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

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Abstract

This paper finds that U.S. consumer prices fell substantially due to increased trade with China. With comprehensive price micro-data and two complementary identification strategies, we estimate that a 1pp increase in import penetration, stemming from supply shocks in China, causes a 1.9% decline in consumer prices. This price response is one order of magnitude larger than in standard trade models that abstract from strategic price-setting. We find a large fall in domestic prices, driven by intensified competition and declining markups. The estimates imply that trade with China increased U.S. consumer surplus by about $400,000 per displaced job, and that product categories catering to low-income consumers experienced larger price declines. This large impact of trade on aggregate consumer surplus per displaced job transforms the cost-benefit analysis of trade policies and their distributional effects.

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I Introduction

What are the price effects of trade? Canonical trade models predict that trade benefits consumers through lower prices but may hurt some workers through reduced earnings (e.g., Stolper and Samuelson (1941)). While recent reduced-form evidence indicates that increased trade with China had a large adverse impact on U.S. labor markets (e.g., Autor et al. (2013), Autor et al. (2014), Pierce and Schott (2016), Bloom et al. (2019)), much less is known about the potential benefits to U.S. consumers through lower prices. The magnitude of the price response is an empirical question, because various mechanisms could be at play. As trade with China increases, to what extent do retailers adjust prices facing U.S. consumers? Are price changes driven by products imported from China, or is there a broader impact on prices of domestically-produced goods? To the extent that prices fall, which consumers benefit most and how do the gains in purchasing power for consumers compare to the losses for workers through job disruptions? Data limitations explain the relative scarcity of evidence on these questions, which can only be answered with comprehensive price data.

In this paper, we use micro data from the U.S. Bureau of Labor Statistics (BLS) to obtain comprehensive coverage of price dynamics over a long panel, going back to the 1980s with both consumer prices and producer prices. We estimate the response of prices to the rise in trade induced by supply shocks in China. Estimating the causal response of U.S. consumer prices is challenging because of potential omitted variable biases and reverse causality. For example, China has a comparative advantage in specific product categories that may be on different inflation trends, such as consumer electronics or apparel.

To overcome this challenge we use two complementary research designs borrowed from recent work studying the consequences of trade with China on employment across U.S. industries. Pierce and Schott (2016) leverage a change in U.S. trade policy passed by Congress in October 2000, which eliminated potential tariff increases on Chinese imports.[1] This research design uses transparent policy variation and lends itself to year-by-year tests for pre-trends. But the effects of trade induced by changes in policy uncertainty may differ from those of more common permanent changes in foreign productivity. To gauge the generalizability of our main estimates, we also use the empirical strategy of Autor et al. (2014), who instrument for changes in import penetration from China in the U.S. with contemporaneous changes in eight comparable economies.

[1] A similar research design was developed independently and concurrently by Handley and Limão (2017).

To assess the plausibility of a causal interpretation of our estimates, we implement several falsification and robustness tests. We find no evidence for pre-trends. With the instrument from Pierce and Schott (2016), we implement a stringent triple-difference test using price data from France. We find that there is no similar reaction of prices in France, where there was no policy change.

Our IV estimates indicate that the price effects of increasing trade with China are large. With the instrument from Pierce and Schott (2016), a one percentage point increase in the import penetration rate from China causes a fall in inflation of 2.2 percentage points (s.e. 0.47). With the instrument from Autor et al. (2014), the corresponding fall in consumer prices is 1.4 percentage points (s.e. 0.45). With both instruments jointly, the IV coefficient is -1.9 percentage points (s.e. 0.38).

We investigate several potential mechanisms that could account for the IV estimate. We first show how to interpret our IV coefficient within the structure of standard quantitative trade models. Conceptually, the estimated price effect is a useful identified moment that can serve as a diagnostic tool to distinguish between classes of trade models (e.g., *à la* Nakamura and Steinsson (2018)). In the set of trade models characterized by Arkolakis et al. (2012), the price response across product categories is predicted to be equal to the inverse of the trade elasticity. We find that our estimated price effect is about one order of magnitude larger than predicted by these models. To account for the observed effect, this class of models requires an implausibly small trade elasticity, around 0.3, while common estimates are around 4.25 (Simonovska and Waugh (2014)).

We focus on linking our cross-industry IV specification to the price response predicted by the Melitz (2003)-Chaney (2008) model, which we take as our preferred member of the Arkolakis et al. (2012) class.[2] We study the predicted price reponse in this model, in general equilibrium, and highlight that it differs from our IV estimate by one order of magnitude, even after accounting for the potential divergence between the measured CPI and the model-based exact price index. We also show formally that other members of the Arkolakis et al. (2012) class make very similar quantitative predictions, including Armington (1969) and models with intermediate inputs as in Caliendo and Parro (2015) and Ossa (2015); so do other leading trade models outside this class, such as Arkolakis et al. (2019).

To uncover the relevant mechanisms, we document which products drive the price response.

[2] Specifically, we study a trade model with CES preferences and heterogeneous firms engaged in monopolistic competition (Melitz (2003)) whose productivity follows a Pareto distribution (Chaney (2008)).

Using statistical decompositions, we isolate the roles of continued products (as opposed to new products) and domestically-produced goods (as opposed to foreign products). We find that continued products account for approximately 70% of the overall price effects. To isolate the role of U.S.-produced goods, we identify U.S. goods in the Consumer Price Index (CPI) sample using specification checklists. We find that domestic prices account for a substantial fraction of the overall price effects, between 44% and 85% depending on the specification. We confirm the role of the domestic price response using the Producer Price Index (PPI) sample, which covers domestic manufacturers only.

The domestic price response for continued products could result from two potential effects of increased trade with China on U.S. manufacturers: changes in production costs, or changes in markups. We first assess the role of changes in domestic production costs, which we decompose into several potential sources: wages, intermediate inputs and offshoring, and returns to scale and productivity.

Although changes in domestic production costs are theoretically plausible, in practice we find that they can account for only a small fraction of the estimated price response. Wages fall in response to trade with China, but both public data and administrative data used in prior studies (e.g., Autor et al. (2014)) indicate that the wage effects are much smaller than would be needed to explain the domestic price response.[3] To assess the role of intermediate inputs, we use the BEA's input-output table and measure upstream and downstream changes in trade with China for each product category. We find that upstream and downstream trade does not help explain the estimated price effects. Finally, by displacing domestic goods and reducing the scale of domestic production, increased import competition with China could affect domestic production costs through (decreasing) returns to scale. In fact, empirical studies find that tradable U.S. industries have *increasing* returns to scale; explaining the estimated price response would require an elasticity of the opposite sign and about five times larger in magnitude than benchmark estimates of returns to scale.

Next, we turn to the potential relevance of markups. Using the setting of Edmond et al. (2015), we show theoretically that the large price effects can be explained by models that feature strategic interactions in pricing. Intuitively, as Chinese producers become more productive they reduce their prices, which leads U.S. producers to reduce their markups through strategic interactions. Because

[3] Because the labor share in total domestic output for the relevant product categories is very low, explaining the estimated 2% fall in domestic prices (due to a 1pp increase in import penetration from China) requires a very large wage response, on the order of 20%, which we can reject empirically.

of the fall in U.S. prices, U.S. consumers do not substitute as much toward the products from China. Therefore, the equilibrium change in import penetration rate from China is lower than it would be without the price response for U.S.-produced goods. As a result, the model yields a large reduced-form relationship between changes in import penetration and price changes across product categories.

We conduct empirical tests of the markup channel. We examinine the response of estimated markups for publicly-listed firms in Compustat, following the methodology of De Loecker et al. (2020) to estimate markups. We observe a fall in estimated markups: when the import penetration rate from China increases by one percentage point, domestic markups fall by 1.8 percentage points (s.e. 0.85). This estimate is large in magnitude and statistically indistinguishable from the IV coefficient for the response of domestic prices. Moreover, the observed changes in the *distribution* of markups are consistent with the predictions of the model: as trade increases, markups fall primarily at the top of the markup distribution (e.g., there is no effect at the 10th percentile but a large effect at the 90th percentile). Finally, given the limited coverage of the Compustat sample, we return to our main sample and assess whether heterogeneity in the estimated price effects is consistent with the predictions of the markup channel. We document that the price effects are significantly larger in industries where domestic market concentration is higher and where China's initial market share is lower. These patterns are in line with the model: there is more domestic market power to be disrupted by China when the domestic market is more concentrated.

Finally, we discuss how our estimates shed light on the distributional effects of the "China shock." We first benchmark our estimates of the price response, which benefits consumers, to the employment effects estimated in prior work. Using the IV estimates for the price and employment effects, our baseline specification indicates that falling prices in product categories that are more exposed to trade with China create $411,464 in consumer surplus for each displaced job. The estimates vary from $288,147 to $477,555 across specifications.[4] These large magnitudes suggest that it may be possible to compensate those who suffer from the labor market impacts of trade shocks. In contrast, in the class of standard trade models nested by Arkolakis et al. (2012), the predicted increase in consumer surplus per displaced job would be attenuated by a factor of ten and would be on the order of $40,000 per displaced job, similar to average annual labor earnings in the sample.

[4] In a related analysis assuming no general equilibrium effects affecting prices in all product categories (i.e., the standard "missing intercept"), we find that in 2007 the (annual) purchasing power of the representative U.S. household increased by about $1,500 thanks to lower prices induced by increased trade with China from 2000 to 2007.

Lastly, we investigate distributional effects across consumers and find that the price response is larger in product categories that cater to lower-income households. For example, for product categories with a share of sales to college graduates *below* median, the magnitude of the price response is about five times larger than for the categories with a share above median. The patterns are similar with other proxies for consumer income. These results indicate that distributional effects can arise because of differences in the price responses to trade shocks. This channel appears to be quantitatively important and is novel relative to other mechanisms investigated in prior work (e.g., Fajgelbaum and Khandelwal (2016), Carroll and Hur (2020) and Borusyak and Jaravel (2021) examine differences in spending shares on imports, and Hottman and Monarch (2020) document differences in import price inflation across income groups).

This paper relates and contributes to several literatures. First, our estimates of the benefits of trade with China for consumers through lower prices complement a large literature that has documented adverse effects for employment (e.g., Autor et al. (2013), Autor et al. (2014), Pierce and Schott (2016) and Bloom et al. (2019)), mortality (Pierce and Schott (2020)), marriage, fertility and children's living circumstances (Autor et al. (2019)), domestic innovation and investment (Pierce and Schott (2018) and Autor et al. (2020a)), and political polarization (Autor et al. (2020b)). By estimating a large impact of trade on aggregate consumer surplus per displaced job, our findings transform the cost-benefit analysis of trade policies and their distributional effects.

Second, a growing literature examines the reduced-form impact of changes in trade on producer prices, but no paper uses comprehensive data on consumer prices as we do. Amiti et al. (2019b), Cavallo et al. (2021), Fajgelbaum et al. (2020) and Flaaen et al. (2020) estimate the effects of the 2018 "trade war" on import and producer prices over a one-year horizon. Our work predates these studies and complements them by estimating the response of consumer prices to the historical "China shock" over a long horizon, close to a decade.[5] The price effects of the China shock are also studied by Amiti et al. (2020) for producer prices in manufacturing,[6] and by Bai and Stumpner (2019) for consumer packaged goods.[7] Our findings advance the literature by leveraging

[5]Moreover, focusing on the historical "China shock" allows us to draw a comparison between the gains to consumers through lower prices and the losses to workers through job disruptions in a unifed empirical setting.

[6]Amiti et al. (2020) study the impact of China's WTO entry on prices using the U.S. PPI as well as data on the unit value of imports. They find that a key mechanism is China lowering its own import tariffs on intermediate inputs.

[7]For our purposes, scanner data such as those used by Bai and Stumpner (2019) suffer from three drawbacks. First, the sample covers fast-moving consumer goods and is not representative of several important product categories for trade with China (e.g., apparel, consumer electronics, appliances, and other slow-moving consumer goods). Second, the sample starts in 2004, making it impossible to test for pre-trends prior to the "China shock" or to study the period 2000-2007, which has been the focus of the literature studying the labor market effects of trade with China.

a comprehensive data set representative of the market basket of U.S. consumers, which allows for an in-depth investigation of the identifying assumptions for causal identification (e.g., with pre-trend tests). Moreover, we link our specification and data to the predictions of leading quantitative trade models.[8]

Third, our results indicate that the quantitative trade models that are most commonly-used for policy analysis, in particular the Melitz (2003)-Chaney (2008) model and more broadly the members of the Arkolakis et al. (2012) class, cannot offer a good approximation to observed price changes and their distributional effects. By showing the importance of the "pro-competitive effects of trade" to explain the observed price response, our paper is part of a large literature that has investigated the relationship between international trade and markups (e.g., Brander and Krugman (1983), Levinsohn (1993), Krishna and Mitra (1998), Atkeson and Burstein (2008), Epifani and Gancia (2011), Edmond et al. (2015), Feenstra and Weinstein (2017), Feenstra (2018), Impullitti and Licandro (2018), and Arkolakis et al. (2019)). Complementary to the structural approaches in these papers, we use reduced-form identification strategies to provide direct causal evidence.[9] We find that the estimated price effects are consistent with models featuring strategic price setting (e.g., Atkeson and Burstein (2008) and Edmond et al. (2015)) but that they are too large to be rationalized by models featuring monopolistic competition and variable elasticities of substitution (with conventional parameter values, e.g. Arkolakis et al. (2019)).

The paper is organized as follows: Section II present the data and variable definitions, Section III estimates the reduced-form effect of increased trade with China on U.S. consumer prices, Section IV distinguishes between potential mechanisms, and Section V estimates the distributional effects.

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.

Third, it is not possible to isolate domestic goods or track a set of products that were already available before China joined the WTO.

[8]In Appendix C.D, we show that there is a growing empirical consensus about the large effects of foreign supply shocks on producer prices. Relative to this prior work, our contribution is (i) to study consumer prices rather than producer prices; (ii) to show that the large magnitude of the price effects is robust to multiple potential concerns about causal identification that could not be addressed in prior work due to data limitations; (iii) to show formally that these cross-industry results are inconsistent with leading trade models used for policy analysis.

[9]Nakamura and Zerom (2010), Auer et al. (2021) and Amiti et al. (2019a) also take a reduced-form approach but examine exchange-rate and input cost shocks, instead of foreign competition shocks as we do. De Loecker et al. (2016) study India's trade liberalization and domestic markups using producer price data; relative to them, we study a high-income economy and examine consumer prices, inclusive of potential changes in retail markups.

II.A Data Sources, Samples and Variable Definitions

Consumer Price Index. Our main outcome variable is inflation faced by U.S. consumers across product categories. We measure this outcome using the micro data underlying the Consumer Price Index, available from the Bureau of Labor Statistics' internal CPI Research Database (CPI-RDB). The CPI-RDB contains all product-level prices on goods and services collected by the BLS for use in the CPI since January 1988, excluding shelter. A product is defined as a specific item available in a specific store, such as a 500 ml bottle of Coca-Cola on the shelf of a specific Whole Foods Market store in Washington, DC. The BLS data collectors track prices monthly or bi-monthly, depending on the product category, and they identify products using bar codes whenever possible.

Our goal is to estimate the price effects of trade shocks defined at the level of a product category, therefore we aggregate the product-level price changes into category-level price changes. We do so following the BLS' procedure to compute official aggregate inflation statistics, which is described in Appendix A.A. We obtain 222 product categories spanning the full range of final consumption goods and services, with the exception of shelter. 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. For example, a bottle of Coca-Cola belongs to the "Carbonated Drinks" ELI; other examples of ELIs include "Washers & Dryers," "Woman's Outerwear," or "Funeral Expenses."

We leverage the price micro data to build alternative category-level price indices, which we use for various robustness tests and extensions. Alternative category-level price indices help us address potential measurement issues. For example, the baseline CPI index uses quality adjustments when the BLS data collector is unable to find the exact same product in the exact same store from one period to the next (e.g., the 500 ml bottle of Coca-Cola might no longer be on the shelf at Whole Foods and might have been replaced with a 500 ml bottle of Pepsi). Given that BLS quality adjustments may not perfectly account for potential changes in underlying product characteristics in such cases, we build an alternative price index based solely on price changes for "continued products" (i.e., those instances when the same item in the same store is observed from one period to the next). We also leverage the micro data to build alternative price indices that help decompose the sources of the price effects we document. For example, we can isolate the role of the price response of products made in the United States.[10]

[10] See Section IV for a complete discussion. Note that such robustness tests and statistical decompositions would

In addition to its flexibility for inflation measurement, the CPI price data set features other noteworthy advantages. The CPI data set is available over a long panel and covers the representative consumer's market basket comprehensively. This allows us to implement stringent tests for "pre-trends" and assess the plausibility of a causal interpretation of our IV estimates.[11] Although the main data set extends back to 1988, to conduct a more complete analysis of pre-trends we build a similar data set going back to 1977, following Nakamura et al. (2018). Online Appendix A.B describes the construction of this extended sample. Moreover, the CPI measures prices inclusive of retail margins, which is the relevant price for consumers.[12]

A limitation is that the sample frame keeps a fixed number of items in each product category, which makes it impossible to study changes in product variety over time. The available evidence to date suggest that increased trade with China may lead to an increase in product variety, which lowers consumers' effective price index through love of variety.[13]

Trade Data. Our main independent variable is the import penetration rate from China over time and across product categories. For product category i, the import penetration rate from China at time t is defined as:

$$ChinaIP_{it} = \frac{Imports_{it}^{China}}{DomesticProduction_{it} + TotalImports_{it} - TotalExports_{it}}, \tag{1}$$

where the denominator corresponds to domestic absorption. To make our results comparable with prior work examining the impact of increased import competition with China on employment, we use the measures of import penetration from China built by Acemoglu et al. (2016) at the level of Standard Industrial Classification (SIC) industries. Following their approach, we consider long differences, i.e. the change in the China import penetration rate over two relatively long periods, 1991-2000 and 2000-2007. In a robustness test, we adjust the denominator in equation (1) for

not be possible by using the publicly-available inflation series from the BLS. Another downside of the public data from the BLS, relative to the CPI-RDB dataset, is that the publicly available product categories are coarser than ELIs and their definitions change over time; as a result it is difficult to build a balanced panel of detailed product categories over a long time horizon in this data set.

[11]In contrast, scanner data is restricted to consumer packaged goods and is only available after 2000, making it impossible to appropriately assess the validity of the research design. For example, the Nielsen scanner data is available from 2004 onward and offers limited coverage of several product categories in which trade with China is particularly important, such as consumer electronics, household appliances and apparel (for a discussion of expenditures coverage in Nielsen scanner data, see for example Jaravel (2019)).

[12]Therefore we use CPI inflation as our preferred outcome, rather than import or producer price indices.

[13]The impact of trade on product variety remains debated, because domestic exit may offset the increase in foreign varieties available to consumers. Broda and Weinstein (2006) show that the number of foreign varieties increases, but they do not observe domestic varieties in the trade data. Hsieh et al. (2020) suggest that import variety gains are counteracted by exactly analogous domestic variety losses, but they observe plants instead of products. Bai and Stumpner (2019) directly measure changes in product variety using barcode data and estimate that increased trade with China led to a change in product variety that lowered the cost of living for U.S. consumers, as measured by the Feenstra (1994) adjustment factor in a CES framework.

distribution margins. We estimate these margins using the BEA's input-output (IO) table: for each industry the ratio of total output in *purchaser* prices to total output in *producer* prices gives the distribution and transportation margins.

Main Analysis Sample. Our main analysis sample brings together the CPI inflation data (by ELI categories), the trade data (by SIC industries) and the instruments (by SIC industries for Autor et al. (2014) and NAICS industries for Pierce and Schott (2016)). The ELI categories are more aggregated than SIC and NAICS industries, therefore we build many-to-one crosswalks from SIC and NAICS industries to ELIs and aggregate all variables accordingly.[14]

Input-Output Sample. To investigate robustness to aggregation choices and test specific mechanisms, we also build a linked data set at the level of 6-digit IO industries. We use the BEA's 2007 IO table because it is the most disaggregated during our sample. We build a many-to-one match from ELI categories to these industries and then aggregate the data. The variables we build based on input-output linkages are discussed in Section IV and the data construction is described in Online Appendix A.D.

Producer Price Index Sample. To assess the role of domestic prices in the overall price effects, we use data from the BLS's Producer Price Index (PPI) dataset, which tracks producer prices for products manufactured in the United States. Appendix A provides more information on all data construction steps.

Additional Data Sets and Variables. Finally, we supplement our analysis sample with several ELI-level variables to assess the robustness of our main estimates and study heterogeneity in the treatment effect. We use a product hierarchy from the BLS that classifies ELIs in various groups (e.g., to assess the role of apparel or high-tech goods), expenditure shares from the public-use Consumer Expenditure Survey,[15] along with trade elasticities, average wages, capital intensity, total factor productivity, and market concentration from Broda and Weinstein (2006), the NBER-CES Manufacturing Database and the U.S. Census. We also use data from the French CPI to implement placebo tests and Compustat data to measure markups following De Loecker et al. (2020). These variables are introduced when relevant in subsequent sections.

II.B Summary Statistics

Table 1 reports the summary statistics for our main analysis sample, from 1991 to 2007.

[14] The crosswalks are described in Online Appendix A.C.

[15] We use the Consumer Expenditure Survey dataset as processed by Borusyak and Jaravel (2021). This data set provides information on the characteristics of consumers across about 600 very detailed product categories, called UCC. We implement a many-to-one match of UCCs to ELIs, by hand.

The first three rows describe the CPI inflation data. Across non-shelter ELI categories, inflation was on average 1.15% per year, but with a large standard deviation of 6.75 percentage points across industry-years. The share of continued products corresponds to the share of product-level price changes for which the exact same item is priced by the data collector from one month to the next. Continued products account for over 80% of all observations on average, which makes it possible to build a price index based on these observations only. The third row reports the share of unavailable products, which corresponds to instances when the data collector was unable to find the same item from one month to the next.

Rows four and five of Table 1 describe the changes in import penetration rates from China. The average (annualized) change in import penetration from China in the United States is 66 basis points in our sample. There is large variation across ELIs and periods, with a standard deviation of 1.62 percentages points. The change in import penetration from China in developed economies comparable to the United States has similar properties.

The remainder of Table 1 reports summary statistics for several variables defined at the ELI level. The NTR gap is on average 21% and exhibits large variation across ELIs. The table also reports various indicators for product categories, showing the fraction of goods, apparel products, high-tech products, and the set of durable goods defined in Bils (2009), reported in Appendix Table A1.

III Trade with China and U.S. Consumer Prices

In this section, we estimate the effect of trade with China on U.S. consumer prices using two complementary identification strategies.

III.A Research Design

Several challenges arise when estimating the causal effect of increased trade with China, stemming from supply shocks, on U.S. consumer prices. To understand the main threats to identification, suppose we were to estimate a regression of the change in U.S. CPI 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 could be misleading, because there may be many unobserved supply and demand shocks affecting U.S. industries that may correlate with trade with China and have a direct effect on U.S. consumer prices.

For example, China may decide to enter product categories where U.S. suppliers are easy to out-compete due to low TFP growth, implying higher U.S. inflation in these product categories and an upward bias of the OLS estimate. Moreover, omitted variable biases may stem from the fact 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 large for computers, consumer electronics and apparel. Because of high rates of innovation for computers and consumer electronics, and because of the "fashion cycle" for apparel, these categories are characterized by low inflation, implying a downward bias of the OLS estimate. There are thus multiple potential sources of bias with offsetting effects, such that it is not possible to sign the potential bias.

Given these identification challenges, we use two complementary research designs borrowed from recent work.

Variation in the NTR Gap. Pierce and Schott (2016) and Handley and Limão (2017) focus on a specific change in U.S. trade policy passed by Congress in October 2000, which eliminated potential tariff increases on Chinese imports and became effective when China joined the WTO at the end of 2001. 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. Before China was granted PNTR, U.S. import tariffs on Chinese goods needed to be renewed by Congress. 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. The "NTR gap" is the difference between the actual import tariffs on Chinese goods and non-NTR tariffs. We treat the NTR gap instrument as our benchmark, because it allows for stringent falsification tests, discussed below.

Variation in Import Penetration from China in Other Countries. 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. 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 and demand changes in the group of eight comparable economies.

III.B Pre-Trends Analysis

To assess the plausibility of the exclusion restrictions, we implement pre-trend tests.

First, we want to assess whether the NTR gap becomes related to CPI inflation only after the policy change is passed, i.e. after 2000. We use the CPI-RDB database to measure inflation in the pre-period, going back to 1988. We then run a flexible event-study panel specification:

$$\pi_{it} = \sum_{k=1988}^{2007} \beta_k NTR\,Gap_i \cdot 1_{\{k=t\}} + \lambda_i + \delta_t + \varepsilon_{it}, \tag{2}$$

where t indexes year, i indexes ELI categories, π_{it} is the CPI inflation rate, $1_{\{k=t\}}$ is an indicator variable for year t, λ_i is ELI fixed effects, and δ_t is year fixed effects.[16] The path of the year-specific reduced-form coefficients $\{\beta_k\}_{k=1988}^{2007}$ is informative about the plausibility of the identification condition. The exclusion restriction, $\mathbb{E}\left[NTR\,Gap_i \cdot \varepsilon_{it}|i,t\right] = 0$, cannot be tested directly, but if it is valid then there should be no relationship between the treatment and inflation prior to the policy change, and we would expect to find $\beta_k = 0$ for any year prior to 2000.

Panel A of Figure 1 reports the set of reduced-form coefficients from equation (2), along with their 95% confidence intervals (standard errors are clustered by ELIs). This figure shows a striking pattern. From 1988 until 2000, the estimated reduced-form coefficients are small and hover around zero and a F-test cannot reject the null of no effect. But after 2000, the coefficients become negative and statistically significant. This pattern supports the plausibility of a causal interpretation of the relationship between the NTR gaps and inflation outcomes. However, it does not rule out the possibility that other shocks, correlated with both the NTR gap and affecting CPI inflation, may have occured specifically after 2000. We return to this hypothesis later, with a placebo test using French CPI data.

With the instrument from Autor et al. (2014), testing for pre-trends is more challenging. The instrument is the change in import penetration from China in other developed economies, which does not have a precise start date. Trade with China starts increasing in the late 1980s, therefore it is instructive to examine whether there is a relationship between the increase in trade with China in our main analysis sample and inflation in the 1980s.

Panel B of Figure 1 presents the placebo reduced-form specifications in the extended CPI sample (1977-1986), across ELIs. We regress the average inflation rate over the sample on the instrument from Autor et al. (2014) (subfigure (a)) and from Pierce and Schott (2016) (subfigure (b)).[17] With

[16] ELI fixed effects introduce collinearity with the NTR gap, therefore we normalize $\beta_{1988} = 0$.

[17] The specifications are $\bar{\pi}_i = \Delta ChinaOther_i + \nu X_i + \varepsilon_{it}$ and $\bar{\pi}_i = NTR\,Gap_i + \nu X_i + \varepsilon_{it}$, where $\Delta ChinaOther_i$

both instruments, there is no relationship with inflation.

III.C Baseline Estimates

The previous reduced-form specifications support the plausibility of the research design by documenting the absence of pre-trends, but they do not yield properly scaled estimates of the impact of trade with China on U.S. consumer prices. We now turn to IV specifications.

Instrumental Variables Framework. We implement a difference-in-differences IV design after aggregating the data over two long periods, 1991-1999 and 2000-2007. Because the effect of a change in import penetration from China on consumer prices may occur with some delay, an IV specification allowing only for contemporaneous effects (i.e., within the same year) may be misspecified. Following prior work (e.g., Autor et al. (2013), Autor et al. (2014) and Acemoglu et al. (2016)), we implement specifications with contemporaneous effects within periods spanning several years. This approach is natural for both of the instruments we use: the policy change making the NTR gap relevant occurs in the early 2000s, and the increase in the import penetration from China in the other developed economies becomes more pronounced in the early 2000s as China joins the WTO.[18]

The baseline IV specification uses ELI fixed effects, as in the analysis of pre-trends in Subsection III.B. ELI fixed effects allow for each product category to be on its own inflation trend over time. Intuitively, we examine whether ELIs that were relatively more exposed to import competition from China in the 2000s (relative to the 1990s) also have lower inflation rates in the 2000s (relative to the 1990s), using the two instruments.

Our IV specification is:

$$\begin{aligned} \pi_{it} &= \beta \Delta ChinaIP_{it} + \nu X_{it} + \delta_i + \delta_t + \varepsilon_{it}, \qquad (3) \\ \Delta ChinaIP_{it} &= \gamma \mathbf{Z_{it}} + \widetilde{\nu} X_{it} + \tilde{\delta}_i + \tilde{\delta}_t + \eta_{it}, \end{aligned}$$

where i indexes ELIs, t indexes periods (1991-1999 and 2000-2007), π_{it} is the average annual CPI inflation rate over the period, $\Delta China_{it}$ is the average annual change in import penetration rate from China, X_{it} is a set of time-varying controls, δ_i ELI fixed effects, and δ_t period fixed effects.

is the annualized change in import penetration from China in other developed economies from 1991 to 2007, $\bar{\pi}_i$ is average annual inflation for ELI i from 1977 to 1986, and X_i is a vector of fixed effects for apparel and durables.

[18] Permanent Normal Trade Relationship were granted to China by the U.S. Congress in October 2000 and became effective upon China's accession to the WTO at the end of 2001. U.S. prices may react during 2001 in anticipation of increased import competition at the end of the year, or the response might materialize only after 2001. Empirically, we find that the IV estimates are similar in our baseline panel specification using long differences and in an alternative panel specification considering shorter periods after 2001 (Appendix Table A2).

$\mathbf{Z_{it}}$ is a vector of instruments, which varies across specifications. Under the identification condition $\mathbb{E}\left[\mathbf{Z_{it}} \cdot \varepsilon_{it}|X_{it}, i, t\right] = 0$ and relevance condition $\mathbb{E}\left[\mathbf{Z_{it}} \cdot \Delta ChinaIP_{it}|X_{it}, i, t\right] \neq 0$, the coefficient β gives the relationship, causally induced by a supply shock in China, between a 1 percentage point increase in the import penetration rate from China and the level of inflation faced by U.S. consumers.[19]

We start with just-identified IV specifications with a single instrument, using in turn the NTR gap and the change in import penetration from China in the other developed economies. Since the NTR gap is relevant only after 2000 (after the policy change), we set $\mathbf{Z_{it,1}} = (NTR\,Gap_i \cdot PostPNTR_t)$, with $PostPNTR_t = 1$ for the period 2000-2007. The change in import penetration from China in the other developed economies offers variation in both periods: $\mathbf{Z_{it,2}} = \Delta ChinaIP\,Other_{it}$. After using the two instruments separately, we use them jointly.

Results. Figure 2 reports binned scatter plots depicting the first-stage and reduced-form specifications using the NTR gap as the instrument. Panel A shows the first stage: the larger the NTR gap, the larger the increase in import penetration from China. Panel B depicts the reduced-form relationship: the CPI inflation rate is significantly lower in ELIs with a higher NTR gap.

Panel A of Table 2 reports the baseline IV estimates, using the NTR gap as the source of identifying variation in equation (3). The OLS coefficients for the first-stage and reduced-form relationships are reported in Columns (1) and (2). We find that a 10 percentage point increase in the NTR gap leads to an increase in the import penetration rate from China of 33.3 basis points and to a fall in the inflation rate of 74.3 basis points. These findings indicate that the policy change had a large impact of trade with China and on consumer prices.

