the response of prices for Chinese products:

$$dp_{China} = \frac{1}{1+\Gamma}dmc_{China} + \frac{N\Gamma}{1+\Gamma}\left(\frac{1+\Gamma}{1+(N+1)\Gamma}\left(\frac{1+(3-N)\Gamma}{1+(2-N)\Gamma}\right)dp_{China} - \frac{1}{1+(N+1)\Gamma}dmc_{China}\right)$$
$$dp_{China}\left(\frac{(1+\Gamma)(1+(N+1)\Gamma)(1+(2-N)\Gamma) - N\Gamma(1+\Gamma)(1+(3-N)\Gamma)}{(1+\Gamma)(1+(N+1)\Gamma)(1+(2-N)\Gamma)}\right) = \left(\frac{1}{(1+(N+1)\Gamma)}\right)dmc_{China}$$
$$dp_{China} = \left(\frac{\Lambda}{(1+(N+1)\Gamma)}\right)dmc_{China}$$

with $\Lambda = \frac{(1+(N+1)\Gamma)(1+(2-N)\Gamma)}{(1+(N+1)\Gamma)(1+(2-N)\Gamma)-N\Gamma(1+(3-N)\Gamma)}$.

For the U.S. price response, we get:

$$dp_{US} = \left[\frac{1+\Gamma}{1+(N+1)\Gamma}\left(\frac{1+(3-N)\Gamma}{1+(2-N)\Gamma}\right)\left(\frac{\Lambda}{(1+(N+1)\Gamma)}\right) - \frac{1}{1+(N+1)\Gamma}\right]dmc_{China}$$

A first-order approximation yields:

$$dp = Sdp_{China} + (1-S)dp_{US}$$
$$dlogS = (1-\sigma)(1-S)(dp_{China} - dp_{US})$$

Therefore,

$$\begin{aligned} dS &= -(\sigma-1)S(1-S)(dp_{China} - dp_{US}) \\ &= -(\sigma-1)S(1-S)\left(\frac{\Lambda+1}{(1+(N+1)\Gamma)} - \frac{1+\Gamma}{1+(N+1)\Gamma}\left(\frac{1+(3-N)\Gamma}{1+(2-N)\Gamma}\right)\left(\frac{\Lambda}{(1+(N+1)\Gamma)}\right)\right)dmc_{China} \end{aligned}$$

$$dp = \left(\frac{S\Lambda-(1-S)}{(1+(N+1)\Gamma)} + (1-S)\frac{1+\Gamma}{1+(N+1)\Gamma}\left(\frac{1+(3-N)\Gamma}{1+(2-N)\Gamma}\right)\left(\frac{\Lambda}{(1+(N+1)\Gamma)}\right)\right)dmc_{China}$$

Finally,

$$\frac{dp}{dS} = -\frac{\left(\frac{S\Lambda-(1-S)}{(1+(N+1)\Gamma)} + \frac{(1-S)(1+\Gamma)}{1+(N+1)\Gamma}\left(\frac{1+(3-N)\Gamma}{1+(2-N)\Gamma}\right)\left(\frac{\Lambda}{(1+(N+1)\Gamma)}\right)\right)}{(\sigma-1)S(1-S)\left(\frac{\Lambda+1}{(1+(N+1)\Gamma)} - \frac{1+\Gamma}{1+(N+1)\Gamma}\left(\frac{1+(3-N)\Gamma}{1+(2-N)\Gamma}\right)\left(\frac{\Lambda}{(1+(N+1)\Gamma)}\right)\right)}$$

We use the expression for Γ derived by Amiti et al. (2018) under Betrand competition. With a Cobb-Douglas aggregator across sectors, for firm f with market share s_f,

$$\Gamma_f = \frac{(\sigma-1)s_f}{1+(\sigma-1)(1-s_f)},$$

where σ is the elasticity of substitution within the industry. The markup elasticity is increasing in s_f. For the calibration, we set $s_f = 1/N = H/10,000$, where H denotes the Herfindahl index in the industry and N the number of "equally-size firms" that would exist in the industry given this Herfindahl index.