The IV estimate in Column (3) indicates that a one percentage point increase in the import penetration rate from China leads to a fall in inflation of 2.23 percentage points. This coefficient is precisely estimated, with a 95% confidence interval ranging from -3.15 to -1.30. The F-statistic indicates that the instrument is strong. In Column (4), we run the same specification with OLS. The relationship between trade and prices remains large, but not as strong as with the instrument: the coefficient is -0.90, which suggests that omitted variables biases or reverse causality attenuate the estimated relationship between trade and consumer prices by over 50%. Finally, since the policy change was implemented in 2000, it is instructive to restrict the sample to the second period only (2000-2007). With only one period, ELI fixed effects would absorb the entire variation in the data, therefore we only include fixed effects for durable goods and apparel. Column (5) reports

[19] All specifications use consumption weights. Results without weights are similar, see Appendix Table A3.

the results: the estimated IV coefficient of -2.15 remains large, statistically significant, and is very similar to the baseline in Column (3). The standard errors increase by over 60% in Column (5) relative to Column (3), which shows it is useful to leverage the full sample with ELI fixed effects to increase power.

Panel B of Table 2 present the results using as an instrument the change in trade with China in other developed economies. Column (1) reports the corresponding IV coefficient: when import penetration from China increases by one percentage point, consumer prices fall by 1.44%. Column (2) repeats the specification after restricting the sample to the second period only: the IV coefficient remains similar, equal to -1.27. These coefficients are precisely estimated and the F statistics are strong.

Column (3) reports the IV estimate when using both instruments jointly. The IV coefficient is -1.91 and is precisely estimated, with a standard error of 0.38. Because we now have an over-identified equation, we can run the test of over-identifying restrictions of Hansen (1982). With a p-value for the J statistic of 0.21, we cannot reject that the over-identification restrictions are valid.[20]

III.D Robustness

We now implement several robustness tests. In Columns (1) through (4) of Panel A of Table 3, we examine whether the estimates remain stable as we change the set of fixed effects and time varying controls, and we examine their sensitivity to the exclusion of outlier categories with particularly low inflation rates. The NTR gap is used as the instrument. Column (1) repeats the IV specification after replacing the 222 ELI fixed effects with a set of fixed effects for ten broad product categories defined by the BLS (called "major categories", they are defined by the first 2 digits of each ELI). The IV coefficient falls slightly to -2.75. In Column (2), we re-introduce ELI fixed effects as in the baseline but also include period-specific fixed effects for apparel and durable goods (i.e., inflation can vary systematically across periods). The IV coefficient remains similar, increasing slightly to -1.78. In Column (3), we exclude ELIs in the bottom 10% of the inflation distribution over our sample. Doing so leaves the IV coefficient virtually unchanged compared to the baseline, at -2.26. In Column (4), we control for inflation in the 1990s, interacted with period fixed effects. The results remain unchanged. Column (5) repeats the specification after including the period-specific controls

[20]The Hansen test could reject due to heterogeneous treatment effects, even when the exclusion restrictions hold. Therefore, rejecting would not necessarily be a sign that either of the instrument is invalid. Although our two instruments leverage different sources of variation, we can hypothesize that there is a common value of β. The J test shows that we cannot reject this hypothesis.

used by Pierce and Schott (2016) (a fixed effect for high-tech sectors and controls for contract intensity and union membership), which again leaves the IV coefficient almost unaffected, at -2.10. We also assess the sensitivity of our results by aggregating the data to the level of coarser industries, the 6-digit IO industries defined by the BEA's 2007 input-output table, with 170 industry-by-period observations. In Column (6), the IV coefficient is -2.94 and is significant at the 5% level.

The estimated effects so far do not account for the possibility of correlated changes in the patterns of overall trade across ELIs. Trade with other countries may be a source of omitted variable bias. If other countries tend to *increase* their import penetration in the U.S. at the same time as China, then we might conflate the price effects of China with those of other trading partners. Column (1) of Panel B of Table 3 shows that, in fact, China tends to *displace* other trading partners of the US: when import penetration from China increases by 1 percentage point, overall import penetration increases by only 78 basis points. The IV coefficient based on the overall change in import penetration is larger than when considering trade with China alone, because overall trade increases by *less* than the change in trade with China alone suggests. Columns (2) and (3) report the results when instrumenting the change in overall import penetration with the NTR gap. The IV coefficients fall further, to approximately -3.70.

Due to space constraints, we report several additional robustness checks in Appendix C.A.

III.E Falsification Tests using French CPI Data

One potential confounding factor remains unaddressed so far: unobserved time-varying shocks could bias our estimates. With this in mind, we implement a placebo test using data from the French CPI, which is publicly available across 132 detailed product categories called COICOP. We link our main analysis sample to COICOP categories, aggregate all variables at that level, and repeat the IV strategy from equation (3) with the French CPI as the outcome, using the NTR gap as the instrument.

Panel A of Figure 3 reports the placebo reduced-form. There is no relationship between the NTR gap and inflation across product categories in France. Panel A of Table 4 reports the results: the first-stage in Column (1) and the IV estimate for the U.S. in Column (2) are similar to the preceding analysis, except that we now run the regression across COICOP categories rather than ELIs. Column (3) shows that the reduced form with the French CPI is not significant, and Column (4) reports a precisely estimated null IV coefficient with the French CPI, at -0.074 (s.e. 0.38). The coefficient remains small and insignificant with the alternative specification in Column (5).

We also estimate a triple-difference IV specification, reporting the estimates in Panel B of Table 4. The specification is the same as in equation (3), except that the outcome is now the *difference* between U.S. CPI inflation and French CPI inflation. With this differenced outcome, we effectively control for category-by-period fixed effects for inflation; the estimated IV coefficient only depends on inflation differences between the United States and France for the same product category. We still allow for COICOP fixed effects, i.e. for permanent differences in inflation rates between the U.S. and France for each product category. Panel B of Figure 3 depicts the clear negative reduced-form relationship with this differenced outcome. Column (2) of Panel B of Table 3 reports the corresponding coefficient. The IV coefficients in Columns (3) and (4) are similar to the baseline results, ranging from -2.08 to -2.52, and are statistically significant at the 5% level. These facts alleviate the remaining concerns over time-varying unobserved shocks.

IV Mechanisms

We now investigate a series of potential mechanisms that could account for the estimated price effects of trade with China across product categories. We show how to interpret the estimated price effects in light of standard quantitative trade models. Using statistical decompositions, we demonstrate the important contributions of continued and domestic products to the overall price effects. Finally, we study heterogeneity in the estimated price effects across product categories to distinguish between different potential channels that could explain the response of domestic products, including intermediate inputs, offshoring, changes in wages and TFP, and markups. We find empirical support primarily for the markup channel. Using a simple model of strategic price setting, we also establish that the markup channel is plausible quantitatively.

IV.A Connecting the IV Estimate to the Melitz-Chaney Model

Our IV estimate is a useful identified moment that can serve as a diagnostic tool to distinguish between classes of trade models, *à la* Nakamura and Steinsson (2018). We connect our IV estimate to the standard quantitative trade model of Melitz (2003) and Chaney (2008), with N countries engaging in international trade. The representative consumer in country j has Cobb-Douglas preferences across S sectors indexed by s, $U_j = \Pi_{s=1}^{S} \left(Y_j^s\right)^{\mu_s}$ with $\sum_s \mu_s = 1$. Each sector consists of differentiated varieties over which the representative consumer has CES preferences with an elasticity of substitution $\sigma > 1$, $Y_j^s = \left(\sum_{i=1}^{N} \int_{\Omega_{ij}^s} y_{ij}^s(\omega)^{\frac{\sigma-1}{\sigma}} d\omega\right)^{\frac{\sigma}{\sigma-1}}$, where Ω_{ij}^s is the set of varieties from sector s available to the consumer in country j and produced in country i, and $y_{ij}^s(\omega)$ is the quantity of each such variety $\omega \in \Omega_{ij}^s$.

Firms in country i have aggregate productivity A_i^s and idiosyncratic productivity z that is distributed according to $G_i^s(z)$. They are monopolistic competitors within a sector and produce varieties according to a linear production technology that takes labor as an input, $y_{ij}^s(z) = A_i^s z l_{ij}^s$. Firms take the economy-wide wage w_i as given, face an iceberg cost τ_{ij}^s and pay a labor-denominated fixed cost $w_i f_{ij}^s$ to operate in the market, which they pay as long as their profits are positive. In this setting, firms' markups are constant and there is an endogenous entry cutoff. Finally, we denote the trade elasticity by θ, which is the Pareto shape parameter when the idiosyncratic firm productivity distribution is Pareto. Appendix B.A.1 provides additional detail about this standard setting.

We now perturb the equilibrium with shocks to foreign country f's marginal costs of production, which can be heterogeneous across sectors. Proposition 1 characterizes the equilibrium cross-sector relationship between changes in import shares and changes in prices indices, using the following notation: P_s denotes the exact consumer price index in sector s, S_{sd} the expenditure share on domestically-produced goods, and S_{sf} on products from trading partner f.

Proposition 1 ***[changes in import shares and exact price indices in the Melitz-Chaney model].*** *Sector-specific supply shocks for trading partner f induce a cross-sector relationship in the domestic economy between import shares and consumer price indices, which can be characterized to the first order as follows:*

- *in partial equilibrium, holding fixed both wages and product entry/exit, we have:*

$$\frac{d\log(P_s)}{dS_{sf}} = -\frac{1}{(\sigma-1)(1-S_{sf})}.$$

- *assuming that the distribution of firms' productivity is Pareto, in general equilibrium with endogenous wages and entry-exit we have:*

$$\frac{d\log(P_s)}{dS_{sd}} = \frac{1}{\theta \cdot S_{sd}}. \tag{4}$$

Proof: see Appendix B.A.2.

Equation (4) corresponds to the empirical cross-sector relationship $\Delta\log(P_s) = \frac{1}{\theta}\Delta\log(S_{sd})$, with a standard estimate of $\theta \approx 4.25$ for the trade elasticity (Simonovska and Waugh (2014)).[21]

[21] As noted by Arkolakis et al. (2011), the trade literature and the international macro literature do not agree on the value of the trade elasticity. Macro models, which focus on short-run fluctuations, generally set a low value for this parameter (e.g., an Armington elasticity of 1.5 in Backus et al. (1993)). In contrast with the international macro studies, our empirical analysis focuses on medium-run responses, for which the elasticities from the trade literature are the natural benchmark.

Therefore, with the log change in the domestic expenditure share as the endogenous variable, the Melitz-Chaney model predicts that our IV specification (3) should recover an estimate related to the inverse of the trade elasticity: $\widehat{\beta} = \frac{1}{\theta}$.[22] In Appendix B.C, we show that this prediction also more broadly in the set of models considered by Arkolakis et al. (2012).

Thus, using the log change in the domestic expenditure share as the endogenous variable, standard trade models predict an IV coefficient of $\widehat{\beta} = \frac{1}{\theta} \approx 0.23$. To test this prediction, we implement our IV specification with the log change in the domestic expenditure share as the endogenous variable.[23] The estimates are reported in Table 5 and are large in magnitude: 2.57 (s.e. 0.96) with the instrument from Pierce and Schott (2016), 3.46 (s.e. 1.41) with the instrument from Autor et al. (2014), and 3.10 (s.e. 0.96) with both instruments. These estimates are much larger than the predicted IV coefficient of 0.25. The trade elasticity that would be necessary to match the point estimate (with both instruments) is $\hat{\theta} = \frac{1}{3.10} \approx 0.32$. This trade elasticity is implausibly small: benchmark estimates are all above 1 and generally close to 4. These results show that standard quantitative trade models do not match the estimated price response.

Proposition 1 shows that the IV estimate is about ten times too large relative to what would be expected from the change in trade flows, according to standard trade models. Because of endogenous entry and exit, the changes in the exact CES price index characterized in Proposition 1 could differ from changes in the "measured" Consumer Price Index we use in our empirical analysis, which does not account for changes in product variety. For example, if there is significant product exit, the exact price index will be smaller than the measured CPI. We characterize this difference in Corollary 1.1, denoting by $\widetilde{P}_s$ the measured price index for U.S. consumers for sector s, by $\widetilde{P}_{sd}$ the measured price index over domestically-produced goods, and by S_{si} the expenditure share on country i.

Corollary 1.1 *[changes in import shares and measured CPI in the Melitz-Chaney model].* *The exact price index can be decomposed into the measured CPI and an unobserved product variety correction, such that equation (4) becomes:*

$$\underbrace{\frac{d\log(P_s)}{dS_{sd}}}_{exact\ price\ index} = \underbrace{\frac{d\log(\widetilde{P}_s)}{dS_{sd}}}_{measured\ CPI} + \underbrace{\frac{\sum_i S_{si} \cdot d\log(E_{si})}{dS_{sd}}}_{product\ variety} = \frac{1}{\theta \cdot S_{sd}},$$

[22] When the trade elasticity varies across product categories, our IV estimator recovers a weighted average of the trade elasticities.

[23] We focus on the predictions of trade models about the relationship between price changes and trade flows across industries, not on the overall welfare gains from trade, which depend on additional GE effects (e.g., through input-output linkages and roundabout production).

with $d\log(E_{si})$ the correction for entry-exit defined in Appendix B.A.3, equation (B8).

Moreover, the change in the measured CPI is null for domestic products:

$$\frac{d\log(\widetilde{P}_{sd})}{dS_{sd}} = 0.$$

Proof: see Appendix B.A.3.

Available evidence suggest that overall product variety (weakly) increases in response to foreign supply shocks.[24] In that case, the exact price index should fall more than the measured CPI. Thus, the first part of Corollary 1 shows that the divergence between the theoretical and measured price index cannot help standard models match our IV estimate.[25] Furthermore, the second part Corollary 1 derives a sharp prediction: in the Melitz-Chaney model, prices of domestically-produced goods do not respond to foreign supply shocks, which we proceed to test in the next subsection.

IV.B The Roles of Continued and Domestic Products

In order to understand the discrepancy in magnitudes between our IV estimate and the theoretical relationships above, next we empirically document that U.S. prices did in fact respond to increased import penetration from China. We begin our empirical investigation of potential mechanisms with a simple statistical decomposition by product characteristics, documenting the extent to which new products and products that were made in the U.S. generated the estimated price effect.

Statistical decompositions. We will begin our decomposition of the estimated price effect by denoting the subset of interest by A, and let s_i^A be the share of items within product category i that belongs to subset A (which, as we define below, will correspond to continued products and domestic products). Omitting time subscripts and letting B denote the complementary set, we obtain an exact decomposition for the CPI inflation rate for each product category as

$$\pi_i = \underbrace{s_i^A \pi_i^A}_{\equiv \widetilde{\pi}_i^A} + \underbrace{s_i^B \pi_i^B}_{\equiv \widetilde{\pi}_i^B}, \tag{5}$$

where π_i is the inflation rate for product category i as in Section III, π_i^A is the inflation rate for products within subset A and s_i^A is the spending share on A. Finally, $\widetilde{\pi}_i^A$ is the contribution of

[24] Bai and Stumpner (2019) measure changes in product variety using barcode data and estimate that increased trade with China led to a change in product variety that lowered the cost of living for U.S. consumers, using the Feenstra (1994) adjustment factor in a CES framework.

[25] Furthermore, in Appendix B.A.3 we use the Melitz-Chaney model to quantify the decline in product variety in foreign countries that would be required to match the IV estimate. First, we quantify the impact of the exit of domestic products, which leads to an increase of the theoretical price index of 0.0625pp. Second, we derive a bound showing that with unmeasured entry-exit the IV estimate using the measured CPI is predicted to be inferior to 0.302. We conclude that unobserved changes in product variety cannot reconcile the predictions of the Melitz-Chaney model with our IV estimate.

subset A to overall inflation in category i, which depends both on the inflation rate within A and on how much spending is devoted to A.

In the remainder of this section, we examine the contributions of continued goods and domestic goods to overall inflation. We first run our IV specification (3) with continued goods inflation or domestic goods inflation as the outcome (π_i^A), which is directly informative about the price response for these sets of goods. These results do not provide a proper decomposition because they ignore the share of spending on the relevant set of products. If a set of products accounts for a small share of spending, its overall impact on category-level inflation may be small even if it has a large inflation response to trade. Therefore we repeat the IV specification with the share-adjusted inflation rate ($\widetilde{\pi}_i^A$) as the dependent variable. By linearity of OLS, the ratio of the IV coefficient with the share-adjusted inflation rate ($\widetilde{\pi}_i^A$) to the baseline IV coefficient (with outcome π_i) gives the share of the overall effect accounted for by products within subset A.

In the remainder of this Section we focus on the NTR gap instrument. The results with the change in import penetration from China in other countries are similar (Appendix Table A4).

The Role of Continued Products. Panel A of Table 6 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 new products (termed "product substitutions" by the BLS) from the computation of inflation. This decomposition allows us to test whether the overall price response to trade stems from declining prices for new products (i.e., inflation would fall via product substitutions) or from declining prices for pre-existing products (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) indicate that inflation for continued products falls by 3 percentage points for each 1 percentage point increase in import penetration from China. Using the decomposition in equation (5), Columns (3) and (4) show that continued products account for approximately 70% of the overall price effects from Table 2.

The Role of Domestic Products. We now examine the contribution of domestic products. We first continue working with the CPI data set, before presenting additional evidence from the PPI data set.

To assess whether the price effects 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 have explicit flags for country of origin information (e.g., "Was the product made in the United States; Yes or No?"), others have entries that the data collectors populate with text (e.g., "Write in the country in which the product was made.").[26]

Panel B of Table 6 reports the response of prices to trade with China when only taking into account U.S. goods in the CPI sample. Columns (1) and (2) show that prices for domestic goods experience a large fall, similar to the full sample, with point estimates ranging from -1.94 to -2.73 across specifications. Using the statistical decomposition, Columns (3) and (4) show that domestic prices change account for a substantial fraction of the overall price effects, between 44% and 85% depending on the specification.

Evidence from the PPI Sample. We assess the robustness of our results using the producer prices from the Producer Price Index. The PPI sample only takes into account price changes for products manufactured in the U.S. We run an IV specification identical to (3), except that the outcome variable is now the PPI inflation rate, and that the level of observation is a 6-digit NAICS code.

Panel C of Table 6 reports the results in the PPI sample. Columns (1) and (2) show that the prices of domestic U.S. manufacturers fall in response to trade with China. The point estimates are very similar to the CPI sample, ranging from -2.50 to -1.86 across specifications, and are statistically significant at the 1% level. Columns (3) and (4) show that the point estimates remain similar in magnitude, falling by about 20 to 50 basis points only, when we repeat the estimate with PPI inflation for continued products as the outcome. These results confirm the importance of continued and domestic products in accounting for the overall price effects.

IV.C The Role of Changes in Domestic Production Cost

The response of domestic prices could result from changes in production cost for U.S. manufacturers, or changes in markups. With a standard production function, cost minimization yields the change in the domestic production cost,

$$\Delta \log(c_i) = -\Delta \log(A_i) + \alpha_i^K \Delta \log(r_i) + \alpha_i^L \Delta \log(w_i) + \alpha_i^I \Delta \log(p_{I,i}), \tag{6}$$

[26] Appendix A.A describes the specification checklists and the parsing algorithms we use to retrieve countries of origin from text entries. Appendix Table A5 reports summary statistics on the number of product categories with explicit flags for country of origin.

where A_i is total factor productivity, the factor shares $\alpha_i^K, \alpha_i^L, \alpha_i^I < 1$ sum to one. r_i is industry i's rental rate for capital, $w_i$is industry i's wage, and $p_{I,i}$ is the price of a composite bundle of intermediate inputs to industry i. We now investigate whether changes in domestic production costs across industries can account for the price effects across industries, using various proxies for the terms in equation (6).

Imported 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 an industry's change in import penetration from China happens to be correlated with changes in Chinese import competition faced by that industry's domestic suppliers. Similarly, if the industry sells to other domestic producers, then the Chinese import penetration measure could be correlated with import competition faced by downstream industries. Conceptually, exposure to rising import penetration from China via buyer-supplier linkages could be a source of omitted variable bias across product categories.[27]

To examine whether buyer-supplier linkages affect our results, we first compute the correlations between our baseline measure of import competition and indirect exposure via domestic suppliers or domestic buyers. The results are reported in Figure 4 and Appendix Table A21.[28] We find that the correlations are positive but small: when the import penetration rate from China increases by 1 percentage point in industry j, the share of intermediate inputs from China in industry j's total output increases by only ten basis points, and there is only a 2 basis point increase in import competition via domestic buyer industries.

In Panel A of Table 7, we directly establish that the price effects are not driven by I-O linkages by repeating our IV specification from equation (3) while controlling for indirect exposure to trade with China via suppliers or buyers. Controlling for supplier and buyer effects in turn (Columns (2) and (3)) or jointly (Column (4)) yields stable point estimates hovering between -2.89 and -3.24, which are very close to the baseline result of -2.94 in Column (1).

Next, we highlight standard quantitative models with intersectoral linkages predict much smaller price effects than our IV estimates. To introduce intersectoral linkages into the Melitz-Chaney model of Section IV.A, we follow Caliendo and Parro (2015) and assume that firms use a linear production technology using labor and intermediate inputs: $y_{ij}^s(z) = A_i^s z \left(l_{ij}^s\right)^{\gamma^s} \Pi_{s'=1}^S \left(m_{ij}^{s'}\right)^{\gamma^{s,s'}}$,

[27] Note that our focus is to investigate the observed relationship between changes in trade and changes in prices *across industries*. This exercise is conceptually different from an assessment of the role of intermediate inputs in the gains from trade (for example, see Ossa (2015)).

[28] Appendix C.B discusses the data construction steps.

where m^s_{ij} denotes the composite intermediate good from sector s used in production by firm i, and $\gamma^s + \widetilde{\gamma}^s = 1$, where $\widetilde{\gamma}^s \equiv \sum_{s'=1}^{S} \gamma^{s,s'}$ denotes the share of intermediate inputs in value-added. Given our empirical finding that industries that are more exposed to import competition are only slightly more exposed to the imported intermediate inputs channel (Figure 4), we assume that the change in the price index for intermediates experienced by a given sector is smaller than the price change of the sector itself. This assumption delivers the bound on the IV estimate reported in Corollary 1.2.

Corollary 1.2 ***[bound for changes in import shares and exact price indices with intersectoral linkages].*** *Assuming that* $\sum_{s'} \gamma^{s,s'} d\log(P_{s'}) < \widetilde{\gamma}^s d\log(P_s)$ *and that the distribution of firms' productivity is Pareto with shape parameter* θ*, then supply shocks for trading partner* f *induce a cross-sector relationship in the domestic economy between import shares and consumer price indices which, in general equilibrium with endogenous wages and entry-exit, satisfies:*

$$\frac{d\log(P_s)}{dS_{sd}} < \frac{1}{\theta \cdot (1 - \widetilde{\gamma}^s) \cdot S_{sd}}.$$

Proof: see Appendix B.A.3.

Corollary 1.2 shows that, with intermediate inputs, equation (4) needs to be adjusted by a factor $(1 - \widetilde{\gamma}^s)$. According the the BEA input-output table, in our sample $\widetilde{\gamma}^s = 56.4\%$, implying $\frac{d\log(P_s)}{dS_{sd}} < 0.63$, which is much smaller than the IV estimate. This result formalizes the idea that intermediate inputs cannot explain the magnitude of the IV coefficient.[29]

Offshoring. Intermediate inputs may play a role independent of I-O linkages. For example, a U.S. manufacturer of water bottles could use plastic imported from China, in which case imported intermediate inputs would be accounted for by our I-O analysis above, because "plastic" and "water bottles" are distinct product categories. But if the U.S. producer offshores production to China and re-imports the finished product (i.e., the water bottle, not plastic), then the I-O analysis would not accurately account for trade-induced changes in production cost. The potential concern is that increased trade with China in an industry does not correspond to intensified import competition, but rather to an increase in "offshoring" trade between related parties.

We examine the importance of this potential channel using the related-party trade database of the U.S. Census Bureau, as in Antràs and Chor (2013). Related-party trade includes trade by U.S.

[29] Furthermore, in Appendix B.B.2 we show that given the low correlation between direct and indirect exposure to trade in Figure 4, this class of models predicts $\frac{dlog(P_s)}{dS_{sd}} < 0.30$, i.e. the upper bound in Corollary 1.2 can be viewed as conservative.

companies with their subsidiaries abroad as well as trade by U.S. subsidiaries of foreign companies with their parent companies. If offshoring drives the price effects, we expect to find larger effects (for a given increase in trade with China) in product categories where related-party trade accounts for a larger fraction of trade with China.

The share of trade with China occurring between related parties is very low during the period we study, with a median of 4% (Appendix Table A6). Although these summary statistics suggest that offshoring may not drive our results for the average category, related-party trade is important for a small fraction of product categories: the 90th percentile of the distribution of related-party shares is 38%. In Column (1) of Panel B of Table 7, we repeat our IV specification after interacting the endogenous variable with an indicator for categories with a share of related-party trade with China above the 90th percentile; the instrument is also interacted with this indicator. We find that the estimated price effects remains stable and that the interaction term is not significant.

Returns to scale and productivity. Increased import competition with China could affect domestic production costs by displacing domestic goods and reducing the scale of domestic production. To rationalize the evidence in Table 6 through decreasing returns to scale, the marginal cost of production should fall by 2% as domestic production falls by 1% (due to displacement by China). Recent empirical studies have estimated this elasticity (e.g., Costinot et al. (2019), Jaravel (2019) and Faber and Fally (2017)). They find that for tradable U.S. industries returns to scale are *increasing*, with elasticities of prices to quantities ranging between -0.1 and -0.4; we would need an elasticity of the opposite sign and five times larger in magnitude.

In our context, two mechanisms could potentially yield an elastic marginal cost of production: industry-specific factors and endogenous changes in technology. If an industry relies on industry-specific factors, then a fall in production could lead to a substantial fall in production costs, because the supply curve is inelastic for these factors. For example, capital investments may be irreversible, in which case the industry-specific rental rate of capital may fall substantially as quantities fall. According to equation (6), this effect should be particularly important for capital-intensive industries (through the term $\alpha_i^K \Delta \log(r_i)$ in equation (6)).

In Column (2) of Panel B of Table 7, we examine whether the magnitude of the price effect varies across sectors depending on their capital intensity. Using an indicator variable for industries above the median capital intensity, we find no heterogeneity in the effect.

Another possibility is that import competition may affect productivity through endogenous technology. If increased competition spurs domestic firms to adopt or invent cost-reducing technologies (e.g., Bustos (2011), Bloom et al. (2016), Aghion et al. (2018)), then change in productivity could rationalize our results, through the term $\Delta \log(A_i)$ in equation (6). However, recent evidence about the China shock in the United-States suggests that innovation by domestic firms fell in response to the shock (Autor et al. (2020a)).

To further examine the potential productivity channel, we use our IV framework to examine the response of Total Factor Productivity, as measured in the NBER-CES database for manufacturing industries.[30] In Panel C of Table 7, Columns (1) and (2) report that both TFP measures fall in response to increased trade with China, which is consistent with the evidence from Autor et al. (2020a) using patent data. We caution that the evidence on TFP should only be viewed as suggestive, because we do not have access to the underlying micro data and cannot investigate the sensitivity of the estimates to alternative measures of TFP.

Wages. Changes in wages across industries could be another reason for changes in domestic production cost. Although this channel is theoretically plausible, we find that in practice it can explain little of the evidence on domestic prices.

The first piece of evidence is that industries exposed to trade with China are not very labor intensive: the labor share of total cost is small ($\alpha_{L,i}$ in equation (6)). The NBER-CES Manufacturing database linked to our sample indicates that the share of labor in total value added for product categories within manufacturing was about 27% in our sample period. Furthermore, the share of labor in total domestic output is only 10.9%, because these industries use intermediate inputs intensively. To explain a 2% fall in domestic prices due to increased import penetration from China, the wage response should be very large, on the order of 20%.

Using worker-level administrative data is provided by Autor et al. (2014), find that a one percentage point increase in the import penetration rate from China leads to a 39.3 basis point fall in wages (Column (3) of their Table III). In Panel C of Table 7, we use public wage data from the NBER-CES and County Business Patterns databases. We find no significant wage effects, either in County Business Patterns data for all workers (Column (3)), or in NBER-CES data for production or non-production workers (Columns (4) and (5)). Although the public data is imperfect and likely fails to capture the negative effects that Autor et al. (2014) were able to estimate precisely, we can confidently rule out the large wage changes that would be required to meaningfully affect domestic production costs.

[30] The 5-factor TFP measures uses non-production workers, production workers, energy, materials and capital. The 4-factor TFP measure is calculated similarly, but using total materials cost spending rather than separating it into energy and non-energy materials. These measures attempt to capture TFPQ, as defined in Hsieh and Klenow (2009).

IV.D The Role of Changes in Markups

Having established that changes in domestic production costs are unlikely to drive the price effects, we now examine the potential relevance of markups.

Connecting the IV specification to oligopolistic competition models. 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? We first show that, in a flexible model of oligopolistic competition, the domestic price response is predicted to be of the same magnitude as the overall price response, consistent with the empirical evidence from prior sections. We then highlight that, in a stylized Cournot competition model, conventional parameter choices are consistent with the magnitude of the price response observed in the data, as well as with auxiliary evidence on the response of domestic markups.

We consider a standard setting following Edmond et al. (2015), where the economy consists of two countries, Domestic and Foreign, with a single factor of production, labor, that is in inelastic supply and immobile between countries.[31] We focus on the domestic country throughout. A representative consumer has nested-CES preferences in which oligopolistic competition arises from the existence of only a finite number of competitors within nests. Specifically, there is a continuum of sectors indexed by $s \in [0,1]$ such that consumers' utility is given by $Y = \left(\int_0^1 y(s)^{\frac{\epsilon-1}{\epsilon}} ds\right)^{\frac{\epsilon}{\epsilon-1}}$, where $\epsilon > 1$ is the elasticity of substitution across sectors. Each sector s consists of a finite number of domestic and foreign intermediate producers, such that consumers' consumption aggregator in each sector combines n_{sd} domestic and n_{sf} imported products, with $y(s) = \left(\sum_{j=1}^{n_{sd}} y_j^d(s)^{\frac{\gamma-1}{\gamma}} + \sum_{j=1}^{n_{sf}} y_j^f(s)^{\frac{\gamma-1}{\gamma}}\right)^{\frac{\gamma}{\gamma-1}}$,where $\gamma > \epsilon$ is the elasticity of substitution across goods j within a sector s. In our data, sectors correspond to ELIs.

Within a sector, firms produce using a linear production technology taking labor as an input, $y_j^i(s) = a_{sij} l_{sij}$, where producer-level productivity a_{sij} is drawn from a sector-specific distribution in each country $i \in \{d, f\}$. Firms take as given their country's wage w_i, face an iceberg trade cost τ_{si}, and pay a labor-denominator fixed cost $w_i f_{si}$ to operate in the market.

Firms compete oligopolistically within a sector. We first derive a proposition based on a nonparametric representation of oligopolistic competition using markup elasticities, as in Amiti et al. (2019a). Let p_{sij} and μ_{sij} denote respectively the price and markup of firm j from country i in sector s. A change in a firm's marginal cost passes-through into its own price at a rate given by $\frac{1}{1+\Gamma_{sij}}$, where $\Gamma_{sij} \equiv -\frac{\partial \log(\mu_{sij}(.))}{\partial \log(p_{sij})}$ is the firm's "own-price markup elasticity". Under monopolistic

[31] This setting is also very close to Atkeson and Burstein (2008).

or perfect competition, $\Gamma_{sij} = 0$.

We now perturb the equilibrium with a change in Foreign's marginal costs of production. Proposition 2 provides a decomposition isolating the role of domestic prices, and gives a bound for the change in the domestic price index, relative to the overall price index, in response to these supply shocks. We use the following notation: P_s denotes the overall consumer price index in sector s, P_{sd} the consumer price index for domestically-produced goods in sector s, S_{sd} the expenditure share on domestically-produced goods, and S_{sf} on foreign products, S_{sij} the expenditure share on firm j from country i's output and, finally, η denotes the trade elasticity with respect to a change in costs (see equation (B24) of Appendix B.D.2).

Proposition 2 *[decomposition and bound for the price response in an oligopolistic competition model].* *Perturbing the equilibrium with a change in Foreign's marginal production costs, the first-order approximation to the cross-sector relationship between inflation for domestic consumers and changes in the import penetration rate from Foreign is:*

$$\frac{d\log(P_s)}{dS_{sf}} = \frac{-1}{(\gamma-1)S_{sd}} + \frac{d\log(P_{sd})}{dS_{sf}},$$

with

$$\frac{d\log(P_{sd})}{dS_{sf}} = \frac{-1}{(\gamma-1)S_{sd}} \sum_{j=1}^{n_{sd}} \omega_{sdj} \frac{\Gamma_{sdj}}{1-S_{sdj}},$$

where weights are defined by $\omega_{sdj} = \frac{S_{sdj}\frac{1-S_{sdj}}{1-S_{sdj}+\Gamma_{sdj}}}{\sum_{j'=1}^{n_{sd}}\left(S_{sdj'}\frac{1-S_{sdj'}}{1-S_{sdj'}+\Gamma_{sdj'}}\right)}$.

Moreover, the difference between the overall price index and the price index for domestic products satisfies the following bounds:

$$0 \leq \frac{-d\log(P_s)}{dS_{sf}} - \frac{-d\log(P_{sd})}{dS_{sf}} \leq \frac{1}{\eta \cdot S_{sd}}.$$

Proof: see Appendix B.D.2.

The first part of Proposition 2 shows that the overall price response can be decomposed into two terms: while the first term is analogous to the Melitz-Chaney model, capturing the substitution between domestic and foreign goods as in Proposition 1, the second term reflects the domestic price response due to changes in domestic markups, which is equal to zero when markups are constant, i.e. markup elasticities are null.

The second part of Proposition 2 delivers a specific testable quantitative prediction, holding in a general model of oligopolistic competition with unrestricted firm heterogeneity. Indeed, the response of the domestic price index is predicted to be smaller than (in absolute value) but very close to the change in the overall price index, with an upper bound for the difference of $\frac{1}{\eta \cdot S_{sd}}$.[32] With $\eta = 4.25$ (Simonovska and Waugh (2014)) and $S_{sd} = 1 - 0.0452$ (Acemoglu et al. (2016), for 1999), we obtain that the response of the domestic price index must be within 0.25pp of the overall price response, which is in line with our results in Tables 2 and 6.[33] This prediction stands in contrast with models where the domestic price response stems from intermediate inputs, where the predicted domestic price response is much smaller, as shown in Corollary 1.2.

Next, to assess whether conventional parameter values in oligopolistic price-setting models are consistent with the magnitude of our empirical estimates, we consider a stylized, tractable setting in which one U.S. producer and one Chinese producer compete in each sector. The magnitude of the price response, in terms of observables and elasticities, is given by Corollary 2.

Corollary 2 ***[price effects in a stylized head-to-head Cournot competition model].*** *Assuming head-to-head Cournot competition between Domestic and Foreign within each sector, the first-order approximation to the cross-sector relationship between inflation for domestic consumers and changes in the import penetration rate from Foreign is:*

$$\frac{d\log(P_s)}{dS_{sf}} = \frac{1 + \Gamma_{sd}/S_{sf}}{(1-\gamma)S_{sd}}, \tag{7}$$

with

$$\Gamma_{sd} = \frac{(\gamma - \epsilon)S_{sf}}{\gamma(\epsilon - 1) + (\gamma - \epsilon)S_{sf}}(\gamma - 1)S_{sd}.$$

Proof: see Appendix B.D.3.

As in Atkeson and Burstein (2008) and Edmond et al. (2015), Cournot competition implies that markups depend on firms' market shares. Domestic markups fall as the market share of the foreign producer increases. The magnitude of the fall in markups is governed by Γ_{sd}, which depends on expenditure shares and the elasticities γ and ϵ. We calibrate γ, ϵ and the relative productivity of Domestic and Foreign in order to match (i) our IV estimate of 1.91 using equation (7), (ii) the trade elasticity $\eta = 4.25$ (Simonovska and Waugh (2014)) using equation (B24) in Appendix B.D.2, and (iii) the foreign expenditure share, set to $S_{sf} = 0.0452$ (Acemoglu et al. (2016), for 1999).

[32] Given our assumption, in line with Edmond et al. (2015)'s benchmark model, that there is no entry or exit, the theoretical price indices in Proposition 1 are equal to the measured price indices in our data. For a discussion of the potential divergence between theoretical and measured price index, see Sections IV.A and B.A.3.

[33] The domestic CPI price response is -1.94 (Col. 2 of Panel B of Table 6) and the overall CPI response is -2.23 (Col. 3 of Panel A of Table 2). These point estimates are statistically indistinguishable and the difference between them is 0.29pp, very close to the bound derived in Proposition 2.

We obtain $\gamma = 8.72$ and $\epsilon = 1.43$, which is close to conventional parameters in the literature.[34] Moreover, these estimates imply a value for the markup elasticity $\Gamma_{sd} = 0.59$, which is very close to the untargeted benchmark empirical estimate $\widehat{\Gamma_{sd}} = 0.62$ of Amiti et al. (2019a).[35] These results show that, with standard parameter choices in oligopolistic price-setting models and with a level of markup elasticities consistent with auxiliary empirical evidence, the magnitude of the reduced-form relationship we estimate is expected to be one order of magnitude larger than in the Melitz-Chaney model.[36]

Intuitively, Chinese producers reduce prices when they experience a positive productivity shock, which leads U.S. producers to also reduce prices due to strategic interactions. Because of the U.S. price response, the equilibrium change in the spending share on the product from China is lower than it would be absent this price response. As a result, the relationship between changes in import penetration from China and price changes can be large. Having established that the markup channel can plausibly explain large price effects, we now conduct specific tests to assess its empirical relevance.[37]

The Response of Estimated Markups. We examine whether estimated markups for domestic producers fall in response to increased trade with China. We follow the methodology of De Loecker et al. (2020) to estimate markups for publicly-listed firms in Compustat.[38] In this sample, indexing firms by i and years by t, the gross markup can be written $\mu_{it} = \theta^v \cdot \frac{SALES_{it}}{COGS_{it}}$, where θ^v is the elasticity of output to variable inputs, which multiplies the ratio of sales to the cost of goods sold. Intuitively, the gross markup corresponds to the ratio of the consumer price to the producer's shadow value of an additional unit of output.

Although the production approach to markup estimation has well-known limitations (e.g., Raval (2019)), it provides an instructive test for our purposes. Estimated markups from the Compustat sample can be used to test two predictions from the theoretical framework introduced above. First,

[34] For example, in a rich structural model with firm heterogeneity, Edmond et al. (2015) obtain $\gamma = 10.5$ and $\epsilon = 1.24$. Estimating a full structural model with oligopolistic competition and firm-level heterogeneity is beyond the scope of our paper.

[35] We obtain the benchmark estimate from Table 1, Column 5 of Amiti et al. (2019a): their coefficient for the passthrough of changes in marginal cost is $\hat{\alpha} = 0.616$, implying $\hat{\Gamma} \equiv 1/\hat{\alpha} - 1 = 0.6234$.

[36] The results with Betrand competition instead of Cournot are similar (Appendix B.D.3). Although a full-fledged quantitative analysis is beyond the scope of this paper, the calibration results from the stylized Cournot and Bertrand competition models suggest that oligopolistic competition model can deliver an IV estimate of the correct order of magnitude.

[37] In Appendix B.E, we show that models featuring endogenous markups through Variable Elasticity of Substitution (VES) preferences, as Arkolakis et al. (2019), predict a domestic price response that is one order of magnitude too small relative to our IV estimates.

[38] We compute gross markups over time for each firm in the Compustat sample and we aggregate the firm-level data to 6-digit NAICS codes, using sales weights.

do we observe a fall in estimated markups as trade with China increases in a product category? Second, do we see a larger response at the top of the markup distribution?

Panel A of Table 8 present the results of the analysis with estimated markups as the outcome. We repeat our IV specification (3) over two periods (1991-1999 and 2000-2007), but the level of aggregation is now a 6-digit NAICS code (instead of an ELI) and the outcome is the annualized change in the net markup (instead of the annualized inflation rate). Expressed in percentage points, the net markup is defined as $\tilde{\mu}_{it} = (\mu_{it} - 1) \cdot 100$. Column (3) reports the IV coefficient: when the import penetration rate from China increases by one percentage point, domestic markups fall by 1.75 percentage points (s.e. 0.848). This estimate is statistically indistinguishable from the IV coefficients for the response of domestic prices (from Table 6).

Panel (a) of Figure 5 reports this relationship for the average markup. Futhermore, Panels (b), (c) and (d) of Figure 5 document changes in the distribution of markups across industries that are differentially exposed to increased trade with China. Panel (b) shows that there is no change at the bottom of the markup distribution: the reduced-form is flat for the 10th percentile of markups. In contrast, there is a negative relationship for the 50th percentile (Panel (c)), and the relationship becomes steeper for the 90th percentile (Panel (d)). Consistent with the predictions of oligopolistic competition models, the response of markups is much stronger at the top of the markup distribution. Finally, Panels (e) and (f) of Figure 5 show that profitability ratios deteriorate in industries that are more exposed to trade with China.[39] Appendix C.C discusses additional results.

Heterogeneity by market structure. To collect evidence beyond the sample of publicly-listed Compustat firms, we now assess whether heterogeneity in the estimated price effects *across* product categories is consistent with the predictions of the markup channel. We can (indirectly) test for the relevance of the markup channel by studying heterogeneity in the IV estimates across subsamples.

First, per Proposition 2 and Corollary 2, the predicted price effect is increasing in the domestic markup elasticity. The markup elasticity depends on market structure and can therefore vary across industries. In a model with firm heterogeneity, it can be shown that is larger when the domestic market is more concentrated. This prediction is intuitive: when the domestic market is more concentrated, an increase in import competition from China disrupts domestic market power relatively more, therefore we expect to estimate larger price effects. Second, the expression for the

[39]These results are consistent with the findings of Autor et al. (2020a), who document a negative cross-industry relationship between rising import penetration from China and firms' book values and stock market values (their Table 1). The fact that profitability deteriorates in sectors more exposed to rising trade with China is an additional piece of evidence suggesting that falling production costs do not drive the domestic price response.

predicted effect in Corollary 2 shows that the magnitude of the effect is decreasing in China's initial market share (starting from an equilibrium with a small spending share on Chinese goods, as in the data). Intuitively, there is less room for China to disrupt market power (at the margin) in an industry where it already has a high market share.

To measure domestic market concentration, we work with the PPI sample. The PPI sample frame provides weights for "value of shipments" for each establishment, therefore we are able to construct a Herfindahl index directly from the sample, instead of linking external data on market concentration. We create two indicator variables, one for product categories with a Herfindahl index above the median and one for product categories with an initial import penetration rate from China above the 75th percentile. We then implement our IV specification in subsamples and with interaction terms, interacting the indicator variables with the endogenous variable and the instrument.

Panel B of Table 8 presents the results. The specifications with interactions in Column (1) and the subsample specifications in Columns (2), (3) and (4) show that, in response to increased trade with China, PPI inflation falls more in product categories that are more concentrated and falls less in categories that were initially more exposed to trade with China. The interaction terms in Column (1) are precisely estimated and significant at the 1% level. In the subsample of categories with domestic concentration below median (Column (3)), the point estimate is close to the prediction of Arkolakis et al. (2012). Appendix C.C shows that the results are similar with CPI data.

Overall, the observed heterogeneity in price effects across product categories suggest that markup responses are an important explanatory mechanism.

V The Distributional Effects of the China Shock

In this section, we discuss how our estimates help shed light on the distributional effects of the China shock.

V.A Displaced Jobs vs. Consumer Surplus

While we have documented that prices decline in U.S. industries with rising import penetration, numerous studies have shown that increasing import penetration rates from China have disrupted the U.S. labor market (e.g, Autor et al. (2013), Autor et al. (2014), Acemoglu et al. (2016), and Pierce and Schott (2016)). Employment declines in U.S. industries more exposed to rising import competition, which is detrimental to displaced U.S. workers who are not able to transition costlessly to another industry.

Using our IV estimates, we can characterize the tradeoff between rising consumer surplus and displaced jobs across industries.[40] If the import penetration rate from China increases by one percentage point more in industry A than in industry B, what is the impact on (relative) consumer surplus and jobs in these two industries? We can answer this question using IV estimates for the price effects (denoted β_{price}) and the employment effects (denoted β_{emp}), provided that they are scaled properly.

A first-order approximation to the change in consumer surplus (in dollars) from the trade shock for industry j is given by $\Delta CS_j = \left(\frac{-\beta_{price}}{100}\Delta ChinaIP_j\right) \cdot Cons_j$, where "$Cons_j$" is total consumption (or "domestic absorption") for industry j and "$\frac{-\beta_{price}}{100}\Delta ChinaIP_j$" is the fall in prices induced by industry j's trade shock. Similarly, the number of displaced jobs is $\Delta Jobs_j = \left(\frac{-\beta_{emp}}{100}\Delta ChinaIP_j\right) \cdot Emp_j$, where Emp_j is total employment in industry j.

Assuming that industries A and B initially have the same levels of total consumption and employment, if import penetration increases by one percentage point more in A than in B, the tradeoff between rising consumer surplus and displaced jobs in A relative to B is given by

$$\frac{\Delta CS_j}{\Delta Jobs_j} = \frac{\beta_{price}}{\beta_{emp}} \cdot \frac{Cons_j}{Emp_j}. \tag{8}$$

If product category j employs few workers but accounts for large share of aggregate consumption, then a large amount of consumer surplus can be created per displaced job, as long as β_{price} and β_{emp} are similar.

Panel A of Table 9 reports informative summary statistics about the ratio $\frac{Cons_j}{Emp_j}$, focusing on the set of ELIs within goods only (for which we obtain data on domestic absorption and employment from the NBER-CES Manufacturing database). The summary statistics are reported for 2000, at the outset of the China shock. The first row shows that average annual labor earnings in the sample are about \$33,000 on average. Because the labor share is low, the average value-added of domestic producers per job is higher, around \$120,000 (row 2). And because these product categories use a lot of intermediate inputs, total domestic sales per job is much higher, about \$305,000 on average (row 3). Finally, since trade is important for consumption in these product categories, total domestic

[40] The partial-equilibrium calculations in this section reflect differences in exposure to rising import penetration from China across industries. GE effects could affect all industries. For example, there could be job reallocations, not merely job destructions (Bloom et al. (2019)). If displaced manufacturing jobs lead to more job creation in other industries, then the increase in consumer surplus per "destroyed" job would be larger than the increase in consumer surplus per "displaced" job. In this sense, not adjusting for job reallocation is conservative for our purposes.

absorption per job is even higher, approximately \$390,000 per job (row 4).

For comparability with the estimated price effects, we run IV specifications for employment in our sample. We repeat specification (3) with the log change in employment as the outcome. We estimate that a one percentage point increase in import penetration from China leads to a fall in employment of 1.83% with the NTR gap instrument, 1.77% with the change in import penetration in other developed economies, and 1.82% with both instruments (Appendix Table A8). The estimates are similar whether we consider all employment, or production workers and non-production workers separately; the magnitudes are in line with prior work (e.g., Table 2 of Acemoglu et al. (2016)).

Panel B of Table 9 characterizes the tradeoffs between rising consumer surplus and displaced jobs across industries, using our IV estimates and equation (8). Because the ratio $\frac{Cons_j}{Emp_j}$ varies across industries, the tradeoff depends on which industry is affected by rising import competition.

We first consider a counterfactual increase in the import penetration rate from China of one percentage point for a representative industry with the average ratio of total consumption to employment (in our sample of goods). We compute $\frac{\Delta CS}{\Delta Jobs} = \frac{\beta_{price}}{\beta_{emp}} \cdot \frac{\sum_j Cons_j}{\sum_j Emp_j}$. In Column (1), with the NTR gap instrument, consumer surplus increases by \$477,555 for each job displaced by trade with China. The estimate remains large, at \$317,383, when using trade with China in other developed economies as the instrument (Column (2)). With both instruments, the estimate yields \$411,464 in consumer surplus per displaced job (Column (3)).

Next, we repeat these calculations by focusing on the industries that were affected by the rise in import penetration from China between 2000 and 2007. If the ratio $\frac{Cons_j}{Emp_j}$ is systematically higher or lower for affected industries, the tradeoff between consumer surplus and employment for the historical China shock could differ from what the previous analysis suggests. We compute $\frac{\Delta CS}{\Delta Jobs} = \frac{\beta_{price}}{\beta_{emp}} \cdot \frac{\sum_j \Delta ChinaIP_j \cdot Cons_j}{\sum_j \Delta ChinaIP_j \cdot Emp_j}$, i.e. the consumption-to-employment ratio is computed with rising import penetration from China as weights. The results are reported in Columns (4) to (6) of Panel B of Table 9. They are slightly attenuated compared to the baseline but remain very large in magnitude, ranging from \$288,147 to \$433,565 across specifications.[41]

Thus, our estimates imply that product categories that are more exposed to trade with China create hundreds of thousands of dollars in consumer surplus for each displaced job. Using the predicted price effects from the class of standard trade models nested by Arkolakis et al. (2012), the increase in consumer surplus would be attenuated by a factor of ten and would be on the order

[41]The implications of declining markups for U.S. producer surplus are ambiguous: if markups reflect market power and economic profit, then producer surplus may have fallen; but if markups merely offset fixed costs such that a zero-profit condition holds, then there is no change in producer surplus.

of \$40,000 per displaced job, which is similar to average annual labor earnings in this sample.[42]

V.B Distributional Effects via the Expenditure Channel

Finally, we examine whether the price response differs across product categories that cater to households of different income levels.

A growing literature characterizes the distributional effects of trade through the expenditure channel, focusing on differences in spending shares on imports across consumer groups (e.g., Fajgelbaum and Khandelwal (2016), Borusyak and Jaravel (2021), He (2018), and Hottman and Monarch (2020)). We investigate a distinct mechanism: does the rate of pass-through of trade shocks into consumer prices vary systematically with consumer income?

We proceed in two steps. First, we repeat our IV strategy in subsamples of product categories catering to different income groups; second, we use these new estimates to quantify whether this mechanism has a substantial impact on distributional effects across income groups.[43]

We start by running our IV specification (3) in subsamples of product categories whose expenditure shares vary across groups of consumers. For robustness, we split the sample around the median using three alternative variables reflecting consumer income: the share of sales to college graduates, the expenditure elasticity, and the shares of sales to households with an annual income above \$60,000.[44]

The results are reported in Panel A of Table 10. The price effects are large and significant in all subsamples, but they are much larger in product categories that sell to lower-income households. Columns (1) and (2) show that the point estimate for product categories with a share of sales to college graduates above median is only 21% (= 0.91/4.28) of the point estimate for the categories below median. The difference is similar when splitting by expenditure elasticity (0.83/4.62 = 18.3%, in Columns (3) and (4)), while it is attenuated when splitting by the share of sales to households with income above \$60,000 (1.18/2.93 = 40.2%, in Columns (5) and (6)).[45]

[42] In Appendix Table A9, we compute the equivalent variation for increased trade with China from 2000 to 2007, for the average U.S. household. We find that in 2007 the (annual) purchasing power of the representative U.S. household was about \$1,500 higher, thanks to lower prices induced by increased trade with China from 2000 to 2007. Assuming that prices do not revert back in the longer run, this result indicates that the China shock increased the purchasing power of U.S. households by about 2%.

[43] In a sample of consumer packaged goods, Bai and Stumpner (2019) examine whether price responses to trade shock differ across income groups *within* the same detailed product category (e.g., between different varieties of beer) and find no difference. In contrast, we document substantial heterogeneity in price responses *across* product categories that tend to target different income groups (e.g., between beer and wine).

[44] We use the spending shares from the CEX for the year 2000, as processed by Borusyak and Jaravel (2021). We match the CEX consumption categories (UCCs) to ELI as explained in Online Appendix A.C.

[45] Because we split the sample, the first-stage F statistics fall. The table reports the results with LIML, which yields very similar point estimates and alleviates concerns about weak instruments. To maximize power, we use both

Next, we examine whether the estimated heterogeneity in price effects implies substantial distributional effects across income groups. We compute a first-order approximation to the equivalent variation from a change in prices for each consumer group i, expressed as a percentage of initial expenditures for each group,

$$EV_i = \sum_j s_j^i \hat{p}_j,$$

where s_j^i is the expenditure share by consumer group i on product category j, and $\hat{p}_j$ is the percentage change in product category j's price index that is induced by the trade shock. We compute this price change as $\hat{p}_j = \frac{\beta_j}{100}\Delta ChinaIP_j$, where β_j is our IV estimate for j (which can vary across product categories as in Panel A of Table 10) and $\Delta ChinaIP_j$ is the increase in import penetration rate from China in j between 2000 and 2007.

We compute the difference in the equivalent variation for high-income and low-income groups, standardized by the average equivalent variation across groups, given by

$$\Delta_i EV \equiv \frac{EV^{HI} - EV^{LI}}{EV^{All}} = \frac{\sum_j \left(s_j^{HI} - s_j^{LI}\right)\beta_j \Delta ChinaIP_j}{\sum_j s_j^{All}\beta_j \Delta ChinaIP_j}.$$

Intuitively, income group i benefits more if it spends more on categories that are more exposed to rising trade with China ($\Delta ChinaIP_j$) and that feature a larger price response to the shock (β_j).[46]

Panel B of Table 10 reports the results. Column (1) imposes a homogeneous price response to trade shocks, using our baseline estimate for β for all categories (-1.91%, from Table 2). We find that higher-income groups benefit proportionally more from increased trade with China: 6.19% more for college-educated households relative to those without a college degree; 8.39% more for households earnings above \$60,000 a year relative to those earning less; and 14.53% more for households earning above \$100,000 relative to below \$30,000.

These differences result from the fact that, between 2000 and 2007, import penetration from China increased faster in product categories that sell relatively more to higher-income groups (e.g., in consumer electronics rather than in food products). This finding is confirmed in Column (4) in a sample restricted to goods only (including services tends to attenuate the differences, because higher-income groups spend more on services and services are not exposed to trade with China). These patterns are consistent with prior work by Borusyak and Jaravel (2021).

instruments jointly. The Hansen J statistics indicate that we cannot reject the overidentifying restrictions. We obtain similar results with interaction terms in a single specification, instead of repeating the analysis in subsamples.

[46] As shown in these formulas, when we compare the effects across consumer groups we difference out any GE effect affecting all product categories. For this reason, our cross-industry IV estimates are well-suited for the estimation of distributional effects: although they cannot recover aggregate GE effects without additional assumptions, they characterize cross-industry effects accurately.

In Column (2), we allow the price response to vary across product categories, depending on the share of sales to households earning above \$60,000 a year, as in Panel A of Table 10. In this case, the patterns are *reversed* and higher-income groups now benefit proportionally *less*: 9.64% less for college relative to non-college; 19.54% less for those earnings above \$60,000 relative to those below; and 23.13% less for those above \$100,000 relative to below \$30,000. In Column (3), these differences are magnified, ranging from 13.94% to 36.29%, when we specify heterogeneous price effects using the estimates based on expenditure elasticities (because with these estimates, the price effects are even larger for low-income groups, as shown in Panel A of Table 10).

Columns (5) and (6) confirm these findings in the sample of goods: with heterogeneous pass-through of the trade shocks from China, higher-income groups benefit relatively less, while they benefit relatively more with homogeneous pass-through. The patterns are similar when using heterogeneous pass-through rates by the share of sales to college-educated households (not reported).

Taken together, these findings indicate that accounting for heterogeneous price responses across product categories can be important to accurately characterize the distributional effects of trade via the expenditure channel.

VI Conclusion

This paper has presented new evidence on the price effects of trade by leveraging a comprehensive price data set from the Bureau of Labor Statistics. Most previous work on the "China shock" emphasized its detrimental consequences for U.S. employment. Our findings convey a different message: the price effects of trade with China were large and beneficial to U.S. consumers. We estimate that falling prices in product categories that were more exposed to trade with China created hundreds of thousands of dollars in consumer surplus for each displaced job. These prices effects are particularly large in product categories selling to low-income consumers.

Our estimates of the impact of rising import penetration on consumer prices are much larger than predicted by standard quantitative trade models such as Melitz (2003)-Chaney (2008) and other members of the Arkolakis et al. (2012) class. We showed that there is a large fall in *domestic* prices, driven by intensified competition and declining markups. By disrupting domestic market power, trade can have substantial price effects that benefit consumers. These findings highlight the importance of including endogenous markups and strategic pricing into quantitative trade models used for policy analysis. In a period of rising concentration and rising markups in the United States (Autor et al. (2020c), De Loecker et al. (2020)), the pro-competitive effects of trade may be particularly valuable to U.S. consumers.

While the costs of free trade are disproportionately borne by particular workers, industries, and regions, the large magnitude of the price effects suggest that it may be possible to compensate those who suffer from the labor market impacts of trade shocks. Developing and testing such redistribution schemes is a particularly promising direction for research and policy going forward.

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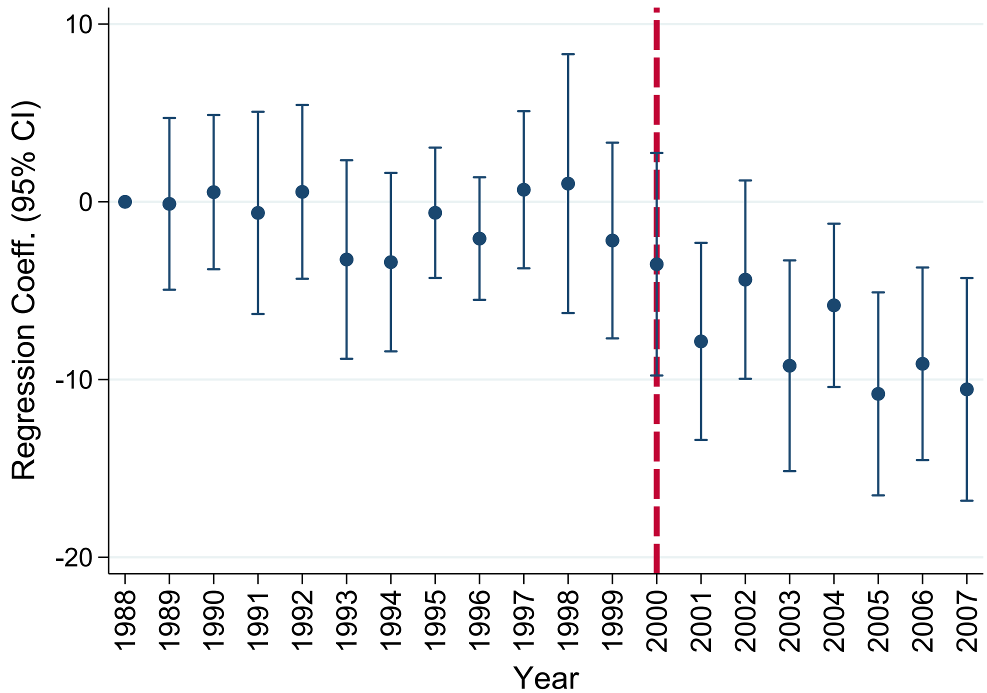
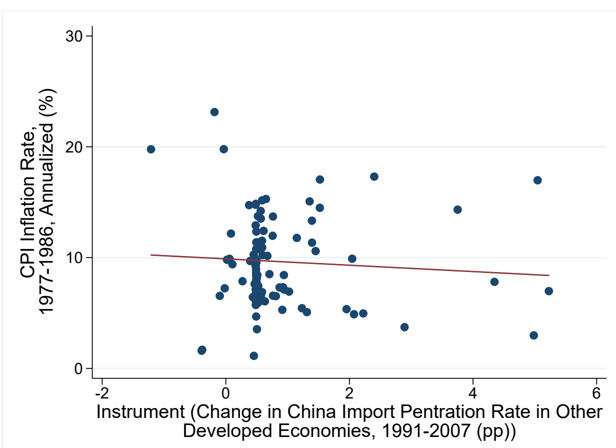
Figure 1: Testing for Pre-trends

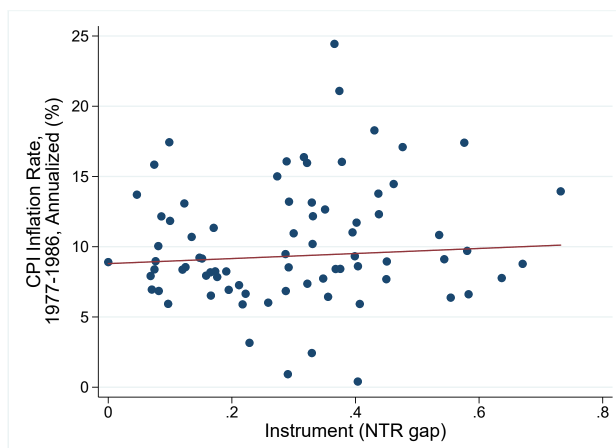
Panel A: Event Study for NTR Gap in Main Analysis Sample



Panel B: Placebo Reduced-Forms in Extended CPI Sample



(a) China IP in other developed economies

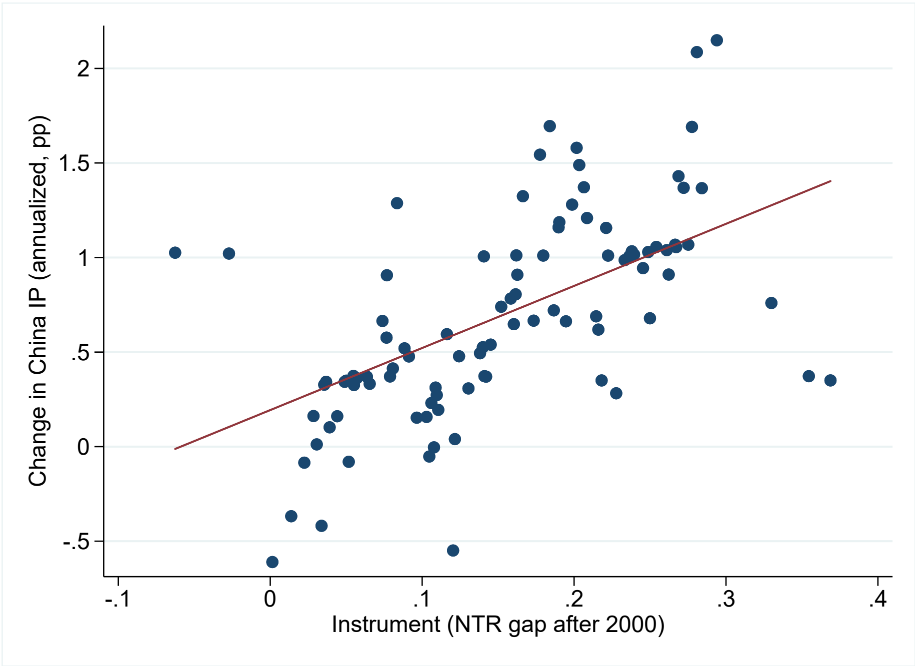


(b) NTR gap

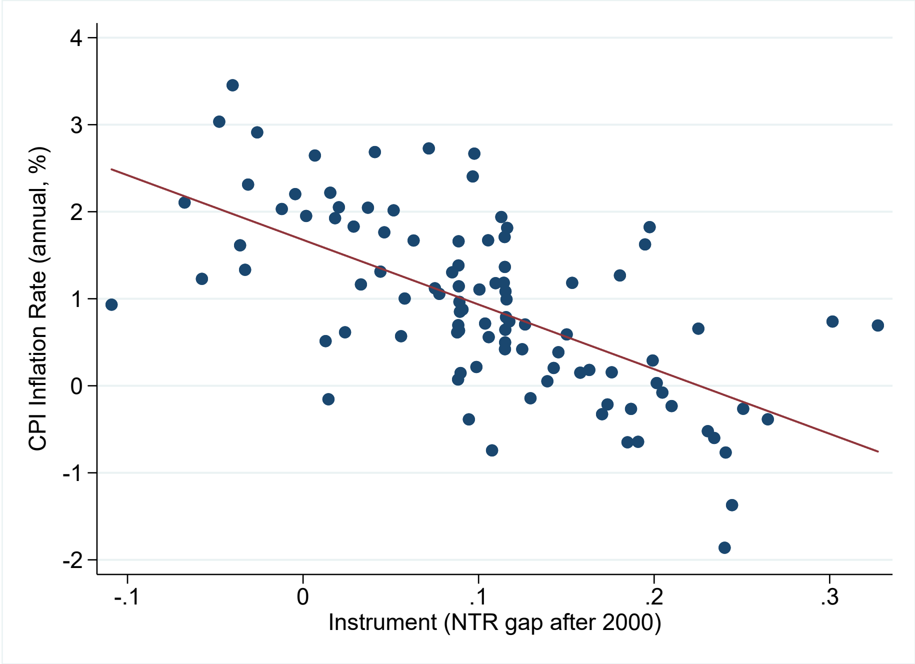
Notes: Panel A reports the estimates from the specification described in equation (2). Panel B reports the binned scatter plots for the reduced-form specifications in the extended CPI sample. Each dot represents 1% of the data and the OLS best-fit line is reported in red. The level of observation is an ELI.