B Online Appendix Tables and Figures

Table A1: Heterogeneity in U.S. Consumer Price Response to Trade with China

Panel A: 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 B: 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 A2: Robustness, Adding Imports/Exports Controls and 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. $^{*}p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table A3: Decomposing the Inflation Response

	Continued Products Inflation		Full CPI Inflation, U.S. Goods Only	
	(1)	(2)	(3)	(4)
Change in China Import Penetration (1999-2011)	-4.5404*** (1.2833)	-2.661*** (0.411)	-3.308*** (1.1306)	-1.783*** (0.3794)
Cragg-Donald	18.272	396.16	22.47	288.75
Kleibergen-Paap F	15.325	116.16	16.50	139.20
IV Strategy	PS (2016)	ADH (2014)	PS (2016)	ADH (2014)
Observations	138	140	137	139
Sample	Manufacturing, Inflation > p5		Manufacturing, Inflation > p5	

Notes: This table presents a decomposition of the full inflation response into components coming from inflation for continued products and from U.S. goods only.

To understand the nature of the decomposition, denote by π_i average annual inflation in industry i during the sample. Then,

$$\pi_i = \underbrace{s_i^C \pi_i^C}_{\widetilde{\pi_i^C}} + \underbrace{s_i^S \pi_i^S}_{\widetilde{\pi_i^S}},$$

where s_i^C is the (average) spending share on continued products in i and π_i^C is the (average) annual inflation in i, while s_i^S and π_i^S are defined similarly for substitutions. A formal decomposition of the IV estimate for the full inflation effect into components resulting from continued products and substitutions can be obtained by running our baseline IV specification with the various components of inflation:

$$\begin{aligned} \pi_i &= \beta Z_i + \epsilon_i, \\ \widetilde{\pi_i^C} &= \beta^C Z_i + \epsilon_i^C, \\ \widetilde{\pi_i^S} &= \beta^S Z_i + \epsilon_i^S, \end{aligned}$$

where Z_i is the instrument from Pierce and Schott (2016) or Autor et al. (2014). β is the full effect and, because $\pi_i = \widetilde{\pi_i^C} + \widetilde{\pi_i^S}$, $\beta^C + \beta^S = \beta$, which provides a convenient decomposition.

Columns (1) and (2) report the IV estimates using $s_i^C \pi_i^C$ as the outcome variable. The difference with the results reported in Table 7 is only that the inflation rate for continued products is now scaled by the relevant spending share. Columns (3) and (4) report the results for inflation for U.S. goods scaled by the relevant spending share, using a similar decomposition:

$$\pi_i = s_i^{U.S.} \pi_i^{U.S.} + s_i^{Non-U.S.} \pi_i^{Non-U.S.}.$$

Table A4: Summary Statistics for Producer Price Index Sample

Panel A: Full Sample

	Mean	Std. Dev.	Observations
PPI Inflation Rate	1.3255	5.1040	5,158
Change in China Import Penetration Rate in the U.S., 1999-2011	0.63397	1.371	3,913
NTR Gap	0.2411	0.1727	4,933
Change in China Import Penetration Rate in Other Developed Economies, 1999-2011	0.60878	1.1798	3,804

Panel B: Tradables Only

	Mean	Std. Dev.	Observations
PPI Inflation Rate	1.180	4.8842	4,662
Change in China Import Penetration Rate in the U.S., 1999-2011	0.65530	1.3892	3,857
NTR Gap	0.2696	0.16066	4,662
Change in China Import Penetration Rate in Other Developed Economies, 1999-2011	0.60878	1.1798	3,804

Notes: This table presents summary statistics for the main variables used in the analysis with the Producer Price Index (PPI) data.

Table A5: Summary Statistics on Country of Origin Flags

	Number of ELIs with flags	Share of Expenditures with flags		Share of Expenditures with China flags	
	All	All	Tradables	All	Tradables
Year	(1)	(2)	(3)	(4)	(5)
2000	51	0.1830	0.3703	0.0074	0.0151
2001	59	0.1760	0.3555	0.0082	0.0171
2002	59	0.1828	0.3630	0.0124	0.0260
2003	63	0.1929	0.3959	0.0127	0.0269
2004	62	0.1860	0.3865	0.0149	0.0323
2005	65	0.2016	0.4300	0.0168	0.0369
2006	60	0.1832	0.3877	0.0166	0.0373
2007	61	0.1743	0.3668	0.0198	0.0454

Notes: This table presents summary statistics on the number of ELIs with a country of origin flag. This ELIs explicitly gather country of origin information (e.g., "Was the product made in the United States; Yes or No?" or "Write in the country in which the product was made.").