Figure 2: IV Estimates with the NTR Gap

Panel A: First Stage



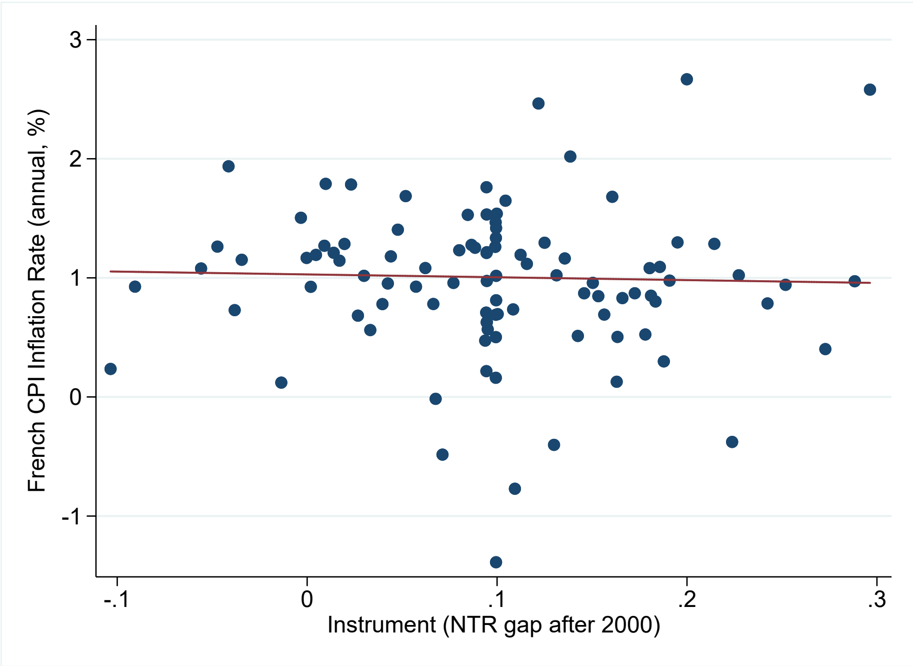
Panel B: Reduced-Form



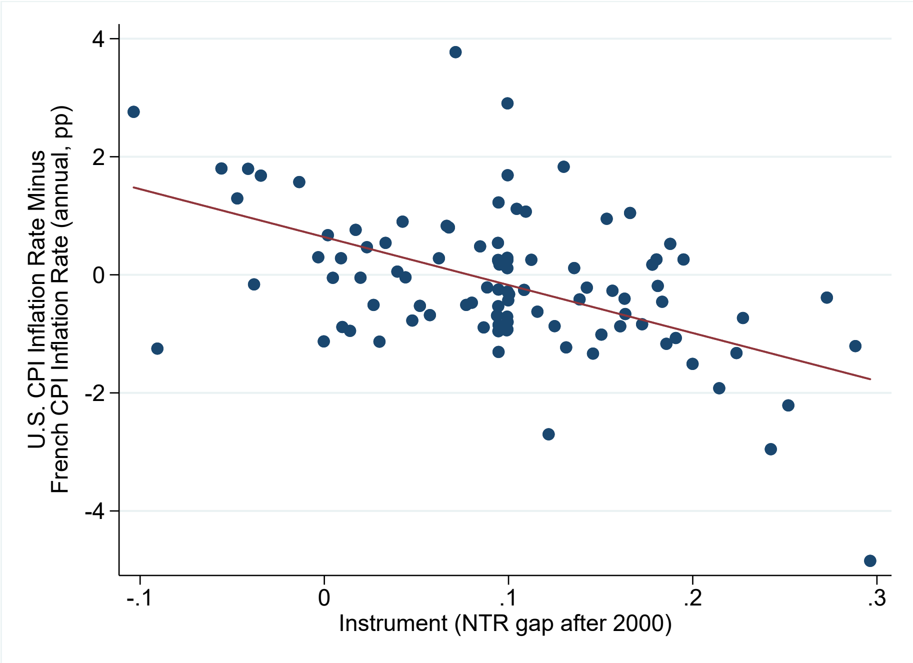
Notes: This figure reports the binned scatter plots for the first-stage (Panel A) and reduced-form (Panel B) relationships of the IV strategy using the NTR gap as an instrument. Each dot represents 1% of the data and the OLS best-fit line are reported in red. The level of observation is an ELI-by-period cell. Consumption weights are used for the OLS best-fit line.

Figure 3: Falsification Tests with the French CPI Data

Panel A: Placebo Reduced-Form



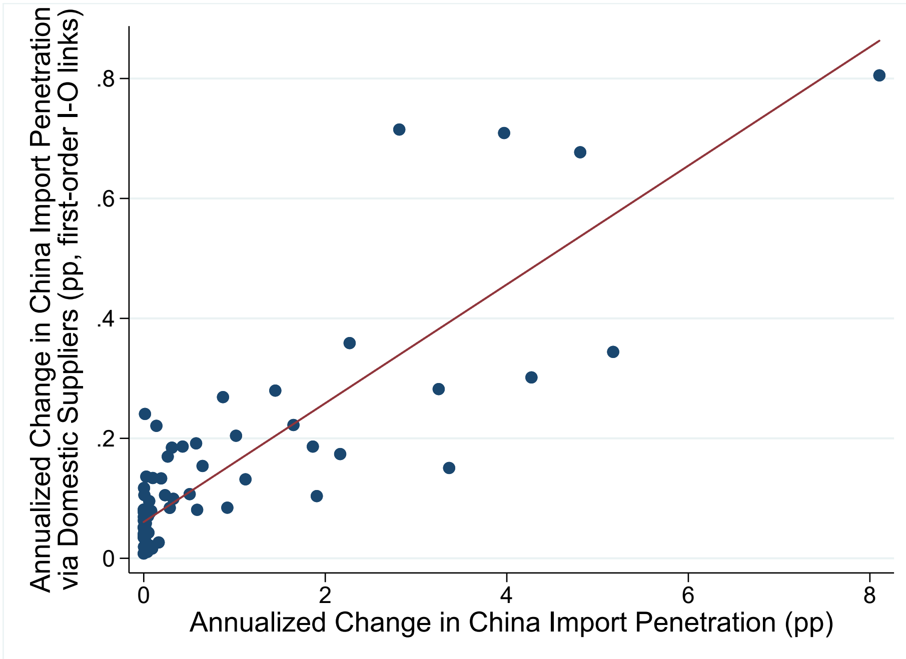
Panel B: Reduced-Form for Triple-Difference Specification



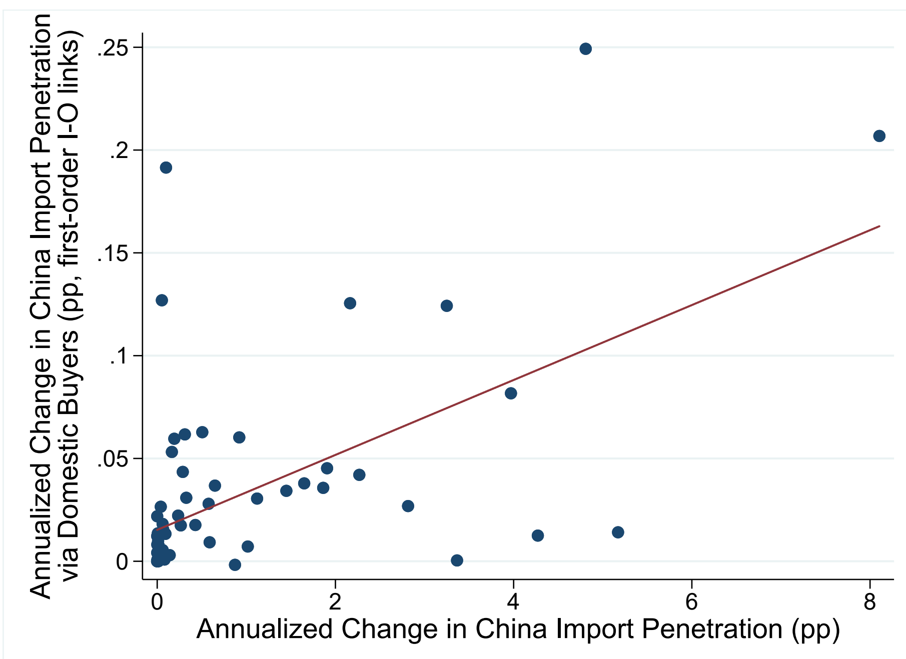
Notes: This figure reports the binned scatter plots for reduced-form relationships for the placebo test and triple difference, using the NTR gap as an instrument in the linked US-French CPI sample. Each dot represents 1% of the data, using consumption weights, and the OLS best-fit line is shown in red.. The level of observation is a COICOP-by-period cell.

Figure 4: The Role of Input-Output Linkages for Exposure to Trade with China

Panel A: Relationship between Direct Import Competition and Exposure via Domestic Suppliers



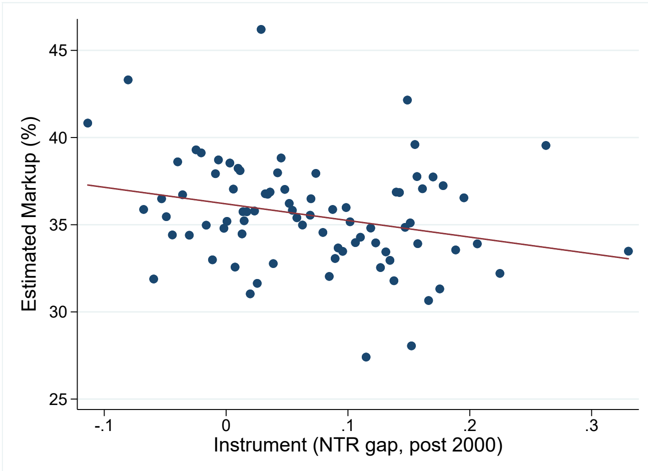
Panel B: Relationship between Direct and Indirect Import Competition



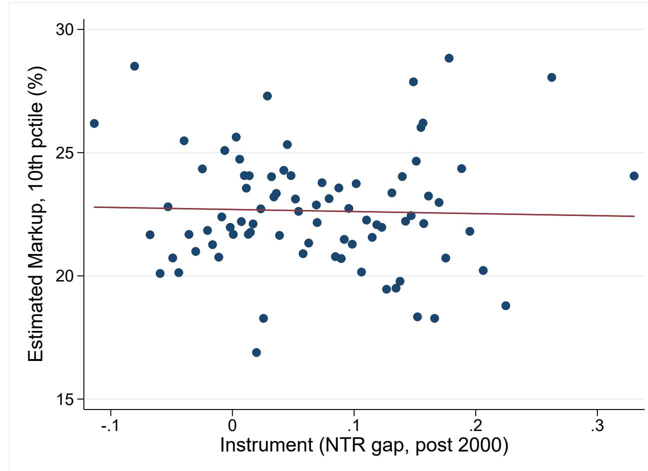
Notes: This figure shows the relationship between direct and indirect exposure to trade with China via domestic suppliers (Panel A) and buyers (Panel B). The level of observation is a 6-digit IO industry-by-period. Each dot represents 1% of the data, using consumption weights, and the OLS best-fit line is shown in red.

Figure 5: The Role of Markups

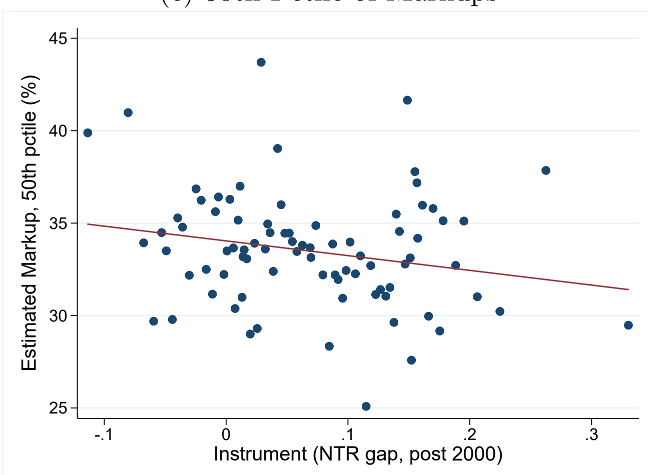
(a) Average Markup



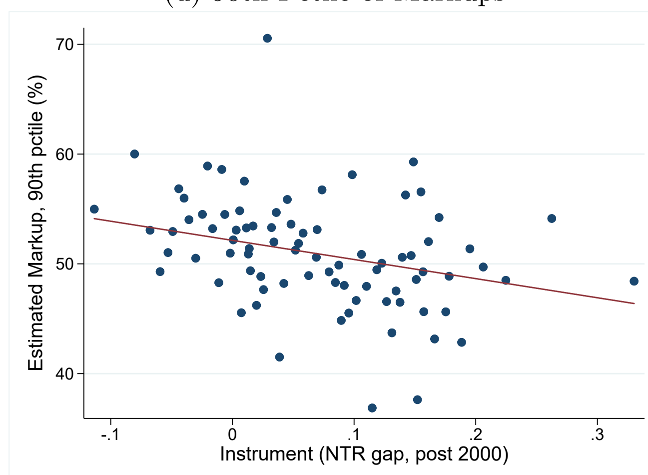
(b) 10th Pctile of Markups



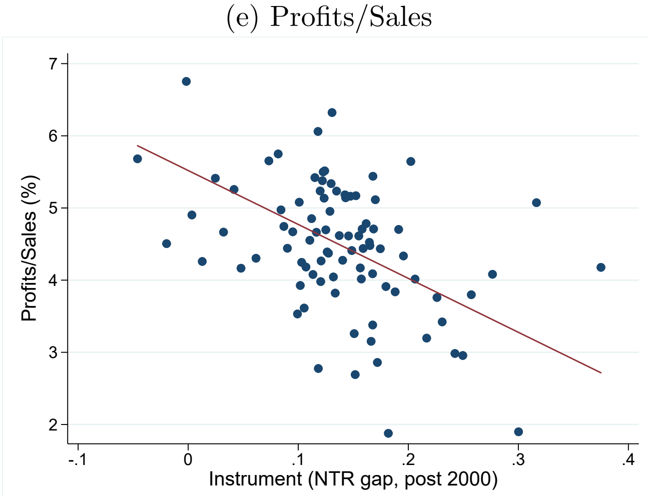
(c) 50th Pctile of Markups



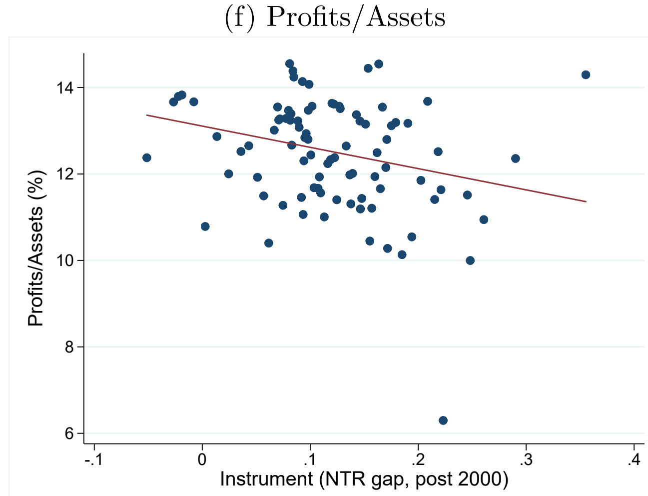
(d) 90th Pctile of Markups



(e) Profits/Sales



(f) Profits/Assets



Notes: This figure reports the reduced-form relationships in the Compustat sample, described in Section IV.D. Each dot represents 1% of the data, with consumption weights. The level of observation is a NAICS industry-by-period.

Table 1: Summary Statistics

	Mean	S.D.	p10	p50	p90	Observations	
						N	Aggreg. Level
Inflation, all (%)	1.15	6.75	-7.48	2.21	7.57		
Share of continued products (%)	80.75					3,774	ELI-by-year
Share of unavailable products	4.92						
ΔChina IP in U.S. (pp, annualized)	0.66	1.62	0.00	0.00	2.63	444	ELI-by-period
ΔChina IP in developed economies	0.47	1.07	0.00	0.01	1.63		
NTR Gap	0.21	0.21	0.00	0.13	0.55		
Share of Goods	0.78						
Share of Durables	0.18					222	ELI
Share of Apparel	0.11						
Share of High Tech	0.08						

Notes: This table presents summary statistics for the main variables used in the analysis, which are described in Sections II.A and II.B. The sample covers years 1991 to 2007, which are divided into two periods: 1991-1999 and 2000-2007. Depending on the variable, the level of observations is an ELI-by-year, an ELI-by-period, or an ELI.

Table 2: Baseline Instrumental Variable Estimates

Panel A: With the NTR Gap

	Δ China IP (pp)	U.S. CPI Inflation (pp)			
	OLS	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)
NTR Gap	3.33^{***}	-7.43^{***}			
	(0.54)	(2.21)			
Δ China IP (pp)			-2.23^{***}	-0.90^{***}	-2.15^{***}
			(0.47)	(0.32)	(0.77)
First-stage F			38.14		23.13
ELI F.E.	✓	✓	✓	✓	
Period-specific Goods F.E.	✓	✓	✓	✓	
2000-2007 only					✓
Goods, Durables & Apparel F.E.					✓
N	444	444	444	444	222

Panel B: With the Change in Import Penetration from China in Other Developed Economies

	U.S. CPI Inflation (pp)		
	IV	IV	IV
	(1)	(2)	(3)
Δ China IP (pp)	-1.44^{***}	-1.27^{***}	-1.91^{***}
	(0.45)	(0.28)	(0.38)
First-stage F	26.23	405.69	27.34
Hansen J			0.21
ELI F.E.	✓		✓
Period-specific Goods F.E.	✓		✓
2000-2007 only		✓	
Goods, Durables & Apparel F.E.		✓	
Instruments:			
Δ China IP Other	✓	✓	
NTR Gap & Δ China IP Other			✓
N	444	222	444

Notes: The specifications are described in Section III.C. The level of observation is an ELI-by-period cell. The sample includes all ELIs from 1991 to 2007, with variables averaged over two periods, 1991-1999 and 2000-2007. Consumption weights are used. Standard errors are clustered by ELIs. *** denotes statistical significance at the 1% level.

Table 3: Robustness of IV Estimates

Panel A: Specifications with Alternative Sets of Controls

	U.S. CPI Inflation (pp)					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ China IP (pp)	-2.75^{***}	-1.78^{***}	-2.26^{***}	-2.49^{***}	-2.10^{***}	-2.94^{**}
	(0.79)	(0.59)	(0.48)	(0.61)	(0.62)	(1.43)
First-stage F	30.23	24.01	37.50	26.59	23.19	9.541
Major Category F.E.	✓					
ELI F.E.		✓	✓	✓	✓	
Period-specific Goods F.E.	✓	✓	✓	✓	✓	✓
Durables & Apparel Time-Varying F.E.		✓				
Excluding Deflationary ELIs			✓			
Time-varying controls for High-tech, Contract intensity and Union membership					✓	
1990s inflation by period F.E.				✓		
6-digit IO Fixed Effects						✓
Instrument: NTR Gap	✓	✓	✓	✓	✓	✓
N	444	444	400	444	444	170

Panel B: Specifications with the Overall Change in Import Penetration

	Δ All IP (pp)	U.S. CPI Inflation (pp)	
	OLS	IV	IV
	(1)	(2)	(3)
Δ China IP (pp)	0.78^{***}		
	(0.15)		
Δ All IP (pp)		-3.68^{**}	-3.67^{**}
		(1.60)	(1.36)
First-stage F		27.59	18.55
ELI F.E.	✓	✓	
Period-specific Goods F.E.	✓	✓	✓
Durables & Apparel Time-Varying F.E.	✓	✓	✓
Instrument: NTR Gap		✓	✓
N	444	444	444

Notes: The level of observation is an ELI-by-period cell and the sample includes all ELIs from 1991 to 2007, with variables averaged over two periods, 1991-1999 and 2000-2007. Column (5) of Panel A is an exception: the data is aggregated from ELIs to 6-digit industries defined in the BEA's IO table. Consumption weights are used. Standard errors are clustered by ELIs or 6-digit IO industries. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table 4: Falsification Tests with the French CPI Data

Panel A: Placebo IV in France

	Δ China IP (in U.S., pp)	U.S. CPI Inflation (pp)	French CPI Inflation (pp)		
	OLS	IV	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)
NTR Gap	3.22***	−2.59***	−0.24		
	(0.71)	(0.904)	(1.82)		
Δ China IP (in U.S., pp)				−0.074	−0.27
				(0.38)	(0.91)
First-stage F		20.71		20.71	15.73
COICOP F.E.	✓	✓	✓	✓	
Period-specific Goods F.E.	✓	✓	✓	✓	
2001-2007 only					✓
Goods, Durables & Apparel F.E.					✓
N	264	264	264	264	132

Panel B: Triple-Difference IV

	Δ China IP (in U.S., pp)	U.S. Infl. *Minus* French Infl. (pp)		
	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)
NTR Gap	3.22***	−8.12**		
	(0.71)	(3.27)		
Δ China IP (in U.S., pp)			−2.52**	−2.08**
			(1.09)	(0.93)
First-stage F			20.71	15.73
COICOP F.E.	✓	✓	✓	
Period-specific Goods F.E.	✓	✓	✓	
2000-2007 only				✓
Goods, Durables & Apparel F.E.				✓
N	264	264	264	132

Notes: The specifications are described in Section III.D. The level of observation is a COICOP-by-period cell, with variables averaged over two periods, 1991-1999 and 2000-2007. Consumption weights are used. Standard errors are clustered by COICOPs. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table 5: IV Estimates with the Log Domestic Expenditure Share

	U.S. CPI Inflation		
	IV	IV	IV
	(1)	(2)	(3)
Δ Log Domestic Expenditure Share	2.57***	3.46**	3.10***
	(0.9601)	(1.411)	(0.961)
First-stage F	13.211	17.197	11.599
Hansen J			0.568
Instruments:			
NTR Gap	✓		✓
Δ China IP Other		✓	✓
N	444	444	444

Notes: This table reports the IV estimates with the log change in the domestic expenditure share as the endogenous variable (the choice of the endogenous variable is the only difference with equation (3) in the main text). As described in Section II.A, the trade data is measured at the level of HS codes, while the domestic production data comes from the NBER-CES Manufacturing database. Column (1) uses the NTR gap instrument, Column (2) uses the change in the import penetration rate from China in other developed economies, and Column (3) uses both instruments jointly. The Hansen J statistic in Column (3) indicates that we cannot reject the overidentification restriction. Consumption weights are used. Standard errors are clustered by ELIs. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table 6: The Roles of Continued and Domestic Goods

Panel A: IV Estimates for Continued Goods in Main Sample (CPI)

	U.S. CPI Inflation, Continued Products (pp)		Contribution to U.S. CPI Inflation (pp) *[%]*	
	(1)	(2)	(3)	(4)
Δ China IP (pp)	-3.00^{***}	-3.23^{***}	-1.54^{***} *[69%]*	-1.54^{***} *[72%]*
	(0.79)	(1.62)	(0.46)	(0.74)
ELI F.E.	✓		✓	
Period-specific Goods F.E.	✓		✓	
2000-2007 only		✓		✓
Goods, Durables & Apparel F.E.		✓		✓
N	444	222	444	222

Panel B: IV Estimates for Domestic Goods in Main Sample (CPI)

	U.S. CPI Inflation, Domestic Products (pp)		Contribution to U.S. CPI Inflation (pp) *[%]*	
	(1)	(2)	(3)	(4)
Δ China IP (pp)	-1.94^{***}	-2.73^{***}	-0.98^{**} *[44%]*	-1.82^{***} *[85%]*
	(0.59)	(0.96)	(0.42)	(0.63)
ELI F.E.	✓		✓	
Period-specific Goods F.E.	✓		✓	
2000-2007 only		✓		✓
Goods, Durables & Apparel F.E.		✓		✓
N	444	222	444	222

Panel C: IV Estimates for Continued and Domestic Goods in PPI Sample

	U.S. PPI Inflation (pp)		U.S. PPI Infl., Continued Products (pp)	
	(1)	(2)	(3)	(4)
Δ China IP (pp)	-2.50^{**}	-1.86^{**}	-2.02^{**}	-1.66^{**}
	(1.01)	(0.78)	(0.93)	(0.81)
First-stage F	19.22	20.07	19.22	20.07
NAICS F.E.	✓		✓	
Period-specific Goods F.E.	✓		✓	
2000-2007 only		✓		✓
Goods, Durables & Apparel F.E.		✓		✓
N	550	275	550	275

Notes: Panel A and B use the main analysis sample, while panel C uses the PPI sample. The specifications are described in Section IV.B. In all panels, the instrument is the NTR gap and the level of observation is an industry-by-period cell. First-stage F statistics in Panel A and B are the same as in Table 2. Standard errors are clustered by industries. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table 7: Mechanisms

Panel A: Indirect Exposure to Trade with China

	U.S. CPI Inflation (pp)			
	(1)	(2)	(3)	(4)
Δ China IP (pp)	-2.943^{**}	-3.214^{**}	-2.892^{**}	-3.241^{**}
	(1.435)	(1.539)	(1.427)	(1.582)
First-stage F	9.541	6.691	8.727	6.270
Controls:				
Δ China IP Supplier (pp)		✓		✓
Δ China IP Buyer (pp)			✓	✓
6-digit IO F.E.	✓	✓	✓	✓
Period-specific Goods F.E.	✓	✓	✓	✓
N	170	170	170	170

Panel B: Offshoring and Returns to Scale

	U.S. CPI Inflation (pp)	
	(1)	(2)
Δ China IP (pp)	-1.685^{***}	-2.01^{***}
	(0.403)	(0.70)
Δ China IP ×Interaction	-0.074	0.43
	(1.274)	(0.71)
First-stage F	9.403	8.05
Interacted indicators:		
Related Trade > p90	✓	
Capital Intensity > Median		✓
Period-specific Goods F.E.	✓	✓
Durables & Apparel Time-Varying F.E.	✓	✓
N	306	306

Panel C: Wages and Total Factor Productivity

	TFP Growth (pp)		Wage Growth (pp)		
	4-factor TFP	5-factor TFP	All	Production	Non-production
	(1)	(2)	(3)	(4)	(5)
Δ China IP (pp)	-0.629^{**}	-0.632^{**}	0.0806	0.0856	0.4105
	(0.290)	(0.292)	(0.1249)	(0.1726)	(0.2994)
First-stage F	24.155	24.155	26.328	26.328	26.328
Period-specific Goods F.E.	✓	✓	✓	✓	✓
Durables & Apparel Time-Varying F.E.	✓	✓	✓	✓	✓
N	300	300	306	306	306

Notes: In Panel A, the level of observation is a 6-digit IO industry-by-period cell. In Panels B and C, the level of observation is an ELI-by-period cell. The sample is restricted to ELIs that can be matched to the NBER-CES Manufacturing database.In all panels, the instrument is the NTR gap.*** denotes statistical significance at the 1% level, ** at the 5% level.

Table 8: The Role of Markups

Panel A: The Response of Estimated Markup in Compustat Sample

	Δ China IP (pp)	U.S. Markups (pp)	
	OLS	OLS	IV
	(1)	(2)	(3)
NTR Gap	5.414^{***}	-9.52^{***}	
	(1.051)	(4.34)	
Δ China IP (pp)			-1.75^{**}
			(0.848)
First-stage F			26.49
NAICS F.E.	✓	✓	✓
Period-specific Goods F.E.	✓	✓	✓
N	796	796	796

Panel B: Heterogeneity by Market Structure in PPI sample

	U.S. PPI Inflation (pp)				
	Interacted Specs.	Subsample Specs.			
	(1)	(2)	(3)	(4)	(5)
Δ China IP (pp)	-0.47^{***}	-3.47^{***}	-0.31	0.18	-1.88^{**}
	(0.26)	(1.72)	(0.40)	(0.57)	(0.82)
Δ China IP×High Concentration	-1.70^{**}				
	(0.96)				
Δ China IP×High China IP	2.31^{**}				
	(1.08)				
First-stage F	111.85	209.20	174.75	26.10	296.58
NAICS F.E.	✓	✓	✓	✓	✓
Period-specific Goods F.E.	✓	✓	✓	✓	✓
Subsample	All	High Conc.	Low Conc.	High China IP	Low China IP

Notes: In both panels, the level of observation is a 6-digit NAICS-by-period cell. Panel A uses the Compustat sample while Panel B uses the PPI sample. In Panel B, "High Concentration" product categories have a level of domestic market concentration above median in 1997 (resp. below for "Low Concentration"). "High China IP" product categories have an import penetration rate from China above the 75th percentile in 1999 (resp. below for "Low China IP"). Standard errors are clustered by 6-digit NAICS industries.*** denotes statistical significance at the 1% level, ** at the 5% level, * at the 10% level.

Table 9: Consumer Surplus per Displaced Job across Product Categories

Panel A: Summary Statistics across Product Categories (year 2000, goods only)

	Total	S.D.	p10	p50	p90
Average Labor Earnings ($)	33,305	10,276	21,318	28,875	43,321
Value-Added of Domestic Producers ($) / Job	121,897	179,052	55,531	98,172	268,606
Total Sales of Domestic Producers ($) / Job	305,250	262,578	103,795	225,279	545,720
Domestic Absorption ($) / Job	390,998	376,320	150,591	357,974	625,686
$N = 174$					

Panel B: Estimates of Consumer Surplus per Displaced Job

	Uniform 1pp Increase in Import Penetration from China			Observed Change in Import Penetration from China, 2000-2007		
	(1)	(2)	(3)	(4)	(5)	(6)
Consumer Surplus per Displaced Job, $	477,555	317,383	411,464	433,565	288,147	373,562
IV Estimates:						
- NTR gap: $\beta_{price} = -2.23$ $\beta_{emp} = -1.834$	✓			✓		
- ΔChina IP Other: $\beta_{price} = -1.44$ $\beta_{emp} = -1.774$		✓			✓	
- Both: $\beta_{price} = -1.91$ $\beta_{emp} = -1.815$			✓			✓

Notes: Panel A presents summary statistics for ELIs matched to the NBER-CES Manufacturing database. Panel B presents estimates of consumer surplus per displaced jobs in this sample, 2000 dollars. Columns (1) to (3) use $\frac{\beta_{price}}{\beta_{emp}} \cdot \frac{\sum_j Cons_j}{\sum_j Emp_j}$, and columns (4) to (6) use $\frac{\beta_{price}}{\beta_{emp}} \cdot \frac{\sum_j \Delta ChinaIP_j \cdot Cons_j}{\sum_j \Delta ChinaIP_j \cdot Emp_j}$.

Table 10: Distributional Effects via the Expenditure Channel

Panel A: IV Estimates across Subsamples

	U.S. CPI Inflation (pp)					
	(1)	(2)	(3)	(4)	(5)	(6)
2SLS: Δ China IP (pp)	-4.28^{***}	-0.91^{***}	-4.62^{**}	-0.83^{**}	-2.93^{***}	-1.18^{***}
	(1.59)	(0.35)	(1.94)	(0.40)	(1.00)	(0.41)
LIML: Δ China IP (pp)	-4.57^{***}	-0.93^{**}	-5.42^{**}	-0.84^{**}	-3.18^{***}	-1.22^{***}
	(1.80)	(0.37)	(2.61)	(0.42)	(1.17)	(0.43)
First-stage F	6.80	8.64	3.07	12.13	10.01	7.39
Hansen J	0.31	0.40	0.64	0.23	0.08	0.36
Above/below median?	$<$	$>$	$<$	$>$	$<$	$>$
Splitting variable	Sales Share to College Educ.		Expenditure Elasticity		Sales Share to Inc. $>$ \$60k	
ELI F.E. & period F.E.	✓		✓		✓	
N	166	166	166	166	166	166

Panel B: Estimates of Distributional Effects

	All Product Categories			Goods Only		
	(1)	(2)	(3)	(4)	(5)	(6)
Distributional Effects, $\frac{EV^{HI}-EV^{LI}}{EV^{All}}$:						
- College vs. non-college	6.19%	-9.64%	-13.94%	19.46%	3.20%	-1.22%
- Income above vs. below \$60k	8.39%	-19.54%	-26.60%	17.47%	-10.03%	-16.98%
- Income above \$100k vs. below \$30k	14.53%	-23.13%	-36.29%	26.97%	-9.35%	-22.04%
IV Estimates:						
- Homogeneous	✓			✓		
- Heterogeneous by sales share to inc. $>$ \$60k		✓			✓	
- Heterogeneous by expenditure elasticity			✓			✓

Notes: Panel A reports the results of IV specifications across subsamples, which are described in Section V.B. The level of observation is an ELI-by-period. Standard errors are clustered by ELIs. *** denotes statistical significance at the 1% level, ** at the 5% level. Panel B reports the estimates of distributional effects across groups, using the formula $\frac{EV^{HI}-EV^{LI}}{EV^{All}} = \frac{\sum_j (s_j^{HI}-s_j^{LI})\beta_j \Delta ChinaIP_j}{\sum_j s_j^{All}\beta_j \Delta ChinaIP_j}$, described in Section V.B.

For Online Publication

Appendix to "What Are the Price Effects of Trade? Evidence from the U.S. and Implications for Quantitative Trade Models"

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Contents

A Data Appendix

A.A Consumer Price Index Data

This section contains information about the Consumer Price Index (CPI). For additional information, we refer the reader to chapter 17 of the BLS Handbook of Methods (U.S. Bureau of Labor Statistics (2018)).

Overview. 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 restricted access 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.[47] Although the number of individual prices used to construct the CPI has changed over time, the BLS currently collects data on approximately 80,000 core products and 130,000 total products per month from about 27,000 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. Descriptions of and summary statistics for the CPI-RDB in prior years of data can be found in Bils and Klenow (2004), Nakamura and Steinsson (2008), and Bils et al. (2012) who base their research on the same dataset.

The CPI-RDB contains prices and sampling weights for each individual item in the non-shelter component of the CPI. 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 222 in order to maintain a consistent definition before and after a 1998 revision to the ELI structure. Examples of ELIs are "Carbonated Drinks," "Washers & Dryers," "Woman's Outerwear," and "Funeral Expenses".

The item structure of the CPI is grouped from broadest to most narrow product category: Major Groups, Item Strata, and ELIs. The Appendix Table of Konny et al. (2019) provides the list of ELIs, item structure, item weights and number of quotes contained in the CPI as of August 2018 (note that the sample used in our paper does not draw upon post-2007 data; the full list corresponding to our sample is available upon request).

Index Construction. The BLS constructs a *matched-model* price index, which means that

[47] The CPI-RDB was extended to cover 1977-1987 by Nakamura et al. (2018).

the BLS selects a set of products and then collects the prices for those products over time. This enables the BLS to construct price changes for the same product each month. These price changes are then aggregated to construct elementary price indexes for each product category.

Sampling. The sampling frame for the non-shelter component of the CPI represents about 70% of consumer expenditures. 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 BLS uses a Point-of-Purchase survey to identify the probability that consumers visit a particular outlet within a defined geographical region. Upon selecting outlets that are representative of consumer points-of-purchase, the BLS uses data provided by individual outlets on sales by product (within the specified ELI) in unison with the Consumer Expenditure Survey to construct probabilities that each product is purchased. Therefore, products within an ELI and geographical region are chosen to be representative by outlet and by product within the outlet. In the last step of sample construction, the BLS constructs multiple representative samples of products and chooses the one that minimizes sampling error through a sample variance reduction algorithm.

Aggregation. Aggregation to the ELI proceeds as follows. Let $p_{i,t}$ be a price quote within a given product category (ELI) in a month t, and let $\omega_{i,t-1}$ be its accompanying sampling weight. Following BLS procedure, we aggregate individual price quotes to the product category level using a *Geometric Laspeyres Index* (or, as it is alternatively called, the "Geometric Mean Index"), in which quantity information is incorporated through the share of expenditures in the base period,

$$I_t \equiv \exp\left(\sum_{i=1}^{N} \omega_{i,t-1} \log\left(\frac{p_{i,t}}{p_{i,t-1}}\right)\right)$$

where N is the supposed number of price quotes collected between times $t-1$ and t, and the sampling weight $\omega_{i,t-1}$ measures product-level expenditures,[48]

$$\omega_{i,t-1} \equiv \sum_{i=1}^{N} \frac{p_{i,t-1}q_{i,t-1}}{\sum_{j=1}^{N} p_{j,t-1}q_{j,t-1}} \ .$$

Relationship between the measured CPI and consumer welfare. To relate the Geometric Laspeyres Index to the change in consumer welfare, we follow Konüs (1939), Deaton (1989) and Fajgelbaum and Khandelwal (2016) and define the change in welfare for the representative consumer as the

[48] The BLS weighting procedure for aggregation to the product category level has two components. First, the main product-level weighting is performed by BLS through probability sampling, i.e. through the selection of retail outlets and individual products within those outlets. Second, the CPI-RDB provides additional weights for each product-level price that correct for sampling error to ensure weights reflect expenditure shares.

equivalent variation $EV_{t-1,t}$ divided by initial expenditures X_{t-1}, which we denote $d\log U_t$. Considering a fixed set of products and small shocks to prices, denoted $d\log p_t \equiv log(p_{i,t}) - log(p_{i,t-1})$, the envelope theorem (Roy's identity) implies that price changes affect consumer welfare in proportion to the initial spending shares across products indexed by i, regardless of the demand system: to the first order, the change in consumer welfare is given by $d\log U_t = -\sum_{i=1}^{N} \omega_{i,t-1} d\log p_t = 1 - \sum_{i=1}^{N} \omega_{i,t-1} \left(\frac{p_{i,t}}{p_{i,t-1}}\right)$.[49] The Geometric Laspeyres Index thus provides a first-order approximation to the change in consumer welfare (see also Konus and Byushgens (1926)).[50] Changes in product variety may introduce first-order changes in consumer welfare that are not captured by the measured CPI, which we discuss in Appendix B.A.[51]

Item Rotation. New products are phased into the CPI once every four years after initial introduction to the index. In other words, about a quarter of items in the CPI are newly introduced within any given year. After the BLS identifies a new outlet and product, the new product is not included in the CPI until a price is recorded for two consecutive periods, thereby creating a record for the item's initial price change, $p_{i,t}/p_{i,t-1}$, for inclusion in the CPI.

Forced Substitutions and Imputations. When a product is unable to be priced in a given month, the BLS implements one of two types of procedures. If the product is only temporarily unavailable, then the BLS imputes a value to the missing price observation. This value tends to be the average price change of all available products, which is therefore equivalent to dropping that product's price change from the index for the period. If the product is no longer available at an outlet, then there are two types of substitutions. The first is a "comparable substitution", which replaces the previous item with one that is similar in sufficiently many dimensions to consider it the same fundamental item. In this case there is no quality adjustment applied to the prices of the new or old product versions. The second is a "non-comparable substitution", which occurs when there is no available item that is a sufficiently close substitute to the old. In this case, the BLS implements a quality

[49] This result holds under standard regularity conditions (see Borusyak and Jaravel (2021), Proposition 1).

[50] Indeed, using $\log(\frac{p_{i,t}}{p_{i,t-1}}) = \frac{p_{i,t}}{p_{i,t-1}} - 1$ and $\exp(\frac{p_{i,t}}{p_{i,t-1}} - 1) = \frac{p_{i,t}}{p_{i,t-1}}$ for small price changes, we have:

$$I_t \equiv \exp\left(\sum_{i=1}^{N} \omega_{i,t-1} \log\left(\frac{p_{i,t}}{p_{i,t-1}}\right)\right) = \exp\left(\sum_{i=1}^{N} \omega_{i,t-1}\left(\frac{p_{i,t}}{p_{i,t-1}}\right) - 1\right) = \sum_{i=1}^{N} \omega_{i,t-1}\left(\frac{p_{i,t}}{p_{i,t-1}}\right) = 1 - d\log U_t \ .$$

[51] Assuming there is no change in product variety, the Geometric Laspeyres Index is the exact price index for a CES price aggregator when the elasticity of substitution is 1. Indeed, the general CES price index is,

$$I_t^{CES} = \frac{P_t}{P_{t-1}} = \sum_{i=1}^{N} \omega_{i,t-1}\left(\frac{p_{i,t}}{p_{i,t-1}}\right)^{1-\sigma} \quad ,$$

where σ is the elasticity of substitution and the CES price aggregator is $P_t = \left(\sum_{i=1}^{N} p_{i,t}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$.

adjustment to net out the difference in price between old and new version that can be attributed to differences in underlying product characteristics. We refer the reader to Moulton and Moses (1997) for a discussion of each type of non-comparable substitution in practice. Bils et al. (2012) document that from 1990-2009 the monthly rate of forced item substitutions is approximately 3 percent and the monthly rate of temporary unavailability is 12 percent.

From the perspective of price index construction, the quality adjustment can be understood as follows. Suppose product i is currently in its v-th vintage or version. Let φ_i^v be consumers' perceived quality from version v of product i. Likewise $p_{i,t}^v$ is the price of the v-th vintage or version of product i. The quality-adjusted price is $p_{i,t}^v/\varphi_i^v$ and therefore the associated quality-adjusted price change in the absence of a substitution is,

$$\frac{p_{i,t}^v/\varphi_i^v}{p_{i,t-1}^v/\varphi_i^v} = \frac{p_{i,t}^v}{p_{i,t-1}^v} \ .$$

When the BLS initiates a substitution, it compares two versions (denote them v and $v+1$) that have different underlying product characteristics and therefore different perceived quality from consumers. The quality-adjusted price change during a product substitution from version v to version $v+1$ of product i is,

$$\frac{p_{i,t}^{v+1}/\varphi_i^{v+1}}{p_{i,t-1}^v/\varphi_i^v} = \frac{1}{\varphi_i^{v+1}/\varphi_i^v} \times \frac{p_{i,t}^{v+1}}{p_{i,t-1}^v} \ ,$$

where $\varphi_i^{v+1}/\varphi_i^v$ is the ideal quality adjustment that the BLS approximates and nets out from price change at substitution.

Product Turnover. Sample attrition can stem from both planned rotations and forced substitutions. In both cases, an exiting product is replaced by a new product in order to maintain sample size by ELI. For the typical ELI, since about 25% of products are subject to a planned rotation each year and about 5% of products face a forced substitution, a given cohort of products is characterized by the following hazard rates: about 70% are still observed after 1 years, 34% after 3 years, 17% after 5 years, and a product is rotated out after this point. Most of the attrition is due to planned rotations.

Alternative Indices*.* We leverage the price micro data to build alternative category-level price indices, which we use for various robustness tests and extensions. Alternative category-level price indices help us address potential measurement issues. For example, the baseline CPI uses quality adjustments when the BLS data collector is unable to find the exact same product in the exact same store from one period to the next (e.g., the 500 ml bottle of Coca-Cola might no longer be on the shelf at Whole Foods and might have been replaced with a 500 ml bottle of Pepsi). Given that

BLS quality adjustments may not perfectly account for potential changes in underlying product characteristics in such cases, we build an alternative price index based solely on price changes for "continued products" (i.e., those instances when the same item in the same store is observed from one period to the next). We also leverage the micro data to build alternative price indices that help decompose the sources of the price effects we document. For example, we can isolate the role of the price response of products made in the United States.[52]

Specification Checklists. When a BLS price collector prices an item for the first time, they create a detailed description of its characteristics. This description is partially contained in a pre-written checklist that ensures the price collector records information that is necessary to identify that item upon returning to the outlet, or to identify an appropriate substitute for that item if it is no longer available. A specification checklist can be also be used to prevent inconsistencies in price collection from month to month.

This paper utilizes specification checklists to identify imported goods in the CPI. For some product categories, there is an explicit field for denoting the product's country of origin (either as a pre-designed checkbox or as a write-in field). For all categories, there are open fields that price collectors use to write information that has not been explicitly coded into checkboxes and will include country of origin if the United States is not the explicit product manufacturer. Product categories that tend to contain an explicit check box for country of origin are apparel, non-perishable food items, furniture and household furnishings, electronics, and motor vehicles.[53]

The procedure by which we identify country of origin is as follows. If a checkbox exists then we can find out whether the U.S. produced the product. If not, then we must rely on a write-in text field. We use a fuzzy text match to identify country of origin in such cases. Though no special denotation is required for domestically produced products, we searched for text strings that denote domestic production such as "United States", "USA", "US", "U.S", "U.S.A", "U.SA", "US.A", "USA.", "U. S.", "domestic", "Alabama", "Alaska", "Arizona", etc. as well as state abbreviations and the names of major U.S. cities. We also searched for text strings denoting non-domestic production such as "Import", "Impt", "Imprt", "Foreign" and the names and abbreviations of possible importing countries (including countries that existed earlier in the sample but do not

[52]See Section IV for a complete discussion. Note that such robustness tests and statistical decompositions would not be possible by using the publicly-available inflation series from the BLS. Another downside of the public data from the BLS, relative to the CPI-RDB dataset, is that the publicly available product categories are coarser than ELIs and their definitions change over time; as a result it is difficult to build a balanced panel of detailed product categories over a long time horizon in this data set.

[53]In fact, the apparel industry lobbied Congress in the 1970s to require that country of origin be placed on tags by law.

exist in 2019) and foreign cities. Remaining cases for which a country of origin was not explicitly identified was assigned to the United States. To validate text matches, a random 10% sample of text fields was manually inspected and multiple text matching algorithms were implemented to ensure robustness.

Data Processing. Price collectors flag substitutions and abnormally large price changes, which analysts use to implement quality adjustments and imputations. However, in order to reduce the sensitivity of price indexes to exceptionally large price changes as well as avoid respondent disclosure (as per BLS disclosure avoidance policy) we exclude positive or negative price changes greater than 500%. These outliers occur rarely in the sample.

ELI definitions changed in 1998 and new ELIs have been introduced since 2007. There are nearly 360 ELIs between 1988-1998 and 270 ELIs after the 1998 revision of definitions. We collapse the number of ELIs to 222 in order to maintain a consistent definition before and after a 1998 revision to the ELI structure. To do this, we matched ELI categories based on the category descriptions available in the BLS' documentation for the CPI Research Database. The full list of ELIs and their average consumption weights over the sample period is available upon request.

Finally, we define a set of ELIs as *Durable Goods*, motivated by the set of products Bils (2009) studied. This set of products tend to be durables that require more use of quality adjustments than the rest of the product categories in the CPI. The ELIs in this list include "personal computers and peripherals", "telephones", "watches", "electric appliances", "refrigerator", "washers and dryers", "microwave ovens", "small kitchen appliances", "clocks", "televisions", "audio equipment", and "other video equipment"; the full list is available from Bils (2009). We use fixed effects for these durable goods to control for inflation trends that may be introduced through methodological issues in the construction of inflation measures for these products.

Data Limitations. Certain data limitations motivate the specifications we estimate. First, the CPI sampling methods limit what can be said of product variety growth over time. The CPI chooses a set of products and follows those products over time. Planned item rotations introduce new products to the sample, but the number of new items is pre-selected. While forced item substitutions could entail product turnover from old to new varieties, the number of price quotes in the CPI is not changed through forced substitution. Therefore, the CPI introduces new product varieties in a way that does not explicitly track the number of varieties in the economy's consumption set.

Second, we follow the aggregation procedures used by the BLS in constructing the CPI. This means that price change within an ELI assumes a particular elasticity of substitution, specifically a unit elasticity. This elasticity is motivated by a desire to allow for consumer substitution in utility, but without the proper data for identifying the structural elasticity of substitution in each ELI. However, this specification constitutes a general first-order approximation to the exact price indices of the quantitative models we study, which is sufficient for our main purposes. Moreover, a unit elasticity of substitution obviates us from identifying the elasticity's value in each ELI. In order to test the robustness of this assumption, we have built a CES index from the micro data, with an elasticity of substitution $\sigma = 5$ or $\sigma = 3$. The alternative elasticities of substitution yield IV point estimates that are very similar in magnitude to our headline estimates reported in Table in the main text.

Aggregation. Whenever we need to aggregate measured inflation from ELIs to a higher level of aggregation, we use weights based on Consumer Expenditure Surveys for each year from 1988–1995, 1999–2004 and 2008-2012. For all other years, we set weights equal to the most recently available year's weights (e.g., assign 1995 weights to 1997). We follow Bils and Klenow (2004), Bils et al. (2012) and Gagnon et al. (2013) in using weights based on the Consumer Expenditure Survey. These weights are also used as regression weights in the baseline specifications.

A.B Historical CPI Data

To check for pre-trends in the CPI data, it is useful to have a long time series. Accordingly, for pre-trend exercises in the CPI data we incorporate pre-1988 inflation by Entry Level Item into our analysis.

The CPI-RDB was extended to cover 1977-1987 by Nakamura et al. (2018). This data was scanned from microfilm cartridges and converted to digital format using Optical Character Recognition software. The final data set contains prices for 80,000 to 100,000 products per month. For each product, the data set contains the product's price (in level and percent change from the preceding period), a product identifier, the Entry Level Item (ELI) classifier for the product, an outlet identifier, the location of the outlet, a flag indicating whether the product was on sale, and a flag indicating whether the product underwent an item replacement procedure (and, if so, the flag indicates what type of quality adjustment or imputation was made).

Because ELI definitions changed after 1987, Nakamura et al. (2018) created a concordance that maps pre-1988 ELIs into post-1988 ELI definitions. We use their concordance to create a consistent set of ELIs across time.

A.C Crosswalks

Our data building process uses a total of eight crosswalks, including five new crosswalks we build by hand.

We build three many-to-one crosswalks to the ELI product categories that define our main analysis sample: from SIC industries to ELIs, from NAICS industries to ELIs, and from UCC consumption categories to ELIs. Because SIC, NAICS and CEX categories are significantly more detailed than ELI categories, a many-to-one match is convenient. Furthermore, we build a many-to-one match of ELIs to 6-digit IO industries from the BEA's 2007 input-output table (as the BEA's industries are a bit less detailed than ELIs). Finally, for the falsification test using French CPI data, we build a many-to-one crosswalk from the (less detailed) COICOP categories to ELIs. The match is made by hand according to a comparison of the description of the product descriptions (as well as individual item names contained in in the CPI-RDB and discussions with BLS analysts).

Finally, we rely on three crosswalks from prior work: HS to NAICS codes from Pierce and Schott (2012), NAICS to IO codes from Borusyak and Jaravel (2021), and SIC to NAICS codes from the U.S. Census Bureau.

A.D Variables based on the 2007 Input-Output Table

We use the BEA's 2007 input-output table to measure indirect exposure to trade with China. We follow the same data construction steps as in Acemoglu et al. (2016)'s study of input-output linkages, except that they use the 1992 IO table. The 2007 IO table is much more disaggregated and hence potentially more accurate.

Indirect exposure via supplier effects. For indirect exposure via supplier effects, we compute the change in the import penetration rate from China in industry j's total output. By definition this quantity will be small if value-added is a high share of industry j's output. In robustness check, we implement a similar procedure to compute the import penetration rate from China in industry j's intermediate inputs (instead of j's output). We carry out this analysis using the BEA's "Use table." In a pre-processing step, we must obtain a square industry Use Table, denoted U^I. Following the methodology of the BEA, we do so by pre-multiplying the original (non-symmetric) Use Table U by the commodity-normalized Make Table M^C (which is close to an identity matrix). The Make Table gives the share of total production of each commodity across all industries, and each of its columns sums up to one.[54]

[54] U is commodity (row) by industries (columns), while U^I is industry by industry. M^C is (row) by commodities

Indirect exposure via buyer effects. For indirect exposure via buyer effects, we compute the change in the import penetration rate from China in "buyer industries", scaled by (1 - share of industry sales to final consumers). This quantity is by definition low if an industry is primarily selling to final consumers. We carry out this analysis using the BEA's "Use table."

A.E Producer Price Index Data

This section contains information about the Producer Price Index (PPI). Further information is available from the chapter 14 of the BLS Handbook of Methods (U.S. Bureau of Labor Statistics (2018)).

Overview. We use data from the PPI's Research Database (PPI-RDB) from January 1987 to August 2008.[55] The BLS defines PPI prices as "net revenue accruing to a specified producing establishment from a specified kind of buyer for a specified product shipped under specified transaction terms on a specified day of the month." Accordingly, BLS requests (via fax or email) each establishment in the PPI sample to report the price of actual shipments transacted, as of the Tuesday of the week containing the 13th of the month. If an establishment fails to respond in a given month, the BLS price collector follows up with a phone call.

Sample Frame. The BLS collects prices from approximately 25,000 to 30,000 establishments for approximately 100,000 individual items on a monthly basis. The sample is constructed from the universe of establishments in the U.S., derived from the Quarterly Census of Employment and Wages business register that is collected in the enforcement of unemployment insurance programs in each U.S. state. Individual establishments within an industry are chosen probabilistically based on the total value of shipments, or total number of employees. Individual items are then selected by a BLS price collector during a field visit to the establishment according to value of shipment.

Industries are defined as a 6-digit NAICS category and span goods producing sectors (e.g., mining, manufacturing, agriculture, fishing, forestry, energy and construction industries) for the whole sample. Service sector industries were introduced to the PPI in 2005, which we exclude from our analysis.

Index Construction. The PPI constructs a *matched-model* price index, much like the CPI does. Once prices have been recorded for an item i at times $t-1$ and t, we can compute price change as $p_{i,t}/p_{i,t-1}$. These price changes are aggregated to the 6-digit NAICS classifications (or any high

(columns). Each column of M^C sums to one because it reflects the share of production of each commodity produced by each industry.

[55]See Nakamura and Steinsson (2008) and Goldberg and Hellerstein (2009) for additional details about the PPI-RDB.

aggregations thereof) according to a *Laspeyres* price index formula. The Laspeyres is constructed as,

$$I_t^L \equiv \frac{\sum_{i=1}^N p_{i,t} q_{i,t-1}}{\sum_{j=1}^N p_{j,t-1} q_{j,t-1}} = \sum_{i=1}^N \omega_{i,t-1} \frac{p_{i,t}}{p_{i,t-1}}$$

where

$$\omega_{i,t-1} \equiv \frac{p_{i,t-1} q_{i,t-1}}{\sum_{j=1}^N p_{j,t-1} q_{j,t-1}}$$

is item i's share of total sales in the sample from the NAICS category. To the first order, by Roy's identity the arithmetic Laspeyres index captures the change in consumer welfare caused by small price shocks.[56]

Item Rotation. Establishments continue to report prices for a given item for five to seven years on average. After these five to seven years, the BLS selects a new sample for the 6-digit NAICS industry. Like item rotation in the CPI, the new sample attempts to better reflect the structure of a particular industry in terms of establishments and products over time.

Forced Substitutions. When an item is no longer produced, or future production has incorporated a change in the product's characteristics, the BLS must initiate a substitution. If the updated product is a sufficiently close substitute for the one it replaces, then the two product versions' prices are compared directly. However, when a close substitute is not available, the BLS and the establishment choose a substitute product that possesses as similar product characteristics as possible. The BLS then implements a quality adjustment to eliminate differences in prices across products that are due to changes in underlying product characteristics. When a comparison between the new and old products is not feasible, or the respondent does not provide a price record in a given month, the BLS imputes the change in price, usually as the average price change across all products for which reliable information is available. The quality adjustment can be represented in the index by introducing notation for product quality, as in Section A.A.

Data Processing. In order to reduce the sensitivity of price indexes to exceptionally large price changes as well as avoid respondent disclosure (as per BLS disclosure avoidance policy) we exclude positive or negative price changes greater than 500%. These outliers occur rarely in the sample. Summary Statistics are reported in Appendix Table A10.

[56]Moreover, the Laspeyres index can be re-expressed as an exact CES price index (see Section A.A) with an assumed elasticity of substitution of zero, which is derived from a Leontief aggregate production technology

A.F Estimated Markups

To estimate markup in Compustat, we follow De Loecker et al. (2020). They derive expressions for markups based on observables by exploiting cost minimization of a variable input of production. Indexing firms by i and years by t in the Compustat sample, the gross markup can be written

$$\mu_{it} = \theta^v \cdot \frac{SALES_{it}}{COGS_{it}}, \tag{A1}$$

where θ^v is the elasticity of output to variable inputs, which multiplies the ratio of sales to the cost of goods sold. Intuitively, the gross markup corresponds to the ratio of the consumer price to the producer's shadow value of an additional unit of output. Using this expression, we compute gross markups over time for each firm in the Compustat sample. We then aggregate the firm-level data to 6-digit NAICS codes, using sales weights. We use the time-invariant and sector-invariant elasticity $\theta^v = 0.85$.

B Theory Appendix

B.A Connecting the IV Specification to the Melitz-Chaney Model

B.A.1 Setting

We use the setting of Melitz (2003) and Chaney (2008).

Consumer's Problem. There are n countries. A representative consumer in country j has Cobb-Douglas preferences over K product categories,

$$U_j = \prod_{k=1}^{K} \left(Y_j^k\right)^{\mu_k} \quad \text{such that} \quad \sum_{k=1}^{K} \mu_k = 1$$

Eachproduct category consists of differentiated items over which the consumer has CES preferences with an elasticity of substitution between items of $\sigma > 1$,

$$Y_j^k = \left(\sum_{i=1}^{n} \int_{\Omega_{ij}^k} y_{ij}^k(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}$$

whereΩ_{ij}^k is the set of varieties from product category k available to the consumer in country j that are produced in country i, and $y_{ij}^k(\omega)$ is the quantity of each such variety $\omega \in \Omega_{ij}^k$. The associated aggregate price for product category k is,

$$P_j^k = \left(\sum_{i=1}^{n} \left(P_{ij}^k\right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}} ,$$

where P_{ij}^k is the accompanying aggregate price of varieties from country i and is given by,

$$P_{ij}^k = \left(J_i^k \int_{z_{ij}^k}^{\infty} p_{ij}^k(z)^{1-\sigma} g_i^k(z) dz \right)^{\frac{1}{1-\sigma}} , \tag{B2}$$

and where J_i^k is the mass of firms from country i and, as discussed below, $g_i^k(z)$ is the density function over country i firms' idiosyncratic productivity. The consumer maximizes utility subject to their budget constraint. Given CES preferences over the differentiated goods, the demand function for variety ω is,

$$p_{ij}^k(\omega) y_{ij}^k(\omega) = \left(\frac{p_{ij}^k(\omega)}{P_j^k} \right)^{1-\sigma} X_j^k \tag{B3}$$

where $p_{ij}^k(\omega)$ is the price of each variety $\omega \in \Omega_{ij}^k$, and $X_j^k \equiv P_j^k Y_j^k$ is total expenditure on varieties in product category k. Total expenditures on varieties in product category k are the sum of domestically produced varieties and imported varieties from each country, $X_j^k = \sum_{i=1}^n X_{ij}^k$. Finally, S_{ij}^k is country j's expenditure share of imported goods in product category k from country i,

$$S_{ij}^k \equiv \frac{X_{ij}^k}{X_j^k} = \left(\frac{P_{ij}^k}{P_j^k} \right)^{1-\sigma} \tag{B4}$$

where the second equality holds due to the consumer demand function in equation (B3). Moreover, by Shephard's Lemma, the total change in country j's aggregate price in category k is,

$$d\log(P_j^k) = \sum_{i=1}^{n} S_{ij}^k \ d\log(P_{ij}^k) . \tag{B5}$$

Firms. Firms within a product category k are monopolistic competitors. Firms in country i have aggregate productivity A_i^k and idiosyncratic productivity $z \sim G_i^k(z)$. These firms produce a variety according to a linear production technology that takes labor as an input, $y_{ij}^k(z) = A_i^k z \ell_{ij}^k$, take the economy-wide wage w_i as given, face an iceberg cost, τ_{ij}^k, and pay a labor-denominated fixed cost $w_i f_{ij}^k$ to operate in the market, which they pay as long as their profits are positive. Firm profits are,

$$\pi_{ij}^k(z) = p_{ij}^k(z) y_{ij}^k(z) - \frac{\tau_{ij}^k w_i}{A_i^k z} y_{ij}^k(z) - w_i f_{ij}^k$$

so that, taking consumer demand in equation (B3) as given, the optimal price is,

$$p_{ij}^k(z) = \frac{\sigma}{\sigma - 1} \frac{\tau_{ij}^k w_i}{A_i^k z} . \tag{B6}$$

This implies an entry cutoff for productivity defined by $\pi_{ij}^k(z_{ij}^k) = 0$ such that,

$$z_{ij}^k = \frac{\sigma}{\sigma - 1} \frac{\tau_{ij}^k w_i}{A_i^k P_j^k} \left(\frac{\sigma w_i f_{ij}^k}{X_j^k} \right)^{\frac{1}{\sigma-1}} . \tag{B7}$$

Trade Elasticities. Expenditures on items from product category k produced in country i and sold in country j are obtained by aggregating individual firms' sales,

$$X_{ij}^k = J_i^k \int_{z_{ij}^k}^{\infty} p_{ij}^k(z) y_{ij}^k(z) g_i^k(z) dz$$

where J_i^k is the mass of firms from country i and $g_i^k(z)$ is the density function over country i firms' idiosyncratic productivity. Using equation (B6), the partial elasticity of relative trade flows from country i to j with respect to an increase in A_i^k, the aggregate productivity of country i firms,[57] which we refer to as *the trade elasticity*, is

$$\frac{\partial \log(X_{ij}^k / X_{jj}^k)}{\partial \log(A_i^k)} = (\sigma - 1) + \frac{g_i^k(z_{ij}^k) z_{ij}^k}{1 - G_i^k(z_{ij}^k)} \cdot \frac{(z_{ij}^k)^{\sigma-1}}{\int_{z_{ij}^k}^{\infty} z^{\sigma-1} \frac{g_i^k(z)}{1 - G_i^k(z_{ij}^k)} dz}$$

where the first term is the *intensive margin* change in sales and the second term is the *extensive margin* change in sales. The intensive margin indicates that firms that were already producing now make more revenue, while the extensive margin measures the additional revenue from new firms that are now producing.