Table A6: Robustness with Alternative Measure of Domestic Market Concentration

	Annual U.S. Inflation Rate			
	(1)	(2)	(3)	(4)
Change in China Import Penetration Rate in the U.S., 1999-2011	-3.39***	-3.30***	-2.16***	-3.06***
	(0.613)	(0.576)	(0.628)	(0.5772)
Change in China Import Penetration Rate in the U.S. (1999-2011) $\times 1(1/Herfindahl > 16)$	1.763**	1.62***	1.83**	1.577*
	(0.833)	(0.809)	(0.902)	(0.877)
Change in China Import Penetration Rate in the U.S. (1999-2011) $\times$1999 China Share	5.631***	4.068***	3.46***	4.74***
	(1.931)	(1.195)	(1.33)	(1.581)
Cragg-Donald F	6.045	8.58	5.71	6.77
Kleibergen-Paap F	3.258	6.32	4.29	3.45
IV Strategy	PS (2016) & ADH (2014)			
Controls:				
$(1/Herfindahl > 16)$	✓	✓	✓	✓
1999 China Share	✓	✓	✓	✓
Tradable	✓		✓	✓
Observations	135	132	121	132
Sample	Full	Tradables Only	Inlf > p5	Inlf > p1

Notes: The level of observation is an ELI. Heteroskedasticity-robust standard errors are reported. $*p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$.

Table A7: Robustness with Alternative Measures of Initial Chinese Import Penetration Rate

	Annual U.S. Inflation Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Change in China Import Penetration Rate	-3.01***	-3.00***	-2.45***	-2.65***	-2.98***	-2.67***
in the U.S., 1999-2011	(0.418)	(0.412)	(0.4159)	(0.2324)	(0.411)	(0.471)
Change in China Import Penetration Rate	2.41***	2.37***	2.821***	2.396***	2.373**	1.592**
in the U.S. (1999-2011) $\times 1(1/Herfindahl > 10)$	(0.749)	(0.737)	(0.760)	(0.844)	(0.727)	(0.710)
Change in China Import Penetration Rate	3.946***	2.523***	0.801	3.011*		4.913**
in the U.S. (1999-2011) ×1999 China Share	(1.671)	(1.164)	(1.396)	(1.700)		(2.09)
Change in China Import Penetration Rate					3.963***	
in the U.S. (1999-2011) ×1995-1999 China Share					(1.645)	
Cragg-Donald F	8.77	17.77	5.82	11.655	11.320	3.662
Kleibergen-Paap F	3.88	20.62	1.63	3.55	4.618	2.160
IV Strategy	PS (2016) & ADH (2014)					
Controls:						
$(1/Herfindahl > 10)$	✓	✓	✓	✓	✓	✓
1999 China Share	✓	✓	✓	✓		✓
1995-1999 China Share					✓	
Tradable	✓		✓	✓	✓	✓
Instrumenting for 1999 China Share						✓
Observations	135	132	121	132	135	135
Sample	Full	Tradables Only	Inlf > p5	Inlf > p1	Full	Full

Notes: The level of observation is an ELI. Heteroskedasticity-robust standard errors are reported. The interacted variables "1999 China Share" and "1995-1999 China Share" are standardized by their standard deviations. In Column (6), the 1999 Chinese import penetration rate in developed economies other than the U.S. (from Autor et al. (2014)) is used as an instrument for the 1999 Chinese import penetration rate in the U.S. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: Distribution of NTR Gaps, Tradables Only

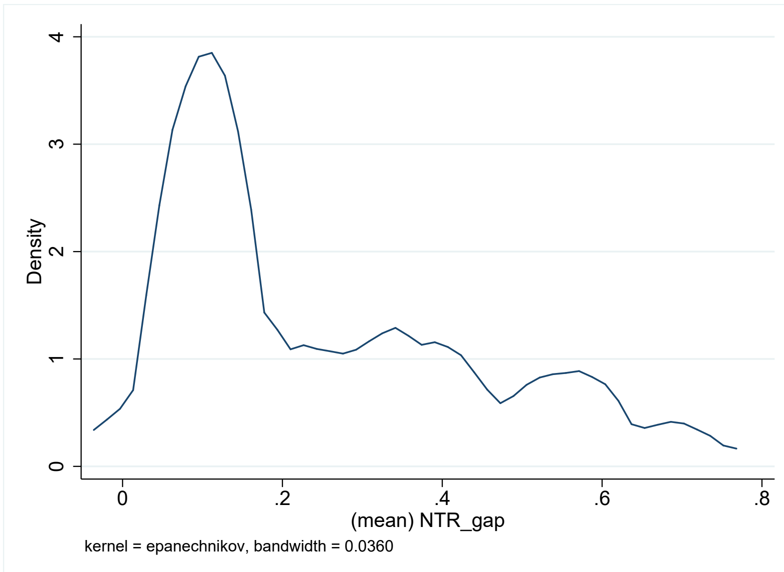


Figure A2: The Response of U.S. Consumer Prices to Granting Permanent Normal Trade Relations to China, Dynamic Effects for Categories with Average Inflation > p10