If firm heterogeneity is characterized by a Pareto distribution, $G_i^k(z) = 1 - (a_i^k)^\theta z^{-\theta}$ such that $\theta > \sigma - 1$, then the trade elasticity is determined solely by the Pareto tail parameter,

$$\frac{\partial \log(X_{ij}^k / X_{jj}^k)}{\partial \log(A_i^k)} = (\sigma - 1) + \frac{\theta (a_i^k)^\theta (z_{ij}^k)^{-\theta-1}}{(a_i^k)^\theta (z_{ij}^k)^{-\theta}} \cdot \frac{(z_{ij}^k)^{\sigma-1}}{\int_{z_{ij}^k}^{\infty} z^{\sigma-1} \frac{\theta (a_i^k)^\theta z^{-\theta-1}}{(a_i^k)^\theta (z_{ij}^k)^{-\theta}} dz} z_{ij}^k \;=\; \theta \,,$$

as in Chaney (2008).

B.A.2 Proof of Proposition 1

Partial equilibrium. We first consider a case where prices change only in the country c that experienced the supply shocks — a "partial equilibrium" case, because it ignores all equilibrium changes in wages and entry-exit induced by the shock, except for entry-exit from the country i.

[57] We can analogously posit a decrease in iceberg trade costs for country i, τ_{ij}, and obtained the same trade elasticity below. The necessary condition is that all country i firms face an equal change in marginal costs under the candidate perturbation.

Using equations (B5) and (B4), we obtain the cross-industry relationship in the domestic economy between import shares and consumer price indices:

$$
\begin{aligned}
&d\log(P_j^k) = S_{ij}^k \cdot d\log(P_{ij}^k),\\
&d\log(S_{ij}^k) = (1-\sigma)(1-S_{ij}^k)d\log(P_{ij}^k),\\
&\frac{d\log(P_j^k)}{dS_{ij}^k} = -\frac{1}{(\sigma-1)(1-S_{ij}^k)}.
\end{aligned}
$$

General equilibrium. We now allow price indices to change in all countries because of wage changes and and entry-exit of firms. Without loss of generality, we use the domestic wage as the numeraire, i.e. $d\log(w_j) = 0$. As a result, the response of the domestic price index only depends on entry-exit of domestic varieties.

To characterize to change in domestic varieties, we use the productivity cutoff for entry given by equation (B7). Due to trade balance and fixed labor supply, we have $d\log(Y_j) = 0$ (since $Y_j = w_j L_j$) and $d\log(X_j^k) = 0$ (since $X_j^k = \mu_k Y$). Therefore, by equation (B7) the change in the domestic productivity thresholds is $d\log(z_{jj}^k) = -d\log(P_j^k)$. Intuitively, domestic firms exit because of increased competition, which is captured by the fall in the category-level price index P_j^k.

From equation (B2), the change in the domestic price index that is caused by this increase in the domestic entry cutoff is $d\log(P_{jj}^k) = -\frac{s^k_{z^k_{jj},j} \cdot g_j^k(z_{jj}^k) \cdot z_{jj}^k}{(\sigma-1)} d\log(P_j^k)$. When firm heterogeneity is characterized by a Pareto distribution, we have $d\log(P_{jj}^k) = -\frac{\theta+1-\sigma}{(\sigma-1)} d\log(P_j^k)$. Plugging this expression into equation (B4), we obtain:

$$
\begin{aligned}
d\log(S_{jj}^k) &= (1-\sigma)\left(-\frac{\theta+1-\sigma}{(\sigma-1)} - 1\right) d\log(P_j^k),\\
\frac{d\log(P_j^k)}{dS_{jj}^k} &= \frac{1}{(\sigma-1)\left(\frac{\theta+1-\sigma}{(\sigma-1)}+1\right) S_{jj}^k}\\
&= \frac{1}{\theta \cdot S_{jj}^k}.
\end{aligned}
$$

B.A.3 Proof of Corollary 1.1

While Proposition 1 characterized the response of the exact CES price index to foreign supply shocks, Corollary 1.1 focuses on the measured Consumer Price Index.

Connecting the measured CPI to the Melitz-Chaney exact price index. The measured CPI can formally be linked to the Melitz-Chaney model using decompositions of price responses into intensive margin and extensive margin price changes. The change in the aggregate price of country i's imports by j is

$$d\log(P_{ij}^k) = \underbrace{\int_{z_{ij}^k}^{\infty} \left(s_{ij}^k(z) g_i^k(z)\right) d\log\left(p_{ij}^k(z)\right) dz}_{\equiv d\log(I_{ij}^k)} + \underbrace{s_{ij}^k(z_{ij}^k) g_i^k(z_{ij}^k) \frac{dz_{ij}^k}{\sigma - 1}}_{\equiv d\log(E_{ij}^k)}, \tag{B8}$$

where $s_{ij}^k(z)$ is country j's expenditure share of the given variety from country i and using $d\log(J_i^k) = 0$ for all i by free entry and trade balance. The first term is the *intensive margin* price change, $d\log(I_{ij}^k)$, which gives price changes due to incumbents firms from country i in product category k. The second term is the *extensive margin* price change, $d\log(E_{ij}^k)$, which measures the price change in product category k due to entry-exit from country i firms.[58]

The intensive margin price change, $d\log(I_{ij}^k)$, corresponds to the BLS' measured price index for a given country i in a product category k. Indeed, under the BLS methodology the Cost of Living Index (COLI) is constructed as a general first-order approximation to a matched-model index.[59] Thus, the overall change in P_j^k can be decomposed into an intensive margin price change corresponding to the measured CPI, $d\log(\widetilde{P}_j^k)$,[60] and an unobserved extensive margin price change, $d\log(E_j^k)$, as,

$$d\log(P_j^k) = \underbrace{\sum_{i=1}^{n} S_{ij}^k \; d\log(I_{ij}^k)}_{\equiv d\log(\widetilde{P}_j^k)} + \underbrace{\sum_{i=1}^{n} S_{ij}^k \; d\log(E_{ij}^k)}_{\equiv d\log(E_j^k)} .$$

Connecting the IV specification to the measured CPI. Using the equation above and Proposition 1, we obtain:

$$\frac{d\log(\widetilde{P}_j^k)}{dS_{jj}^k} + \frac{d\log(E_j^k)}{dS_{jj}^k} = \frac{1}{\theta S_{jj}^k} . \tag{B9}$$

From our IV result, the first term on the left-hand side is about 2, while the right-hand side is about 0.25. Thus, to rationalize the observed IV estimate, we need $\frac{d\log(E_j^k)}{dS_{jj}^k} \approx -1.75$. Conceptually, an unobserved fall in product variety when the foreign expenditure shares decreases would mute the change in the exact price index, potentially addressing the fact that the measured price index falls about ten times more than predicted by the Melitz-Chaney model.

To assess whether this channel is plausible, we can infer the decline in product variety in foreign countries that would be required to rationalize the data, using the decline in product

[58]In Corollary 1.1 in the main text, to streamline notation we use $d\log(E_{si})$ instead of $d\log(E_{ij}^k)$.

[59]The BLS measures a first order approximation to the COLI using a geometric Laspeyres index, which by Roy's identity is the theory-consistent price index for small shocks, as discussed in Appendix A.A.

[60]In Corollary 1.1 in the main text, to streamline notation we use $d\log(\widetilde{P}_s)$ instead of $d\log(\widetilde{P}_j^k)$.

variety in the U.S. as a benchmark. Indeed, for U.S. products we can directly express the change in product variety in terms of the change in the overall price index, using equation B7, which implies $d\log(E_{jj}^k) = -\frac{\theta+1-\sigma}{\sigma-1} d\log(P_j^k)$. Setting $\theta = 4.25$ (Simonovska and Waugh (2014)) and $\sigma = 5$,[61] we obtain that the contribution of the fall in domestic varieties in equation (B9) is:

$$\begin{aligned} \frac{S_{jj}^k \cdot d\log(E_{jj}^k)}{dS_{jj}^k} &= -\frac{\theta+1-\sigma}{\sigma-1} d\log(P_j^k) \cdot S_{jj}^k \\ &= -\frac{\theta+1-\sigma}{\sigma-1}\frac{1}{\theta} = -0.0147, \end{aligned}$$

which is only 0.84% (= 0.0147/1.75) of the required change in the extensive margin that would be required to rationalize the IV estimate. To obtain $\frac{d\log(E_j^k)}{dS_{jj}^k} \approx 1.75$, the extensive margin in foreign countries should contribute over one hundred times more than domestic varieties to the increase in the exact price index, even though the import share is over five times smaller than the domestic expenditure share.[62] This result shows that it is implausible that extensive margin adjustments can explain the magnitude of our IV estimate.

A bound accounting for the price effects of entry-exit. To obtain a tighter bound on the role of extensive margin adjustments, we make the following assumptions: (i) there is no fall in the number of foreign varieties imported from the country experiencing the positive supply shock, e.g. China, which is consistent with empirical evidence (e.g., Broda and Weinstein (2006)); (ii) we assume that the entire observed fall in the import share of foreign countries (exluding the reference country with the shock, e.g, China) results from a loss of varieties. Assumption (ii) maximizes the role of unobserved changes in product variety.

Denoting by F the set of foreign countries excluding China, we use equation (B4) to infer the change in the price index:

$$d\log(P_{Fj}^k) = \frac{1}{(1-\sigma)(1-S_{Fj}^k)S_{Fj}^k} dS_{Fj}^k.$$

Assumption (ii) yields $d\log(P_{Fj}^k) = d\log(E_{Fj}^k)$, i.e. the contribution of foreign countries F to decomposition (B9) is:

$$\begin{aligned} \frac{S_{Fj}^k \cdot d\log(E_{Fj}^k)}{dS_{jj}^k} &= \frac{1}{(1-\sigma)(1-S_{Fj}^k)} \frac{dS_{Fj}^k}{dS_{jj}^k} \\ &= -0.00734 \end{aligned}$$

[61] Setting $\sigma = 5$ allows us to match the power law characterizing the upper tail of the U.S. sales distribution, with tail parameter $1 + \frac{\theta+1-\sigma}{\sigma-1} = 1.0625$ (Di Giovanni et al. (2011)).

[62] In 1999, the domestic expenditure share was 0.85 (Acemoglu et al. (2016)).

using $\sigma = 5$ as previously, $\frac{dS^k_{Fj}}{dS^k_{jj}} = 0.28$,[63] and $1 - S^k_{Fj} = 0.1048$ (Acemoglu et al. (2016) for 1999). Thus, the upper bound we obtain for foreign exit is about half of the effect of domestic exit on the exact price index, while we would need it to be one hundred times larger to rationalize the IV estimate. Starting from decomposition (B9) our upper bound for the measured CPI is:

$$\frac{d\log(\widetilde{P}^k_j)}{dS^k_{jj}} < \underbrace{\frac{1}{\theta S^k_{jj}}}_{=0.28} - \underbrace{\frac{S^k_{jj} \cdot d\log(E^k_{jj})}{dS^k_{jj}}}_{=-0.0147} - \underbrace{\frac{S^k_{Fj} \cdot d\log(E^k_{Fj})}{dS^k_{jj}}}_{=-0.00734},$$

i.e. we expect $\frac{d\log(\widetilde{P}^k_j)}{dS^k_{jj}} < 0.302$, while our IV estimates are close to 2.

Connecting the IV specification to the measured domestic CPI. We denote by $\widetilde{P}^k_{jj}$ the measured price index over domestically-produced goods.[64] Using equation (B8) and Proposition 1, we obtain:

$$\frac{d\log(\widetilde{P}^k_{jj})}{dS^k_{jj}} = 0 \ .$$

Thus, the Melitz-Chaney model predicts that the measured CPI over domestic goods should have no price response, which is inconsistent with our estimates.

B.B Connecting the IV Specification to Trade Models with Intermediate Inputs

B.B.1 Setting

To connect our IV specification to models with intermediate inputs, we use the same setting as in Section B.A.1, except that the production function includes intermediate inputs across sectors, as in Caliendo and Parro (2015) and Ossa (2015). We now have $y^k_{ij}(z) = A^k_i z \left[\ell^k_{ij}(z)\right]^{\gamma^k} \Pi^K_{k'=1} \left[m^{k'}_{ij}(z)\right]^{\gamma^{k,k'}}$, where m^k_{ij} denotes the composite intermediate good from sector k used in production by firms from country i selling in j, with $\gamma^s = 1 - \sum^S_{s'=1} \gamma^{s,s'}$.

Firms price at a constant markup $\frac{\sigma}{\sigma-1}$ over the unit cost such that the price for the good from a firm from country i in sector k selling to country j is:

$$p^k_{ij}(z) = \tau^k_{ij} \cdot \frac{(w_i)^{\gamma^k} \cdot \Pi_{k'} \left(P^{k'}_{ij}\right)^{\gamma^{k,k'}}}{A^k_i z}$$

[63] Empirically, when the import share from China increases by 1pp, as shown in Panel B of Table 3 the overall foreign expenditure share increases by 0.78 pp and there is a 0.22pp fall in the expenditure share from countries other than China, i.e. $\frac{dS^k_{Fj}}{dS^k_{jj}} = \frac{0.22}{0.78} = 0.28$.

[64] In Corollary 1.1 in the main text, to streamline notation we use $d\log(\widetilde{P}_{sd})$ instead of $d\log(\widetilde{P}^k_{jj})$.

B.B.2 Proof of Corollary 1.2

The proof of Corollary 1.2 follows the same steps as the Proof of Proposition 1.

Without intersectoral linkages. First, suppose the good are produced only with labor and materials from the same sector, i.e. there are no inter-sectoral linkages. Therefore, $d\log\left(\Pi_{k'}\left(P_{ij}^{k'}\right)^{\gamma^{k,k'}}\right) = \gamma^{k,k} d\log(P_{ij}^{k'})$. The change in the domestic productivity threshold induced by foreign supply shocks is $d\log(z_{jj}^{k}) = -(1-\gamma_{j}^{k,k}) \cdot d\log(P_{j}^{k})$. Conceptually, the fall in the cost of intermediates implies that (i) there is less domestic exit than in the baseline model without intermediates; (ii) there is a direct impact of the foreign productivity shock on the domestic price index, which falls because of the falling cost of production; (iii) there is a smaller equilibrium change in expenditure shares, because the change in the relative price of foreign and domestic varieties is smaller.

Following the same steps as in Section B.A.2, we obtain:

$$\frac{d\log(P_j^k)}{dS_{jj}^k} = \frac{1}{\theta \cdot (1-\gamma^{k,k}) \cdot S_{jj}^k}.$$

Thus, the price response for domestic consumers is magnified in a way that is proportional to the use of intermediate inputs. Empirically, while the typical industry pays a large share of its gross output to intermediate goods, 56.4% at the mean, the share for the own sector is much smaller, with $\gamma^{k,k} = 3.3\%$. With $\theta = 4.25$ and $S_{jj}^k = 0.85$,, we get $\frac{d\log(P_j^k)}{dS_{jj}^k} = 0.2862$, which is much smaller than our IV estimate.

With intersectoral linkages. With sectoral linkages, the domestic price change in an industry depends on the change in price indices in all other industries. The change in the domestic productivity threshold is $d\log(z_{jj}^k) = -(1-\gamma^{k,k}) d\log(P_j^k) + \sum_{m\neq k} \gamma^{k,m} d\log(P_j^m)$.

Empirically, when the import penetration rate from China increases by 1 percentage point in industry j, the share of intermediate inputs from China in industry$j$'s total output increases by only ten basis points. Thus, empirically industries that are more exposed to import competition are only slightly more exposed to the imported intermediate inputs channel. This fact motivates the assumption that the price change in intermediates experienced by a given industry is *smaller* than the price change of the industry itself, which we formalize by assuming $\sum_m \gamma^{k,m} d\log(P_j^m) < \widetilde{\gamma}^k d\log(P)$, denoting by $\widetilde{\gamma}^s \equiv \sum_{s'=1}^{S} \gamma^{s,s'}$ the share of intermediate inputs in value-added. Using this assumption, we obtain:

$$\frac{d\log(P_j^k)}{dS_{jj}^k} < \frac{1}{\theta(1-\widetilde{\gamma}^k) \cdot S_{jj}^k}.$$

With $\widetilde{\gamma}_j^k = 56.4\%$, we obtain $\frac{d\log(P_j^k)}{dS_{jj}^k} < 0.63$, which remains much smaller than our IV estimate.

This bound is conservative as it consider a case where price indices in $m \neq k$ fall to the same extent as the price index for k, even though import penetration is about ten times smaller. To obtain a closer approximation of the expected magnitude, we assume that $d\log(P_j^m) < \frac{dS_{jj}^m}{dS_{jj}^k} d\log(P_j^k) \forall m \neq k$, setting $\frac{dS_{jj}^m}{dS_{jj}^k} = 0.1$ as in Table A21. Then we get

$$\frac{d\log(P_j^k)}{dS_{jj}^k} < \frac{1}{\theta(1-\kappa^k)\cdot S_{jj}^k},$$

with $\kappa = \gamma^{k,k} + (\widetilde{\gamma}^k - \gamma^{k,k}) \times 0.1 = 3.3\% + (56.4\% - 3.3\%) \times 0.1 = 0.0861$. Thus, the bound is $\frac{d\log(P_j^k)}{dS_{jj}^k} < 0.3028$.

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

In this appendix, we derive our cross-industry IV specification (equation (3) in the main text) from a multi-sector version of the baseline trade model in Arkolakis et al. (2012), which parallels the setting of Armington (1969). We show that the IV specification implied by the model requires using the log change in the domestic expenditure share as the endogenous variable (as we do in Appendix Table 5), rather than the change in import penetration from China (as we do in the baseline specifications in Table 2). We start by discussing the case with a single sector, then move to many sectors.

One sector economy. There are n countries, each producing a good. Suppose that there is a representative consumer in country j with CES preferences over goods varieties $i = 1, \ldots, n$, including the domestic good (e.g., $i = j$). Let the price and quantity demanded of variety i consumed in the home country j (in our case, the United States) be denoted by p_{ij} and q_{ij}, respectively. Accordingly, the representative consumer's preferences are

$$U_j = \left(\sum_{i=1}^{n} q_{ij}^{(\sigma-1)/\sigma}\right)^{\sigma/(\sigma-1)},$$

where σ is the elasticity of substitution between varieties, and the associated price of a representative consumption bundle is

$$P_j = \left(\sum_{i=1}^{n} (w_i\tau_{ij})^{1-\sigma}\right)^{1/(1-\sigma)},$$

where we have assumed that markets are perfectly competitive within a variety so that the price p_{ij} equals the marginal cost of production, w_i, times variable trade costs of importing country i's variety, τ_{ij}. These preferences yield a standard demand function for variety i

$$X_{ij} = \left(\frac{w_i\tau_{ij}}{P_j}\right)^{1-\sigma} Y_j,$$

where X_{ij} is the expenditure on variety i in the home country j, and $Y_j \equiv \sum_{i=1}^{n} X_{ij}$ is total expenditures in country j. Accordingly, denote variety i's expenditure share in country j as $\lambda_{ij} \equiv X_{ij}/Y_j$. Finally, given marginal cost pricing and the demand structure, we can write the elasticity of relative imports with respect to variable trade costs as

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

Next, we derive an expression for the change in real income for country j with respect to a change in variable trade costs. Assume that a representative firm possesses a linear production technology that transforms labor into output of the home country's variety. Labor is the single factor of production, which is perfectly mobile across sectors but immobile across countries. Further assume that country j is endowed with L_j units of labor that receives wage rate w_j (treated as the numeraire and normalized to 1). Accordingly, define real income by $W_j \equiv Y_j/P_j$ and note that trade balance requires that $Y_j = w_j L_j$ such that $d\log(Y_j) = 0$ and $d\log(W_j) = -d\log(P_j)$.

Given that the log change in a weighted average $z = \sum_{i=1}^{n} \alpha_i x_i$ is given by $d\log(z) = \sum_{i}^{n} \frac{\alpha_i \bar{x}_i}{\bar{z}_i} d\log(x_i)$, we can express the log change in the aggregate price as,

$$\begin{aligned}
d\log(P_j) &= \frac{1}{1-\sigma}\sum_{i=1}^{n}\left[\frac{(w_i\tau_{ij})^{1-\sigma}}{\sum_{k=1}^{n}(w_k\tau_{kj})^{1-\sigma}} d\log\left((w_i\tau_{ij})^{1-\sigma}\right)\right] \\
&= \frac{1}{1-\sigma}\sum_{i=1}^{n}\left[\lambda_{ij} d\log\left((w_i\tau_{ij})^{1-\sigma}\right)\right] \\
&= \frac{1}{1-\sigma}\sum_{i=1}^{n}\left[\lambda_{ij} d\log\left(\lambda_{ij}/\lambda_{jj}\right)\right] \\
&= -\frac{1}{1-\sigma} d\log(\lambda_{jj}) + \frac{1}{1-\sigma}\sum_{i=1}^{n}\left[\lambda_{ij} d\log(\lambda_{ij})\right]
\end{aligned}$$

where the second line follows from substituting the demand function into the expression, the third line follows from noting that $w_j = 1$ and $\tau_{jj} = 1$ so that $(w_i\tau_{ij})^{1-\sigma} = \lambda_{ij}/\lambda_{jj}$, and the last line follows from the fact that the expenditure shares sum to one, $\sum_{i=1}^{n} \lambda_{ij} = 1$. Since $\lambda_{ij} d\log(\lambda_{ij}) = \lambda_{ij} \cdot d\lambda_{ij}/\lambda_{ij} = d\lambda_{ij}$, the sum over the change in shares is zero. Therefore we can write the expression for the change in real income with respect to a change in variable trade costs as,

$$d\log(W_j) = \frac{1}{1-\sigma} d\log(\lambda_{jj}).$$

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:

$$\Delta\log(W_j) = \frac{1}{1-\sigma}\Delta\log(\lambda_{jj}) \tag{B10}$$

This expression shows that the change in consumer welfare can be computed directly from the change in the domestic expenditure share, given knowledge of σ. Equation (B10) is a statement about welfare at the aggregate level, which we cannot directly test in the data, where we can only investigate patterns across detailed product categories. However, this class of trade models makes specific quantitative predictions about the strength of the relationship between prices and trade across product categories, which we derive next.

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

$$P_j = \prod_{s=1}^{S} \left(p_s^j\right)^{\eta_s},$$

where p_s^j is the price index for sector s for domestic consumers in j.

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

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

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

$$\Delta \log \left(p_s^j\right) = -\frac{1}{1-\sigma_s} \Delta \log(\lambda_{jj}^s).$$

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

$$\Delta \log \left(p_s^j\right) = \alpha - \frac{1}{1-\sigma_s} \Delta \log(\lambda_{jj}^s) + \epsilon_s^j. \tag{B11}$$

Equation (B11) corresponds to our IV specification using the log change in the domestic expenditure share as the endogenous variable, as we do in Appendix Table 5. Note that our baseline IV specifications are of the form:

$$\Delta \log(p_j^s) = \alpha + \beta \Delta \lambda_{jChina}^s + \epsilon_s^j,$$

where j indexes the home country (the U.S. in our case). This specification can be derived from equation (B11) by making two approximations: (i) China is the only trade partner of the US, i.e.

$\lambda^s_{jj} + \lambda^s_{jChina} = 1 \ \forall s$; (ii) the initial import share from China is small. Under these assumptions, we have

$$\begin{aligned} \Delta \log(P^s_j) &= \alpha - \frac{1}{1-\sigma_s}\Delta \log(1 - \lambda^s_{jChina}) + \epsilon^j_s, \\ &\approx \alpha + \frac{1}{1-\sigma_s}\Delta \lambda^s_{jChina} + \epsilon^j_s. \end{aligned} \tag{B12}$$

Since our empirical specification uses expenditure weights, we should recover an expenditure-weighted average of $\frac{1}{1-\sigma_s}$ if the model is correctly specified. As discussed in Section IV.A, the empirical estimates are about one order of magnitude larger than predicted by this class of trade models.

As shown previously, a version of equation (B11) can be derived for other members of the Arkolakis et al. (2012) class, including Melitz (2003)-Chaney (2008) with a Pareto distribution (as discussed in Section B.A), and models with intermediate inputs as in Caliendo and Parro (2015) and Ossa (2015) (as discussed in Section B.B).

B.D Connecting the IV Specification to Trade Models with Oligopolistic Competition

B.D.1 Setting

We use the setting of Edmond et al. (2015).[65] The economy consists of two countries, a domestic country and a foreign country, denoted by d and f respectively. In what follows, we focus on the domestic economy.

Consumer's Problem. A representative consumer in the domestic country has CES preferences over a continuum of differentiated product categories, with an elasticity of substitution between categories of $\epsilon > 1$,

$$Y = \left(\int_\Omega (Y_s)^{\frac{\epsilon-1}{\epsilon}} ds \right)^{\frac{\epsilon}{\epsilon-1}},$$

where Y_s is the consumption bundle of product category s, and Ω is the set of product categories. The associated price index is $P = \left(\int_\Omega (P_s)^{1-\epsilon} ds \right)^{\frac{1}{1-\epsilon}}$. The consumer maximizes utility subject to their budget constraint, which yields the following demand function for differentiated product category s,

$$S_s \equiv \frac{P_s Y_s}{X} = \left(\frac{P_s}{P} \right)^{1-\epsilon} \tag{B13}$$

where $X \equiv PY$ is total expenditure, and S_s is the domestic country's share of expenditures on product category s.

[65] This setting is also very close to Atkeson and Burstein (2008).

Within each of product category s there are n_{sd} domestic firms and n_{sf} foreign firms that produce closely related product varieties. The elasticity of substitution between the products within a product category is denoted γ, with $\gamma > \epsilon$. Consumers have CES demand for products within product category s that are produced in country $i \in \{d, f\}$

$$Y_{si} = \left(\sum_{j=1}^{n_{si}} (y_{sij})^{1-\gamma} \right)^{\frac{1}{1-\gamma}}$$

and face associated prices,

$$P_{si} = \left(\sum_{j=1}^{n_{si}} (p_{sij})^{1-\gamma} \right)^{\frac{1}{1-\gamma}}$$

where y_{sij} is the output of firm j of country i within category s, and p_{sij} is the associated price. The domestic consumer's demand for firm j's variety from country i within product category s yields the consumer's expenditure share,

$$S_{sij} \equiv \frac{p_{sij} y_{sij}}{X_s} = \left(\frac{p_{sij}}{P_s} \right)^{1-\gamma} \tag{B14}$$

where $X_s \equiv P_s Y_s$ is the total expenditure on products from product category s. Likewise, the domestic consumer's expenditure share of country $i \in \{d, f\}$'s products within category s is,

$$S_{si} = \left(\frac{P_{si}}{P_s} \right)^{1-\gamma} \tag{B15}$$

and we denote the share of the domestic consumer's expenditures on firm j's variety relative to all products from its origin country i within product category s as $\tilde{S}_{sij} \equiv S_{sij}/S_{si} = p_{sij} y_{sij} / P_{si} Y_{si}$.

Product Competition. Within a product category, firms produce according to a linear production technology that takes labor as an input, $y_{sij}(z) = z A_{si} \ell_{sij}$, where A_{si} is aggregate productivity of firms from country i in product category s and z is idiosyncratic productivity that is distributed according to $z \sim G_i^s(z)$. Firms take their country's wage, w_i, as given, face an iceberg cost, τ_i^s, and pay a labor-denominated fixed cost $w_i f_i^s$ to operate in the market.

Firms compete oligopolistically within a sector. In Section B.D.2, we derive a proposition based on a non-parametric representation of oligopolistic competition using markup elasticities, as in Amiti et al. (2019a). Let p_{sij} and μ_{sij} denote respectively the price and markup of firm j from country c in sector s. A change in a firm's marginal cost passes-through into its own price at a rate given by $\frac{1}{1+\Gamma_{sij}}$, where $\Gamma_{sij} \equiv -\frac{\partial \log(\mu_{sij}(.))}{\partial \log(p_{sij})}$ is the firm's "own-price markup elasticity". Under perfect and monopolistic competition with CES preferences, $\Gamma_{sij} = 0$. In Section B.D.3, we derive a corollary under more specific assumptions, using Cournot competition.

B.D.2 Proof of Proposition 2

Price and Expenditure Share Responses. The price response of product category s is obtained by applying Shephard's lemma,

$$d\log(P_s) = S_{sd} d\log(P_{sd}) + S_{sf} d\log(P_{sf}) \ . \tag{B16}$$

where the change in the price index for firms from countries $i \in \{d, f\}$ operating within the product category s is given by

$$d\log(P_{si}) = \sum_{j=1}^{n_{si}} \tilde{S}_{sij} d\log(p_{sij}) \ .$$

The change in the domestic expenditure share within product category s is,

$$d\log(S_{sd}) = (1-\gamma)\Big(d\log(P_{sd}) - d\log(P_s)\Big)$$

and since $dS_{sd} + dS_{sf} = 0$, this can be expressed as,

$$\frac{d\log(P_s)}{dS_{sf}} = \frac{-1}{(\gamma-1)S_{sd}} + \frac{d\log(P_{sd})}{dS_{sf}} \ . \tag{B17}$$

Thus, the price effect consists of two components: the first term is the direct effect of the foreign productivity shock that would be recovered in an economy with constant markups, $-1/(\gamma-1)S_{sd}$, and the second term is an indirect effect from price response of domestic firms, $d\log(P_{sd})/dS_{sf}$.

Characterizing the domestic price response with markup elasticities. To characterize the price response from domestic firms, we follow Amiti et al. (2019a) by log-linearizing the consumer's demand functions and firms' optimality conditions. Each firm's price response is a weighted average of the change in the firm's own marginal cost $c_{sij} \equiv w_i/(z_{sij}A_i)$ and the change in the product category's price index,

$$d\log(p_{sij}) = \frac{1-S_{sij}}{1-S_{sij}+\Gamma_{sij}} d\log(c_{sij}) + \frac{\Gamma_{sij}}{1-S_{sij}+\Gamma_{sij}} d\log(P_s) \tag{B18}$$

where Γ^k_{sij} is the firm's own-price markup elasticity.[66]

We further assume that the foreign country receives a positive productivity shock such that $d\log(A_{sf}) > 0$ and, therefore, we $d\log(c_{sfj}) \neq 0$ for foreign firms. Domestic firms do not experience a productivity shock so that $d\log(c^k_{sdj}) = 0$ for all domestic firms $j = 1, \ldots, n_{sd}$. Accordingly,

[66] In equation (B18) we have applied the result that the own-price markup elasticity equals the cumulative competitor markup elasticity, e.g., $-\partial\log(\mu^k_{sij})/\partial\log(p^k_{sij}) = \sum_{l\neq j}\partial\log(\mu^k_{sil})/\partial\log(p^k_{sil})$. Section B.D.4 discusses the accounting decomposition of Amiti et al. (2019a).

aggregating firms' prices from equation (B18) within the product category, the overall domestic price change is

$$d\log(P_{sd}) = \left(\sum_{j=1}^{n_{sd}} \tilde{S}_{sdj}\frac{\Gamma_{sdj}}{1-S_{sdj}+\Gamma_{sdj}}\right) d\log(P_s), \tag{B19}$$

and the overall foreign price change is

$$d\log(P_{sf}) = \left(\sum_{j=1}^{n_{sf}} \tilde{S}_{sfj}\frac{1-S_{sfj}}{1-S_{sfj}+\Gamma_{sfj}} d\log(c_{sfj})\right) + \left(\sum_{j=1}^{n_{sf}} \tilde{S}_{sfj}\frac{\Gamma_{sfj}}{1-S_{sfj}+\Gamma_{sfj}}\right) d\log(P_s). \tag{B20}$$

Using equation (B16), the price response of all firms within the category is

$$d\log(P_s) = \sum_{j=1}^{n_{sf}} \left(\frac{S_{sf}\tilde{S}_{sfj}\frac{1-S_{sfj}}{1-S_{sfj}+\Gamma_{sfj}}}{\sum_{i'\in\{d,f\}} S_{si'}\sum_{j'=1}^{n_{si'}} \tilde{S}_{si'j'}\frac{1-S_{si'j'}}{1-S_{si'j'}+\Gamma_{si'j'}}}\right) d\log(c_{sfj})\ . \tag{B21}$$

From equations (B16) and (B17) we can express the change in domestic prices with respect to a change in expenditures on foreign products within the product category as,

$$\frac{d\log(P_{sd})}{dS_{sf}} = \frac{-1}{(\gamma-1)S_{sd}} \cdot \frac{d\log(P_{sd})}{S_{sf}d\log(P_{sf}/P_{sd})}. \tag{B22}$$

Finally, substituting equations (B19), (B20) and (B21) into equation (B22) and simplifying yields:

$$\frac{d\log(P_{sd})}{dS_{sf}} = \frac{-1}{(\gamma-1)S_{sd}} \cdot \sum_{j=1}^{n_{sd}} \left(\frac{\tilde{S}_{sdj}\frac{1-S_{sdj}}{1-S_{sdj}+\Gamma_{sdj}}}{\sum_{j'=1}^{n_{sd}} \tilde{S}_{sdj'}\frac{1-S_{sdj'}}{1-S_{sdj'}+\Gamma_{sdj'}}}\right) \frac{\Gamma_{sdj}}{1-S_{sdj}}, \tag{B23}$$

which is the domestic price effect with respect to the change in foreign expenditure share expressed in terms of each domestic firm's market share and markup elasticity within the product category. In particular, the domestic price effect is a weighted average of each domestic firm's competitor-share normalized markup elasticity. Thus in the absence of strategic interactions (if $\Gamma_{sdj} = 0$ for all $j = 1, \ldots, n_{sd}$), the domestic price response $d\log(P_{sd})/dS_{sf}$ would equal zero and we would recover the price effect from the constant markup case in Section B.A.

Trade elasticity. The trade elasticity depends on firms' market power, which generates imperfect passthrough of changes in trade costs into prices, as well as strategic pricing. From (B15), we have

$$d\log(S_{sf}/S_{sd}) = (1-\gamma)\left(d\log(P_{sf}) - d\log(P_{sd})\right).$$

Substituting equations (B19), (B20) and (B21) into this expression, and given $\partial\log(c_{sfj}) = -\partial\log(A_{sf})$, we obtain the trade elasticity:

$$\eta \equiv \frac{\partial\log(S_{sf}/S_{sd})}{\partial\log(A_{sf})} = (\gamma-1)\left(S_{sf}\left(\sum_{j=1}^{n_{sd}} \tilde{S}_{sdj}\frac{1-S_{sdj}}{1-S_{sdj}+\Gamma_{sdj}}\right)^{-1} + S_{sd}\left(\sum_{j=1}^{n_{sf}} \tilde{S}_{sfj}\frac{1-S_{sfj}}{1-S_{sfj}+\Gamma_{sfj}}\right)^{-1}\right)^{-1} \tag{B24}$$

Bounds for the difference between the overall price index and the domestic price index. To obtain the lower bound, notice that $\sum_{j=1}^{n_{sd}} \tilde{S}_{sdj} \frac{\Gamma_{sdj}}{1-S_{sdj}+\Gamma_{sdj}} \leq 1$ as $\Gamma_{sij} > 0$, and therefore equation (B19) implies $0 \leq \frac{-d\log(P_s)}{dS_{sf}} - \frac{-d\log(P_{sd})}{dS_{sf}}$. To obtain the upper bound, we first show that $\eta \leq (\gamma - 1)$. Since $\sum_{j=1}^{n_{si}} \tilde{S}_{sij} \frac{\Gamma_{sij}}{1-S_{sij}+\Gamma_{sij}} \leq 1$ for each country $i \in \{d, f\}$, we have $(\sum_{j=1}^{n_{si}} \tilde{S}_{sij} \frac{\Gamma_{sij}}{1-S_{sij}+\Gamma_{sij}})^{-1} \geq 1$. We can create the following weighted average,

$$S_{sf}\left(\sum_{j=1}^{n_{sd}} \tilde{S}_{sdj} \frac{1-S_{sdj}}{1-S_{sdj}+\Gamma_{sdj}}\right)^{-1} + S_{sd}\left(\sum_{j=1}^{n_{sf}} \tilde{S}_{sfj} \frac{1-S_{sfj}}{1-S_{sfj}+\Gamma_{sfj}}\right)^{-1} \geq S_{sf} + S_{sd} = 1 \ .$$

By equation (B24), the left hand side of the above equation equals $(\gamma-1)/\eta$ and thus $1/\eta \geq 1/(\gamma-1)$. Finally, using equation (B17), we obtain

$$0 \leq \frac{-d\log(P_s)}{dS_{sf}} - \frac{-d\log(P_{sd})}{dS_{sf}} = \frac{1}{(\gamma-1)S_{sd}} \leq \frac{1}{\eta S_{sd}} \ . \tag{B25}$$

Collecting equations (B17), (B23) and (B25) completes the proof of Proposition 2.

B.D.3 Proof of Corollary 2

Price effects with head-to-head Cournot competition. We now consider the special case of Cournot competition, which yields:

$$\Gamma_{sij} \equiv -\frac{d\log(\mu_{sij})}{d\log(p_{sij})} = \frac{(\gamma-\epsilon)(1-S_{sij})}{\gamma(\epsilon-1)+(\gamma-\epsilon)(1-S_{sij})}(\gamma-1)S_{sij} \ . \tag{B26}$$

With head-to-head competition between one domestic firm and one foreign firm, substituting (B26) into equations (B17) and (B23) completes the proof of Corollary 2.

Calibration. We choose two moments to discipline the parameters ϵ and γ. First, we match the elasticity of trade flows in equation (B24) to the empirical estimate of 4.25 from Simonovska and Waugh (2014). Second, we match the estimated price effect of 1.91 in the model from equation (B17). Finally, we parameterize the share of expenditures on items produced in China by $S_{fs} \equiv 0.0452$, which is the average value for 1999 from Acemoglu et al. (2016). Our calibration matches both moments[67] and recovers parameter values of $\epsilon = 1.43$ and $\gamma = 8.73$. These estimates are similar those in Edmond et al. (2015), who estimate their parameters from highly disaggregated 7-digit Taiwanese manufacturing data in a quantitatively model with rich firm heterogeneity. Furthermore, these elasticity parameters imply a markup elasticity $\Gamma_{sd} = 0.59$ that is close to that estimated by Amiti et al. (2019a) on disaggregated 10-digit Belgian data. The empirical estimate of Amiti et al. (2019a), which was not targeted in our calibration, is $\widehat{\Gamma_{sd}} = 0.62$.[68]

[67] The model fits the data moments very tightly, within 6 decimal points of the target.

[68] We obtain this estimate from Column 5 of their Table 1: $\hat{\Gamma} = 1/\hat{\alpha} - 1$, with $\hat{\alpha} = 0.616$.

Price effects with head-to-head Bertrand competition. The preceding results remain similar with Bertrand competition instead of Cournot competition. We have

$$\Gamma_{sij} \equiv \frac{(\gamma-\epsilon)(1-S_{sij})}{(S_{sij}\epsilon+(1-S_{sij})\gamma)(S_{sij}\epsilon+(1-S_{sij})\gamma-1)}(\gamma-1)S_{sij} \ ,$$

and we repeat our calibration of parameters ϵ and γ to match the trade elasticity of 4.25 and price effect of 1.91. Our calibration again tightly matches these empirical moments and recovers parameters values $\epsilon = 2.08$ and $\gamma = 7.47$, implying a markup elasticity $\Gamma_{sd} = 0.48$. As in the Cournot case, these parameters are in line with the literature, highlighting the plausibility of the oligopolistic competition channel to explain our large price effects.

B.D.4 Additional Results using the Setting of Amiti et al. (2019a)

In this section, for completeness we provide more detail on the accounting decomposition of Amiti et al. (2019a) and how to connect our analysis to their setting.

Setting. Consider N industries over which consumers have Cobb-Douglas preferences. Each industry has competing producers from China and the United States. We perturb the equilibrium by a productivity shock that reduces the marginal cost of production for the Chinese producer. We then examine the response of prices, assuming that production costs in the U.S. do not change while markups evolve endogenously. Under the assumption of demand invertibility, the market outcome can be fully characterized in terms of a vector of prices, with a unique corresponding vector of quantities.[69]

Accounting decomposition. Denoting log prices by $\log(p_{is})$, log marginal cost by $\log(mc_{is})$ and log markups by $\log(\mu_{is})$, with i indexing firms and s industries, Amiti et al. (2019a) show that firm i's profit-maximizing price is the solution to a fixed-point equation:

$$\log(p_{is}) = \log(mc_{is}) + \log(\mu_i(p_{is}, p_{-is}, \zeta_s)), \tag{B27}$$

where p_{-is} is the competitor's price, and ζ_s an industry demand shock. This relationship indicates that the competitor's price serves as a sufficient statistic for the best-response of each firm.

Equation (B27) can be totally differentiated to study our proposed perturbation of the equilibrium:

$$d\log(p_{is}) = d\log(mc_{is}) + \underbrace{\frac{\partial \log(\mu_i(.))}{\partial \log(p_{is})}}_{\equiv -\Gamma_i} d\log(p_{is}) + \underbrace{\frac{\partial \log(\mu_i(.))}{\partial \log(p_{-is})}}_{\equiv \Gamma_{-i}} d\log(p_{-is}) + \underbrace{\frac{\partial \log(\mu_i(.))}{\partial \log(\zeta_s)} d\log(\zeta_s)}_{\equiv \varepsilon_s},$$

[69] Amiti et al. (2019a) point out that this assumption rules out the case of perfect substitutes, but it covers many standard demand systems, including CES, linear, Kimball, translog, discrete-choice logit and the non-homothetic demand system of Arkolakis et al. (2019).

which can be simplified to,

$$d\log(p_{is}) = \frac{1}{1+\Gamma_{is}} d\log(mc_{is}) + \frac{\Gamma_{-is}}{1+\Gamma_{is}} d\log(p_{-is}) + \varepsilon_s. \tag{B28}$$

Equation (B28) is the accounting decomposition from Amiti et al. (2019a). It shows how firm i's price change can be decomposed into its own cost shock ($d\log(mc_{is})$), its competitor's price change ($d\log(p_{-is})$) and demand shifters (ε_s). The markup elasticities Γ_{is} and Γ_{-is} govern the pass-through of changes in marginal cost and changes in the competitor's price into firm i's price.

Amiti et al. (2019a) show that if the perceived demand elasticity is a function of the price of the firm relative to the industry expenditure function, then the two markup elasticities are equal: $\Gamma_{is} = \Gamma_{-is}$. Using idiosyncratic variation in the cost of intermediate inputs as an instrument for prices, Amiti et al. (2019a) document that this assumption is valid empirically. Intuitively, this assumption holds when the markup function only depends on the relative price between competitor. In this case, the markup function has the same elasticity with respect to the firm's own price and its competitor's price (in absolute value, with opposite signs).[70]

Perturbation and first-order approximation. Assuming $\Gamma_{is} = \Gamma_{-is}$ for both the US and China such that $\Gamma_s^{US} = \Gamma_s^{-US}$ and $\Gamma_s^{China} = \Gamma_{-s}^{-China}$, and denoting the equilibrium market shares by S_s^{China} and $1 - S_s^{China}$, a first-order approximation to the equilibrium perturbation is given by:

$$\begin{aligned}
d\log\left(p_s^{US}\right) &= \frac{1}{1+\Gamma_s^{US}} d\log\left(c_s^{US}\right) + \frac{\Gamma_s^{US}}{1+\Gamma_s^{US}} d\log\left(p_s^{China}\right), \\
d\log\left(p_s^{China}\right) &= \frac{1}{1+\Gamma_s^{China}} d\log\left(c_s^{China}\right) + \frac{\Gamma_s^{China}}{1+\Gamma_s^{China}} d\log\left(p_s^{US}\right), \\
d\log\left(S_s^{China}\right) &= (1-\sigma_s)(1-S_s^{China})\left(d\log(p_s^{China}) - d\log(p_s^{US})\right), \\
d\log(p_s) &= S_s^{China} d\log(p_s^{China}) + (1-S_s^{China}) d\log(p_s^{US}),
\end{aligned}$$

where the first and second lines follow from (B28) with $\varepsilon_s = 0$, the third is implied by CES demand, and the fourth follows from Roy's identity.

Deriving the IV specification. Assume that there is no change in production cost in the U.S. while there is one in China, i.e. $d\log(c^{US}) = 0$ and $d\log(c^{China}) \neq 0$. One empirically grounded motivation for this supply shock is that a resolution of uncertainty with respect to PNTR encourages Chinese firms to engage in productivity enhancing investments for the purposes of trade (Handley and Limão (2017)) and this results in lower Chinese export prices (Amiti et al. (2020)).[71]

[70] Amiti et al. (2019a) show that this assumption holds for the nested-CES demand structure as well as a first-order approximation for a broad class of models with symmetric preferences.

[71] We thank an anonymous referee for suggesting this motivation for our modeling of the Chinese supply shock.

Therefore we have $d\log\left(p_s^{US}\right) = \frac{\Gamma_s^{US}}{1+\Gamma_s^{US}} d\log\left(p_s^{China}\right)$. Given this, the first two lines in the system of equations above imply:

$$d\log\left(p_s^{China}\right) = \frac{1+\Gamma_s^{US}}{1+\Gamma_s^{US}+\Gamma_s^{China}} d\log\left(c_s^{China}\right),$$
$$d\log\left(p_s^{US}\right) = \frac{\Gamma_s^{US}}{1+\Gamma_s^{US}+\Gamma_s^{China}} d\log\left(c_s^{China}\right).$$

Plugging these expressions into the third and fourth lines of the system of equations above yields:

$$dS_s^{China} = -\frac{(\sigma_s-1)S_s^{China}(1-S_s^{China})}{1+\Gamma_s^{US}+\Gamma_s^{China}} d\log\left(c_s^{China}\right), \tag{B29}$$
$$d\log(p_s) = \frac{S_s^{China}+\Gamma_s^{US}}{1+\Gamma_s^{US}+\Gamma_s^{China}} d\log\left(c_s^{China}\right). \tag{B30}$$

Equation (B29) gives an expression for the change in the import penetration rate from China (in percentage points), while equation (B30) gives the change in the industry price index (in log points). Combining equations (B29) and (B30) give the relationship between the industry price index and the change in the import penetration rate from China:

$$d\log(p_s) = -\frac{1+\Gamma_s^{US}/S_s^{China}}{(\sigma_s-1)(1-S_s^{China})} \cdot dS_s^{China}. \tag{B31}$$

In the data, we work with a first-order approximation to (B31), i.e. with the observed change in import penetration from China, ($\Delta ChinaIP$) and with the observed industry inflation rate (π_s), rather than with the infinitesimal changes dS^{China} and $d\log(p_s)$ that make (B31) hold exactly.

Intuitively, Chinese producers reduce prices when they experience a positive productivity shock, which leads U.S. producers to also reduce prices due to strategic interactions. Because of the U.S. price response, the equilibrium change in the spending share on the product from China is lower than it would be absent this price response. As a result, the relationship between changes in import penetration from China and price changes (our IV coefficient) can be large. To illustrate the logic, consider a limiting case with an extremely high markup elasticity, $\Gamma_j \to \infty$, in which the two producers supply highly substitutable products and become Bertrand competitors. In such a case, the U.S. producer matches the fall in price from the Chinese producer almost entirely, i.e. $d\log\left(p^{US}\right) \approx d\log\left(p^{China}\right)$, as can be seen in the equations above with $\frac{\Gamma_j}{1+\Gamma_j} \to 1$. Because the relative price of the two producers remains almost unchanged, the import penetration rate from China barely changes. Since both p_j^{US} and p_j^{China} fall, so does the industry price index p_j. Therefore we get price effects despite no changes in trade flows: $\frac{d\log(p_j)}{dS_j^{China}} \to \infty$ as $\Gamma_j \to \infty$. In this limiting case, the reduced-form relationship between price changes and changes in trade with China across industries can be unboundedly large.

Contributions of Domestic vs. Foreign Price Changes. The model predicts a larger decrease in the price of a given Chinese firm than from a given US firm, because a reduction in the Chinese firm's marginal cost creates a larger downward price adjustment relative to U.S. firms'. However, US firms account for approximately 95% of initial market share, which puts much greater quantitative weight on the domestic price response.

To see this, suppose that the U.S. firm's marginal cost does not change while the foreign firm's marginal cost does, e.g. $d\log(c^{US}) = 0$ and $d\log(c^{China}) \neq 0$. It is immediate that the magnitude of the U.S. price change is indeed lower than that of the Chinese price change because $d\log(p_s^{US}) = \frac{\Gamma_s^{US}}{1+\Gamma_s^{US}} d\log(p_s^{China})$ (with $\Gamma_s > 0$ but markups are not perfectly elastic).

We can write the aggregate price response as,

$$\begin{aligned} d\log(p_s) &= S_s^{China} d\log(p_s^{China}) + (1 - S_s^{China}) d\log(p_s^{US}) \\ &= (1 - S_s^{China}) \frac{\Gamma_s^{US}}{1 + \Gamma_s^{China}} d\log(p_s^{China}) + S_s^{China} d\log(p_s^{China}). \end{aligned}$$

If $(1 - S_s^{China}) d\log(p_s^{US}) > S_s^{China} d\log(p_s^{China})$, then the domestic price response dominates the foreign price response in the aggregate. This condition is met empirically because we have

$$\Gamma_s^{US} > \frac{\frac{S_s^{China}}{1-S_s^{China}}}{1 - \frac{S_s^{China}}{1-S_s^{China}}} = 0.05$$

given that market shares satisfy $S_s^{China} = 0.0452$, and that the evidence in Amiti et al. (2019a) provide a range of estimates for the markup elasticity that satisfies $\Gamma_d^{US} > 1/3$ (with a preferred estimate of $\Gamma_d^{US} = 0.6$). Thus, the domestic price change dominates the foreign price change in accounting for the aggregate price response.

B.E Connecting the IV Specification to Trade Models with Monopolistic Competition and Variable Elasticities of Substitution

For completeness, we now draw a connection between our results and the predictions of Arkolakis et al. (2019). Arkolakis et al. (2019) study a model in which the univariate distribution of markups is independent of the level of trade costs. Instead of obtaining variable markups by using CES utility with a departure from monopolistic competition such as assuming Bertrand or Cournot competition (as in Bernard et al. (2003), Atkeson and Burstein (2008) and Edmond et al. (2015)), Arkolakis et al. (2019) endogenize markups through consumer preferences featuring varying elasticities of substitution at the firm-level with monopolistic competition.

Monopolistic competition yields markups $m_{si} = \varepsilon_{D_{si}}/(\varepsilon_{D_{si}} - 1)$, where, in the notation of Arkolakis et al. (2019), ε_D denotes the elasticity of demand $D(p_{si}/P_s)$ and $D(.)$ is a strictly decreasing function. Arkolakis et al. (2019) focus on additively separable preferences in the Pollak family, specifying:[72]

$$q_{si} \equiv D(p_{si}/P_s) = (p_{si}/P_s)^{1/\gamma} - \alpha,$$

for firm i operating in category s, which nests the CES case with $\alpha = 0$. Arkolakis et al. (2019) specify $\alpha = 1$ and $\gamma = -0.35$. Under monopolistic competition, the firm's price elasticity is $\frac{\partial \log(p_{si})}{\partial \log(q_{si})} = \gamma \frac{q}{q+\alpha} < 0$ and $\frac{\partial^2 \log(p_{si})}{\partial \log(q_{si})^2} = \gamma \frac{\alpha}{(q+\alpha)^2} < 0$, i.e. demand becomes less elastic as quantities increase, since $\alpha > 0$. In that case, larger firms face a more inelastic demand and have larger markups. In this setting, an increase in foreign productivity leads to a fall in domestic production, leading to a more elastic demand for domestic firms and a fall in domestic markups.

Next, we show that this framework makes two counterfactual predictions. First, we derive the predicted domestic price response to a foreign supply shock in this framework, so that we can compare the prediction to our empirical estimates.[73] We assume that domestic production costs remain unchanged, i.e. we only need to compute the change in markups for a domestic firm, dm_{si}, induced by a foreign supply shock. With $\varepsilon_{D_{sd}} \equiv -\frac{q+\alpha}{q}\frac{1}{\gamma}$ as in Arkolakis et al. (2019), we get $d\varepsilon_{D_{sd}} = \frac{dq_{sd}\alpha}{(q_{sd})^2}\frac{1}{\gamma} > 0$, with $dq_{sd} < 0$ due to the foreign supply shock. Thus, demand becomes more elastic and domestic markups decrease, with $dm_{si} = \frac{-1}{(\varepsilon_{D_{si}}-1)^2} d\varepsilon_{D_{sd}} < 0$. Thus,

$$\begin{aligned}
\frac{d\log(p_{sd})}{dS_{sf}} &= \frac{d\log(m_{sd})}{dS_{sf}} \\
&= -\frac{1}{(\varepsilon_{D_{si}} - 1)^2} \frac{d\varepsilon_{D_{sd}}}{dS_{sf}} \frac{1}{m_{sd}} \\
&= -\frac{\alpha/\gamma}{\varepsilon_D \cdot (\varepsilon_{D_{si}} - 1) \cdot q_{sd}} \frac{d\log(q_{sd})}{dS_{sf}} \\
&= \frac{\alpha/\gamma}{(\varepsilon_D \cdot (\varepsilon_{D_{si}} - 1) \cdot q_{sd} - \alpha/\gamma) \cdot S_{sd}}
\end{aligned}$$

where the fourth line uses $d\log(q_{sd}) = d\log(S_{sd}) - d\log(p_{sd})$[74] and $dS_{sd} = -dS_{sf}$.

To evaluate this expression, we use Arkolakis et al. (2019)'s preferred parameters of $\alpha = 1$ and $\gamma = -0.35$ and $S_{sf} = 0.0452$ from Acemoglu et al. (2016). Furthermore, we consider parameter

[72] See Section 5.1 in Arkolakis et al. (2019).

[73] We focus on the response of the measured domestic price index, rather than the exact price index.

[74] Here we use the fact that, with Cobb-Douglas preferences across categories indexed by s, in general equilibrium total category-level expenditures remain fixed, i.e. $d\log(X_s) = 0$ (see Section B.C).

values for $\varepsilon_{D_{si}}$ and q_{sd} that are consistent with evidence on U.S. markups. According to De Loecker et al. (2020), markups were about 45% above marginal cost in the 2000s, implying $\varepsilon_{D_{si}} = 3.2$ and $q_{sd} = 8$.[75] With these parameters, we obtain the prediction:

$$\frac{\widehat{dlog(p_{sd})}}{dS_{sf}} = -0.0506.$$

Thus, the model predicts that inflation should fall by 5 basis points when the foreign expenditure share increases by 1 percentage point, which is more than one order of magnitude smaller than our IV estimate in Table 6.

In a robustness check, we obtain a similarly small price effect with an alternative calibration strategy, choosing parameter values to match the markup elasticity of $\Gamma_{sd} = 0.6$ in Amiti et al. (2019a) instead of the markup from De Loecker et al. (2020).

Intuitively, models of endogenous markups using oligopolistic competition and strategic interactions are better able to match our large IV estimate (as Bernard et al. (2003), Atkeson and Burstein (2008) and Edmond et al. (2015)), compared to models using variable elasticities of substitution (as Arkolakis et al. (2019)), because strategic interactions can deliver a large fall in prices with small changes in trade flows. As discussed in Section B.D.4, with oligopolistic competition the reduced-form relationship between price changes and changes in trade with China across industries can be unboundedly large in limiting cases. In contrast, with variable elasticities of substitution, conventional parameter values require a large change in trade flows to induce a sizable change in markups.

Second, the framework counterfactually predicts a larger response of domestic markups for smaller firms. For example, there is a choke price such that demand is zero when $p_{si} \geq P_s$: at this level of null demand ($q_{sd} = 0$), the demand elasticity is infinite ($\varepsilon_{D_{sd}} \equiv -\frac{q_{sd}+\alpha}{q_{sd}}\frac{1}{\gamma}$), and the rate of increase in the demand elasticity is locally infinite ($d\varepsilon_{D_{sd}} = \frac{dq_{sd}\alpha}{(q_{sd})^2}\frac{1}{\gamma}$), so the response of markups is largest for infinitesimal firms. This framework's prediction is counterfactual. Instead of finding that the increase in markups is larger for smaller firms in response to an increase to the foreign expenditure share, in Section IV.D we find the opposite: the price response is higher for larger firms, as well as when the market is more concentrated, which is consistent with the predictions of oligopolistic competition models.

[75] Indeed, with $q_{si} = 8$ we have $\varepsilon_{D_{sd}} \equiv -\frac{8+1}{8}\frac{1}{-0.35} = 3.2$ and $m_{si} = 3.2/(3.2-1) = 1.45$, as desired.

C Additional Results

C.A Robustness of Main Estimates

In this section, we describe several robustness tests.

Falsification tests. Appendix Figure A1 reports additional pre-trend tests, suggesting that it is important to at least include fixed effects for apparel and durable to avoid pre-trends. Panel A repeats the estimation of equation (2), but without fixed effects for apparel or durable goods. The figures exhibits pre-trends: ELI categories with a higher NTR gap had lower inflation even prior to 2000. Panel B of Figure A1 shows that once fixed effects for apparel and durable goods are included, the estimated coefficients do not exhibit pre-trends. These result indicate that including fixed effects for apparel and durable goods is important to ensure that a causal interpretation of the estimates is plausible. The validity of the research design would be doubtful if changing the set of controls in (2) had a large impact on pre-trends, but we find that the the results are stable with alternative sets of fixed effects, as long as there are controls for apparel and durables. Table A11 reports the same pre-trend tests, with fixed effects for apparel and durable goods, using using the extended CPI sample going back to 1977. Year-by-year estimates are reported in Figure A2 and show no signs of pre-trends. Figure A3 document similar patterns using publicly-available data from the NBER-CES database, measuring inflation as the change in the NBER-CES price index for the value of shipments.

As an additional falsification test, Table A12 shows that the NTR gap does not predict import penetration from China in France.

Sensitivity and heterogeneity analysis with the NTR gap instrument. We conduct several sensitivity test. Table A2 shows the IV estimates from a specification with more periods, rather than two long periods as in the main text. The period-specific IV estimates are similar to the specification with long differences reported in the main text. Table A13 shows that the NTR gap does not predict changes in import penetration in the U.S. prior to 2000. Table A3 shows that the IV estimates are similar whether or not the specification uses consumption weights, and whether or not the sample is restricted to goods only. This table also shows that the IV estimates remain similar with additional specifications with apparel and durable by period FE, and 2-digit ELI FEs interacted with period dummies. Table A14 is similar to Table 3 in the main text, but follows Pierce and Schott (2016) by including additional controls in Column (2): exposure to MFA quota reductions, Chinese import tariffs from Brandt and Morrow (2017), data on export licensing requirements from

Bai et al. (2017), and data on production subsidies from China's National Bureau of Statistics. The IV estimate remains similar. Furthermore, Online Appendix Table A15 shows that the results are similar when controlling for exports. This finding addresses the potential concern that import penetration from China in the domestic market may mismeasure changes in import competition, which also occurs in foreign markets for exporting firms.

Next, we examine heterogeneity across industries. We investigate the mechanism behind the relevance of the NTR gap instrument. With non-convex adjustment costs, a fall in uncertainty should boost capital investment (e.g., Dixit and Pindyck (1994)), which should especially matter for capital-intensive industries. Consistent with this idea, Online Appendix Table A16 shows that the first-stage relationship is stronger for capital-intensive industries with the NTR gap instrument, but not with the change in import penetration from China in other countries. Finally, using the estimated elasticities from Broda and Weinstein (2006), Online Appendix Table A7 reports that the IV coefficient is stable across subsamples with different trade elasticities.

Sensitivity analysis with the ADH instrument. Online Appendix Table A17 shows that the results are similar when the instrument is the change in import penetration in other developed economies.

Alternative measures of import penetration. We adjust our measure of import penetration from China to account for distribution margins. Intuitively, consider a product category like apparel. China substantially increases its market share in the production of apparel. But a substantial share of the retail price of apparel results from retail and transportation costs, implying that China's "market share" increases much less in the consumer basket. China's market share only increases at the production stage, while, by definition, retail and transportation costs continue to be incurred domestically.

We therefore use the IO sample and adjust the denominator in equation (1) for distribution margins, which are given by the ratio of total output in purchaser prices to total output in producer prices. The results are reported in Online Appendix Table A18. As expected, the IV coefficient becomes more negative when purchaser prices are used (-4.37, s.e. 0.852) rather than producer prices (-2.44, s.e. 0.431), because the effective change in import penetration from China is smaller with purchaser prices. Although it is instructive to note that the price effects become even stronger with the adjustment for distribution margins, for comparability with prior work we focus on the IV estimates with the baseline import penetration measure.

Additional results for specifications with continued products. Online Appendix Table A19 focuses on the subset of goods that existed prior to the "China shock" (specifically, they were available as of 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 documented in the main text are not due to goods that were introduced after the China shock, implying that "reallocation effects" do not drive the observed price response. Furthermore, Online Appendix Table A20 documents that trade with China led to increased product turnover, consistent with the notion that Chinese products displace domestic varieties.

C.B The Role of Imported Intermediate Inputs

This appendix presents additional results about the role of imported intermediate inputs.

To examine whether buyer-supplier linkages affect our results, we first compute the correlations between our baseline measure of import competition and indirect exposure via domestic suppliers or domestic buyers. We conduct this analysis with our Input-Output sample, using the BEA's IO table with the standard proportionality assumptions. To measure industry j's exposure via domestic suppliers, denoted "ΔChina IP Supplier", we compute the change in the share of spending on intermediate inputs from China in industry j's total sales. For exposure via domestic buyers, denoted "ΔChina IP Buyer", we compute the change in the import penetration rate from China in industry j's domestic buyer industries, multiplied by the share of domestic buyer industries in industry j's total sales. By definition, both "ΔChina IP Supplier" and "ΔChina IP Buyer" are low if an industry has a high share of value added or sells primarily to final consumers.

Table A21 reports the correlations between direct and indirect exposure to trade with China. Column (1) shows the raw relationship without any controls: the coefficient is positive and significant, but small in magnitude. When the import penetration rate from China increases by 1 percentage point in industry j, the share of intermediate inputs from China in industry j's total output increases by only ten basis points. The relationship decreases further when we introduce the same set of controls as in our baseline IV specification in Column (2), and when we exclude intra-industry buyer-seller relationships (the diagonal component of the IO table) in Column (3).

For buyer effects, Columns (4) shows that the raw relationship is also positive but even smaller: a 1 percentage point increase in import competition from China in industry j is associated with a further 2 basis point increase in import competition via domestic buyer industries. Columns (5) and (6) report that the relationship becomes a precisely estimated zero with the other specifications.

These results indicate that direct import competition is not correlated with indirect effects, therefore the price effects we document are unlikely to be explained by these channels.

Table A22 shows that the results are similar to the estimates reported in the main text when accounting for higher-order I-O linkages. Table A23 reports similar results in an augmented IV framework, where we instrument for direct and indirect exposure measures simultaneously.

C.C The Role of Markups

In this section, we discuss additional results on the role of markups.