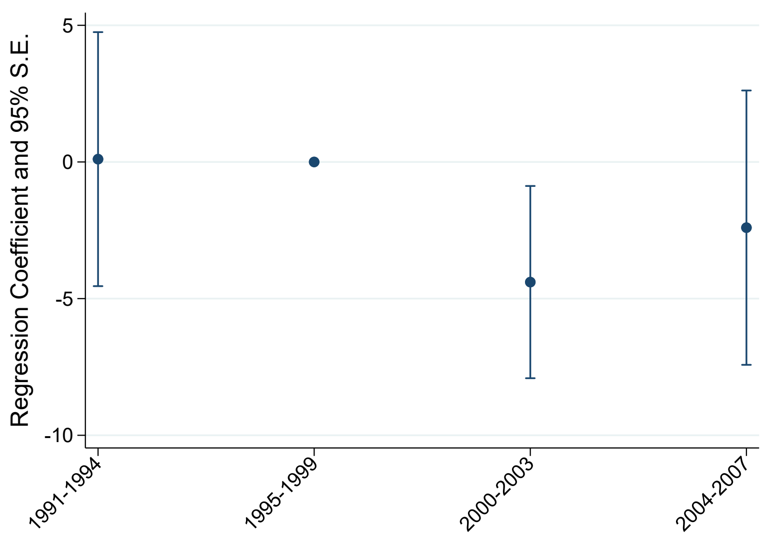
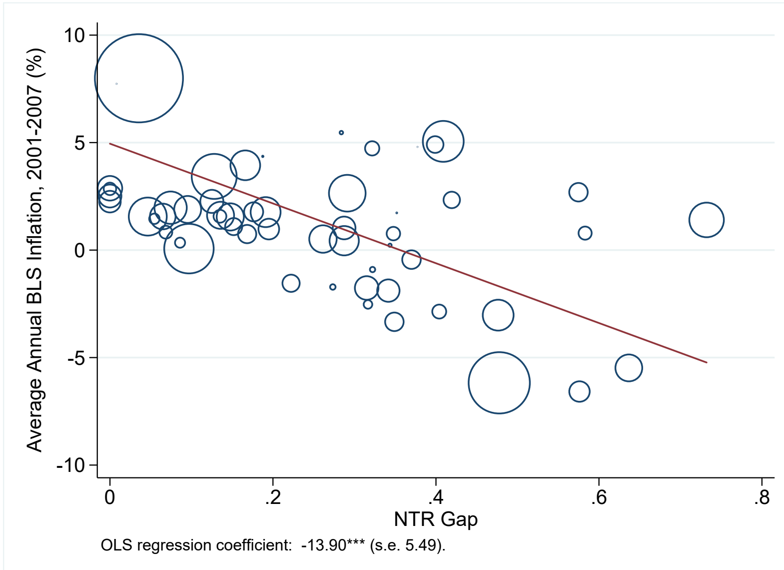
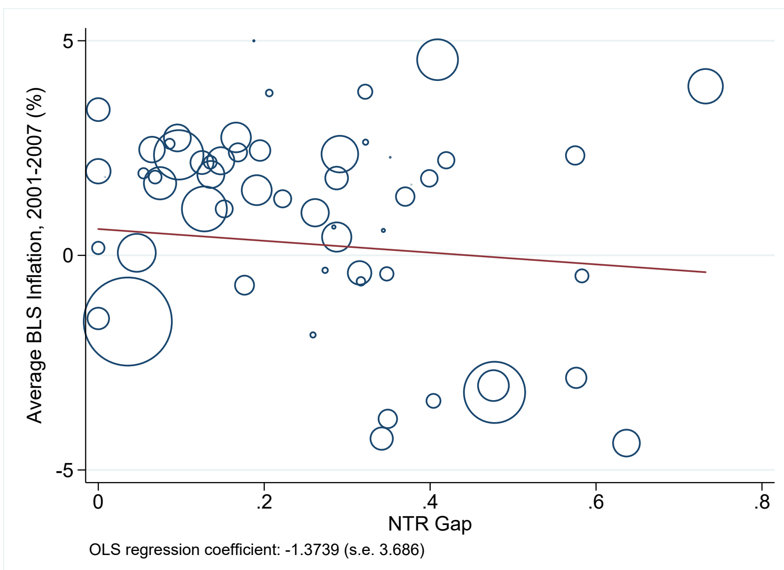


Figure A3: The Relationship between Inflation and NTR Gap across IO6 categories

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.