First, we study changes in the distribution of estimated markups. Table A24 document changes in the distribution of markups across industries that are differentially exposed to the NTR gap. In Column (1), the reduced form coefficient for the 90th percentile of markups is -17.42 (s.e. 7.28); in Column (2) the effect gets attenuated by a factor of over 50%, with a coefficient of -7.97 (s.e. 4.83) for the 50th percentile; in Column (3) the coefficient for the 10th percentile becomes insignificant and is close to zero (-0.84, s.e. 4.023). Consistent with the predictions of the model, the response of markups is much stronger at the top of the markup distribution.

Second, we analyze the response of firm profitability to increased import penetration from China. We compute the ratios of total profits to total sales and to total assets, where profits are computed inclusive of fixed costs incurred by the firm (in contrast, the markup measure from equation (A1) does not use information about fixed costs). Columns (4) and (5) of Table A24 report the corresponding point estimates, which are statistically significant at the 1% level.

Finally, we measure heterogeneity in our IV coefficient using CPI data (in complement to the PPI data analyzed in the main text). To measure domestic market concentration, we obtain data on Herfindahl indices by 6-digit NAICS industries from the Census for 1997 (as in Grullon et al. (2018)), which we link to our CPI sample.

Table A25 presents the results. Consistent with the predictions, Column (1) shows that the price response to a one percentage point increase in the import penetration rate from China is much larger when the domestic market is more concentrated, and is much smaller when the initial China share is small. The price decline is 1.29 percentage points larger in the set of more concentrated industries, and it is attenuated by 1.50 percentage points in the set of industries initially more exposed to trade with China.

Columns (2) to (5) show the robustness of these results by repeating the IV specifications in subsamples. The IV coefficient is large in the subsample of product categories above median concentration (Column (2)), while it becomes insignificant for those below (Column (3)). The point estimate in Column (3) is close to the prediction from the class of models without strategic interactions characterized by Arkolakis et al. (2012). Columns (4) and (5) show that the estimated effect is over twice as large for industries that were initially less exposed to trade with China.

C.D Comparison to Other Estimates in the Literature

In this appendix, we compare the magnitude of our estimates to other studies that have examined the relationship between trade, prices, and markups, in the United States and abroad. We highlight the four contributions we make relative to this literature at the end of this section.

Kamin et al. (2006) study the OLS relationship between Chinese exports and both US import prices and US producer prices. They document that a one percentage point rise in the Chinese import share of a given sector during 1997–2002 was associated with a 1.097 percentage point lower annual import inflation in that sector, which is similar to our OLS estimate for consumer prices (while the IV is larger). They do not find evidence of a significant impact on U.S. producer prices, in contrast with our results and with the other papers described below. Because their analysis with producer prices stops in 2001, the difference in time coverage could potentially explain this discrepancy with our results.

Auer and Fischer (2010) study the impact of U.S. imports from nine low-wage countries between 1997 and 2006. They use an instrument leveraging differences in labor-intensity across sectors, leveraging the idea that low-wage countries have a comparative advantage in labor-intensive industries. They find that when the nine LWCs capture a 1% share in a sector, U.S. producer prices decrease by 2.35%. This point estimate is close to ours.

Carluccio et al. (2018) assess the impact of imports from low-wage countries on CPI and PPI inflation in France during 1994-2014. For the PPI estimates, they use an IV strategy based on differences in labor-intensity across sectors, similar to Auer and Fischer (2010). The find that when the nine LWCs capture a 1% share in a sector, French producer prices decrease by 1.208%. The corresponding estimate when they focus on imports from China is 1.84%, which is close to our estimate for consumer prices in the U.S.[76]

Amiti et al. (2020) study the impact of China's WTO entry on U.S. producer prices. They measure prices in the U.S. using the U.S. PPI as well as data on the unit value of imports. They find that a key mechanism is China lowering its own import tariffs on intermediate inputs. Using

[76] To assess the impact on consumer prices, rather than producer prices, they conduct an accounting exercise at the level of 3-digit COICOP categories, which is not directly comparable to our analysis.

an IV strategy exploiting differences in the level of initial import tariffs, they estimate that the fall in Chinese import tariffs upon WTO entry reduced Chinese firms' costs and in turn lowered their marginal cost and their export prices, which benefited the U.S. market.[77] Relative to them, we measure consumer prices in the U.S., rather than producer prices, and we focus on a complementary mechanism, i.e. the importance of the price response for domestically-produced goods through strategic pricing. Although Amiti et al. (2020) do not focus on estimating the relationship between changes in import penetration and prices in the U.S., their estimates imply a large decline in U.S. producer prices for small changes in import penetration from China, with magnitudes close to our estimates, which is consistent with the mechanism we emphasize.[78]

Bai and Stumpner (2019) estimate the impact of trade with China in U.S. consumer prices using Nielsen scanner data, from 2004 to 2015. The scanner data has the key advantage of measuring changes in product variety over time and heterogeneity across household groups within industries. They find that trade with China led to lower consumer prices for continued products and an increase in product variety in the U.S. While this study focuses on the product category covered in the Nielsen data, much of trade with China occurs in other categories, including consumer electronics, apparel, and slow-moving consumer goods. Our estimates complement this study by examining a broader sample over a different time period. In particular, we are able to test for pre-trends and conduct several test for the identification strategy using the instrument of Pierce and Schott (2016).

De Loecker et al. (2016) study trade liberalization in India, examining declines in input and output tariffs between 1989 and 1997. They find that the change in input tariffs is the dominant force and leads to an increase in the markup of domestic producers. Input tariff liberalization leads to a fall in input costs, with incomplete cost pass-through to prices and increased domestic markups. De Loecker et al. (2016) also provide evidence that output tariff liberalization exerted

[77] When focusing on PNTR, Amiti et al. (2020) find no effect of PNTR on Chinese firms export prices. This result may seem to be at odds with our finding, since we find a response of U.S. consumer prices to PNTR (we do not attempt to isolate the impact of prices at the border). A potential explanation is that changes in the unit value of exports may be subject to changes in composition (for example, higher quality items may be offered at a similar price). The product-level data we use in confidential BLS micro-data addresses such compositional changes.

[78] Amiti et al. (2020) report a negative relationship between the change in the Chinese export price index and the change in the import penetration rate from China in Column (1) of their Table 9, with a point estimate of -0.376 (s.e. 0.194), and a positive relationship with the price index for domestically-produced goods, measured with U.S. shipment deflators in Column (5) of their Table 9, with a point estimate of 0.635 (s.e. 0.164). These two point estimates imply that, when the import penetration rate from China increases by 1pp, the producer price index for domestically-produced goods falls by 1.69pp ($= 0.635/(-0.376)$). This implied relationship is statistically indistinguishable from the point estimates we obtain when focusing on domestically-produced goods in Panels B and C of our Table 6. For example, we obtain a point estimate of -1.94 (s.e. 0.59) in Column (1) of Panel B of Table 6.

pro-competitive pressure on markups, but they find that this effect is smaller that the upward pressure on markups from falling inputs costs.[79] The overall effect, taking into account the average declines in input and output tariffs between 1989 and 1997, is that markups, on average, increased by 12.6 percent following trade liberalization. Accordingly, the authors conclude that, because of markup adjustments, "producers benefited relative to consumers", and that "the short-run gains to consumers appear small, especially considering that we observe factory-gate prices rather than retail prices". In contrast, we study a developed country setting and focus on the import competition shock from China, studying retail prices faced by consumers. We find large price effects benefitting consumers. Most of increased trade with China during the period we study is in final goods, and we do not attempt to study the input cost channel in detail, as we do not have the required firm-level import data.

Although estimates vary across studies and are not always comparable, there is a growing empirical consensus that foreign supply shocks have substantial effects on producer prices and markups. In the context of this literature, our main contribution is fourfold. First, we provide an analysis of the reduced-form effects of trade using micro-data on the prices that *consumers* actually face at the store. This is not the case in almost any of the studies mentioned above. These studies use micro data on import/export prices or producer prices, rather than retail prices, i.e. they do not take into account potential changes in retail margins, which are typically large for traded goods and should matter for consumers. To the best of our knowledge, only Bai and Stumpner (2019) study the impact of trade using data on retail prices. Although Bai and Stumpner (2019) have micro data on consumer prices linked to trade shocks, as previously discussed their sample is subject to limitations that we can relax, in terms of coverage of product categories and time periods. Second, we provide a simple comparative analysis of job losses and price changes in response to increased trade with China for the United States. Our sample frame allows us to compare the job displacement estimates, using the same research design as in prior studies, to the price effects in a unified empirical framework. Third, our setting lends itself to an in-depth analysis of the identification assumption, leveraging several instruments and a series of falsification and robustness tests. We show that the magnitude of the price effects is robust to multiple potential concerns about causal identification that could not be addressed in prior work due to data limitations; we can thus establish that the large estimated magnitude of the price response is not due to confounders and

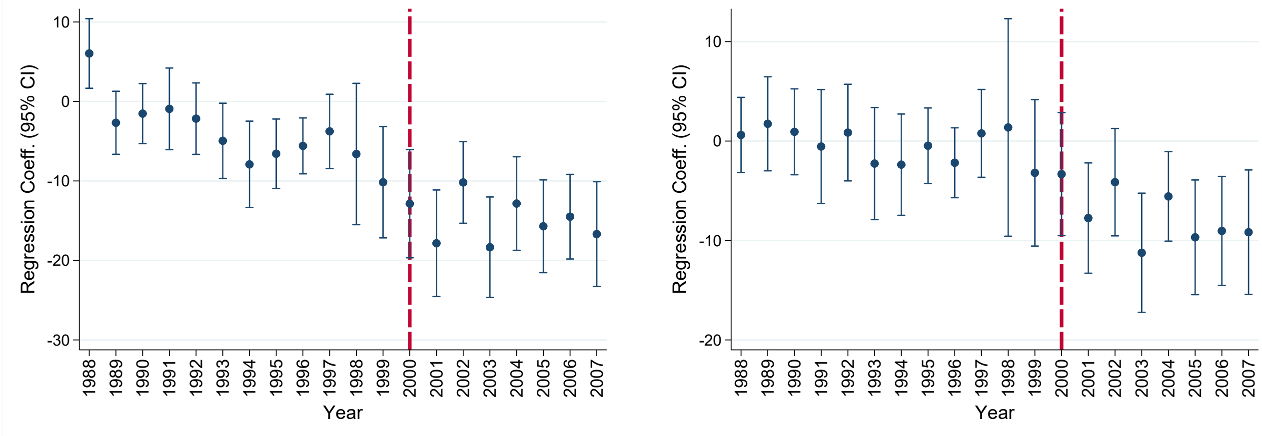
[79] Their estimate is not directly comparable to ours because they do not estimate the equilibrium relationship between changes in domestic markups and changes in import penetration induced by a foreign supply shock.

is an important identified moment for quantitative trade models to match. Fourth, we link our regression specification to standard quantitative trade models, in particular the Melitz-Chaney model, which is new to the literature.[80]

[80]Indeed, prior work did not point out that the relationship between price changes and changes in expenditure share is about one order of magnitude larger than predicted by standard quantitative trade models that abstract from strategic price-setting.

D Online Appendix Tables and Figures

Figure A1: Additional Pre-trends Tests

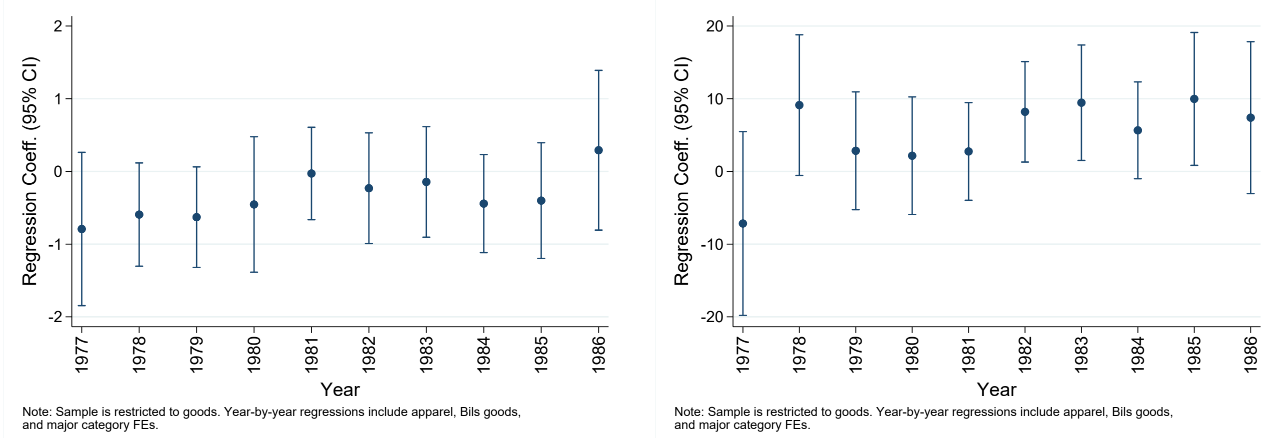


(A) Without Controls

(B) With Apparel & Durables F.E.

Notes: In Panel A, the specification is the same as described in Section III.B, but without any fixed effects. In Panel B, the specification is the same as in Section III.B, but with fixed effects for apparel and durables instead of ELI fixed effects. Panel A exhibits pre-trends, in contrast with Panel A and Figure 1 in the main text. Panel B shows no evidence for pre-trends. These results indicate that including fixed effects for apparel and durables is important to ensure that a causal interpretation of the estimates is plausible, and suggest that ELI fixed effects may not be necessary.

Figure A2: Testing for Pre-trends in the Extended CPI Sample



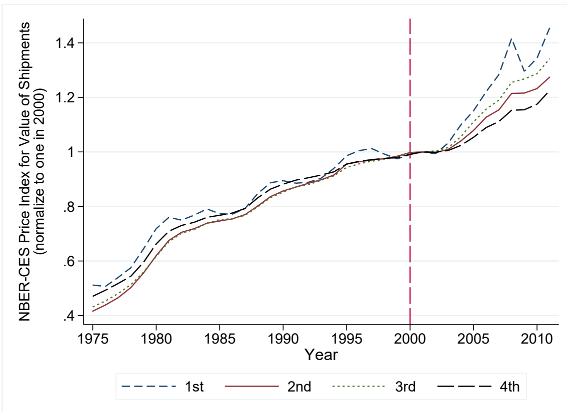
(A) China IP in other developed economies

(B) NTR gap

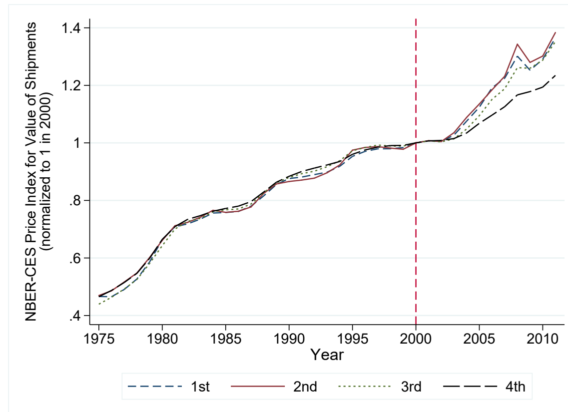
Notes: This figure uses the extended CPI sample with the specification described in Online Appendix A.C. F-tests indicate that we cannot reject that the estimated coefficients are jointly insignificant.

Figure A3: Long-Run Event Studies in NBER-CES Manufacturing Database

Panel A: Excluding NAICS 334, Computers and Electronics

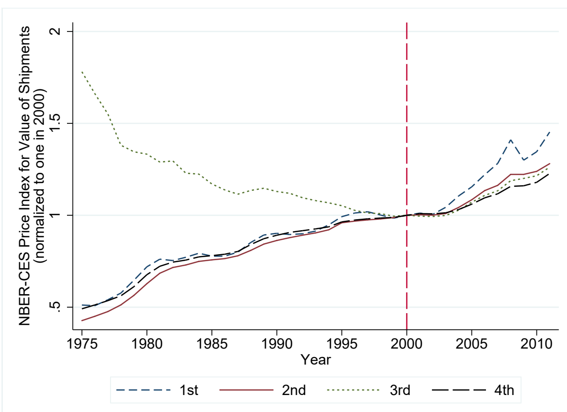


(a) NTR gap, by quartiles

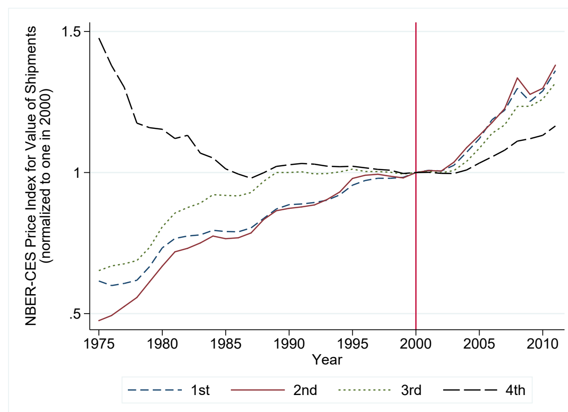


(b) China IP in other developed economies, by quartiles

Panel B: Including NAICS 334, Computers and Electronics



(a) NTR gap, by quartiles



(b) China IP in other developed economies, by quartiles

Notes: This figure reports a long-run analysis of price trends by quartiles of the instruments for trade with China. A higher quartile indicates higher exposure. We thank Teresa Fort for recommending us to conduct this analysis. The data source for prices is the NBER-CES Manufacturing Industry database, which provides a price index for the value of shipments for each 6-digit NAICS industry in each year from 1975 to 2011. All industries within manufacturing are covered, including those providing intermediate inputs. We match this data set to the instruments for trade with China: the NTR gap is available across 6-digit NAICS codes; using the SIC-NAICS described in Online Appendix A.C, we link the data set to the 2000-2007 change in the import penetration rate from China in other developed economies. In all panels, the price index for the value of shipments is normalized to one in 2000 and the price trends are reported by quartiles of exposure to the instruments. Panel A excludes industries belonging to the 3-digit NAICS category "Computers and Electronics" (NAICS 334). In this panel, industries across quartiles of exposure are on similar price trends up to the treatment period (starting in 2000) and start diverging afterwards. With both instruments, more exposed industries have a lower inflation rate after 2000. These results are consistent with the estimates presented in Section III. The specification reported in this figure helps reduce noise by showing cumulative price differences over time. When we run an analysis with fixed effects analogous to specification (2) in the main text, the year-specific estimates are too noisy to discern a statistically significant pattern. Panel B includes industries within "Computers and Electronics": when doing so, large pre-trends appear because these industries are more exposed to the instruments and have been on lower inflation trends for decades. These results indicate the importance of excluding these categories or including suitable controls, as we do in Section III. The results are similar with a median split or by deciles of exposure of the instruments, instead of quartiles (not reported).

Table A1: List of Durable Goods, reproduced from Bils (2009)

Good	Spending share
Watches	0.069
Jewelry	0.416
Personal computers & equipment	0.370
Telephone & equipment	0.080
Calculators, typewriters, etc.	0.014
Electric personal care products	0.021
Luggage	0.027
Infant's equipment	0.018
Curtains & drapes	0.064
Window coverings	0.053
Mattresses & springs	0.146
Bedroom furniture	0.193
Sofas & slipcovers	0.276
Living room chairs	0.122
Living room tables	0.057
Kitchen & dining room furniture	0.162
Infant's furniture	0.025
Occasional furniture	0.148
Refrigerators & home freezers	0.083
Washers & dryers	0.103
Stoves	0.030
Microwaves	0.029
Vacuums	0.064
Small kitchen appliances	0.034
Other electric appliances	0.079
Lamps & lighting	0.040
Clocks & decorative items	0.325
Dishes	0.083
Flatware	0.014
Nonelectric cookware	0.039
Tableware & nonelectric kitchenware	0.057
Power tools	0.058
Misc. hardware	0.096
Nonpowered hand tools	0.026
Medical equipment for general use	0.011
Supportive & convalescent equipment	0.031
Televisions	0.246
Other video equipment	0.104
Audio equipment	0.164
Bicycles	0.044
General sports equipment	0.229
Hunting, fishing, & camping equipment	0.086
Photography equipment	0.057
Sewing machines	0.044
Musical instruments & accessories	0.069

Notes: This table presents the lists of durable goods reported in Table 1 of Bils (2009)

Table A2: IV Estimates from Panel Specification with Additional Periods

Panel A: With NTR gap Instrument

	U.S. CPI Inflation (pp)
	IV
	(1)
Δ China IP (pp) — 2000-2002	-2.03^{**}
	(0.94)
Δ China IP (pp) — 2003-2005	-2.62^{**}
	(1.29)
Δ China IP (pp) — 2006-2007	-2.28^{**}
	(1.01)
First-stage F	17.43
ELI F.E.	✓
Period-specific Goods F.E.	✓
N	1332

Panel B: With Change in Import Penetration in Other Countries

	U.S. CPI Inflation (pp)
	IV
	(1)
Δ China IP (pp) — 2004-2007	-1.64^{**}
	(0.75)
Δ China IP (pp) — 2000-2003	-1.12^{**}
	(0.53)
Δ China IP (pp) — 1996-1999	-1.42^{**}
	(0.72)
Δ China IP (pp) — 1991-1995	-1.24^{**}
	(0.52)
First-stage F	15.21
ELI F.E.	✓
Period-specific Goods F.E.	✓
N	888

Notes: The level of observation is an ELI-by-period cell. Panel A uses the NTR gap as the instrument. The periods are indexed by t, with $t \in \{1991-1993\}, \{1994-1996\}, \{1997-1999\}, \{2000-2002\}, \{2003-2005\}, \{2006-2007\}$. The IV specification is:

$$\pi_{it} = \sum_{k=1991-1993}^{2006-2007} \beta_k \Delta ChinaIP_{it} \cdot 1_{\{k=t\}} + \delta_i + \delta_t + \varepsilon_{it},$$

$$\Delta ChinaIP_{it} = \sum_{k=1991-1993}^{2006-2007} \gamma_k \mathbf{Z_{it}} \cdot 1_{\{k=t\}} + \tilde{\delta}_i + \tilde{\delta}_t + \eta_{it},$$

Panel B uses the same specification with the change in import penetration in other economies as the instrument. The periods are $t \in \{1991-1995\}, \{1996-1999\}, \{2000-2003\}, \{2004-2007\}$. Standard errors are clustered by ELIs. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table A3: Sensitivity Analysis

	U.S. CPI Inflation (pp)				
	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
Δ China IP (pp)	−2.23***	−2.20***	−2.31***	−1.78***	−1.86***
	(0.47)	(0.34)	(0.49)	(0.59)	(0.54)
First-stage F	38.14	52.88	32.69	24.0	26.5
ELI F.E.	✓	✓	✓	✓	✓
Period-specific Goods F.E.	✓	✓	✓	✓	✓
Consumption weights	✓		✓	✓	✓
No weights		✓			
Full sample	✓	✓		✓	✓
Goods only			✓		
Periode-specific Durables & Apparel F.E.				✓	
Period-specific Major Category F.E.					✓
N	444	444	344	444	444

Notes: The level of observation is an ELI-by-period cell. Standard errors are clustered by ELIs. The instrument is the NTR gap. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table A4: The Roles of Continued and Domestic Goods, using the Change in Import Pentration in Other Developed Economics as the Instrument

Panel A: IV Estimates for Continued Goods in Main Sample (CPI)

	U.S. CPI Inflation, Continued Products (pp)		Contribution to U.S. CPI Inflation (pp) *[%]*	
	(1)	(2)	(3)	(4)
Δ China IP (pp)	-1.58^{*}	-2.15^{***}	-0.65 *[45%]*	-1.25^{***} *[98.4%]*
	(0.91)	(0.71)	(0.49)	(0.33)
ELI F.E.	✓		✓	
Period-specific Goods F.E.	✓		✓	
2000-2007 only		✓		✓
Goods, Durables & Apparel F.E.		✓		✓
N	444	222	444	222

Panel B: IV Estimates for Domestic Goods in Main Sample (CPI)

	U.S. CPI Inflation, Domestic Products (pp)		Contribution to U.S. CPI Inflation (pp) *[%]*	
	(1)	(2)	(4)	(5)
Δ China IP (pp)	-1.26^{***}	-1.32^{***}	-0.92^{***} *[64%]*	-1.08^{***} *[85%]*
	(0.48)	(0.31)	(0.38)	(0.25)
ELI F.E.	✓		✓	
Period-specific Goods F.E.	✓		✓	
2000-2007 only		✓		✓
Goods, Durables & Apparel F.E.		✓		✓
N	444	222	444	222

Panel C: IV Estimates for Continued and Domestic Goods in PPI Sample

	U.S. PPI Inflation (pp)		U.S. PPI Infl., Continued Products (pp)	
	(1)	(2)	(4)	(5)
Δ China IP (pp)	-1.45^{**}	-2.13^{*}	-1.02^{**}	-0.96^{**}
	(0.67)	(1.22)	(0.48)	(0.45)
First-stage F	652.20	521.31	652.20	521.31
NAICS F.E.	✓		✓	
Period-specific Goods F.E.	✓		✓	
2000-2007 only		✓		✓
Goods, Durables & Apparel F.E.		✓		✓
N	550	275	550	275

Notes: The specifications are the same as for Table 6 in the main text, except that the instrument is the change in import penetration in other developed economie. Standard errors are clustered by industries. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table A5: Summary Statistics on Country of Origin Flags

	Number of ELIs with flags	Share of Expenditures with flags	
	All	All	Tradables
Year	(1)	(2)	(3)
2000	51	0.1830	0.3703
2001	59	0.1760	0.3555
2002	59	0.1828	0.3630
2003	63	0.1929	0.3959
2004	62	0.1860	0.3865
2005	65	0.2016	0.4300
2006	60	0.1832	0.3877
2007	61	0.1743	0.3668

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."). Country of origin flags are obtained from specification checklists, as explained in Online Appendix A.A.

Table A6: Summary Statistics on Related-Party Trade

	Mean	S.D.	p10	p50	p90	Sample
Share of related trade, All Countries, 2005, %	48.08	25.37	11.85	47.99	82.61	NAICS
Share of related trade, China, 2005, %	26.07	23.49	2.148	17.70	65.55	
Share of related trade, All Countries, 2015, %	50.61	24.86	17.43	50.24	86.20	
Share of related trade, China, 2015, %	27.61	19.84	4.90	25.69	56.49	
Share of related trade, China, 2005, %	11.45	17.24	1.227	4.098	38.38	ELI matched sample

Notes: This table reports summary statistics on the share of U.S. imports occuring between related parties in trade, with all trading partners and with China specifically. The data source is the related-party trade database of the U.S. Census. The original data is provided across NAICS codes, but the patterns are similar once we match the data to our ELI sample (as shown in the fifth row). The average share of related-party trade is smaller in our ELI sample (11% in 2005) than in the full NAICS sample (26% in 2005) because our sample covers final goods and there tends to be more trade between related parties for intermediate products. Although the average share of related-trade is is small, there is susbtantial variation across ELIs. For example, the share of related-party trade from China is particularly high for computer storage devices (72%) and other computer equipment (65%), while is it low for "men's suits and coats" (1.9%) and "women's suits and coats" (2.1%).

Table A7: Testing for Heterogeneity by Trade Elasticities

	U.S. CPI Inflation	
	IV	IV
	(1)	(2)
Δ China IP	-2.363^{***}	-1.911^{**}
	(0.399)	(0.816)
Subsample:	Trade Elasticity $\geq$ p50	Trade Elasticity $<$ p50
Instrument: NTR Gap	✓	✓
N	140	140

Notes: This table reports the IV estimates from the baseline specification from Section III.C in two subsamples, above and below the median trade elasticity as estimated by Broda and Weinstein (2006). The trade elasticities were estimated by Broda and Weinstein (2006) for the period 1990 - 2001 across HS codes, which we match and aggrgeate to the level of ELIs. The IV estimates are a bit larger in the subsample with a higher trade elasticitty. The estimates in both subsamples are similar to the baseline IV results from Table 2. In theory, the relationship between changes in import penetration from China and U.S. consumer prices could have widely varied depending on the trade elasticity. This table indicates that in practice the magnitudes are relatively stable, implying that our baseline IV estimate provides a meaningful summary measure. In other (unreported) IV specifications, we find that when interacting the estimated trade elasticity with the change in import penetration from China, the interaction term is not statistically significant. The level of observation is an ELI-by-period cell. Standard errors are clustered by ELIs. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table A8: Employment Effects of Trade

Panel A: With the NTR Gap

	Δ Non-Prod Emp. (pp)	Δ Prod Emp. (pp)	Δ Total Emp. (pp)
	(1)	(2)	(3)
Δ China IP (pp)	-2.591	-1.893	-1.834
	(0.789)	(0.648)	(0.537)
First-stage F	25.464	25.464	25.464
ELI F.E.	✓	✓	✓
Durables & Apparel Time-Varying F.E.	✓	✓	✓
N	306	306	306

Panel B: With the Change in Import Penetration from China in Other Developed Economies

	Δ Non-Prod Emp. (pp)	Δ Prod Emp. (pp)	Δ Total Emp. (pp)
	(1)	(2)	(3)
Δ China IP (pp)	-2.319	-2.137	-1.774
	(1.174)	(1.002)	(0.930)
First-stage F	13.860	13.860	13.860
ELI F.E.	✓	✓	✓
Period-specific F.E. for Durables/Apparel	✓	✓	✓
N	306	306	306

Panel C: With Both Instruments

	Δ Non-Prod Emp. (pp)	Δ Prod Emp. (pp)	Δ Total Emp. (pp)
	(1)	(2)	(3)
Δ China IP (pp)	-2.506	-1.970	-1.815
	(0.635)	(0.574)	(0.498)
First-stage F	16.234	16.234	16.234
ELI F.E.	✓	✓	✓
Period-specific F.E. for Durables/Apparel	✓	✓	✓
N	306	306	306

Notes: This table reports the results from our baseline IV specification (3), except that the outcome is the change in industry employment (expressed in %). Panel A uses the NTR gap instrument, Panel B uses changes in import penetration in other developed economies, and Panel C uses both instruments jointly. The employment outcomes are measured in the NBER CES database, which distinguishes between "production" and "non-production" workers. We consider in turn employment for production workers, non-production workers, and total employment as outcomes. The results indicate that employment falls by 1.77% to 2.59%, depending on the specification, for each one percentage point increase in the import penetration rate from China. We obtain similar results when we use total employment from the County Business Patterns Database instead (not reported). Standard errors are clustered at the level of ELIs. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table A9: Estimates of the Increase in Consumer Surplus from Increased Trade with China from 2000-2007, in 2007 U.S. Dollars

	(1)	(2)	(3)
Annual Increase in Consumer Surplus, \$/Household	1,711	1,105	1,466
Calibration Parameters:			
- Observed Cumulative Change in China IP, 2000-2007, within Goods (=6.15pp)	✓	✓	✓
- Average Household Spending on Goods in 2007, CEX (=\$12,479)	✓	✓	✓
IV Estimates:			
- NTR gap: $\beta_{price} = -2.23$	✓		
- ΔChina IP Other: $\beta_{price} = -1.44$		✓	
- Both: $\beta_{price} = -1.91$			✓

Notes: This table estimates the gains to U.S. consumers from the fall in prices induced by the increase in trade with China from 2000 to 2007. The results are expressed in 2007 dollars of consumer surplus per U.S. household. Assuming that there are no GE effects affecting prices in all product categories, our cross-industry IV estimates accurately reflect the price changes induced by increasing trade with China at the level of the whole economy. If prices do not revert back in the future, the estimated annual gains reported in the table should persist going forward. Under these assumptions, the estimate in Column (1) should be interpreted as follows: from 2007 onward, the annual purchasing power of the average U.S. consumer is \$1,711 higher thanks to the increase in trade with China between 2000 and 2007 (which is about 2% of total consumption expenditures). The increase in consumer surplus is computed based on three components: (a) the increase in import penetration from China between 2000 and 2007 in the set of all tradable product categories (denoted $\Delta_{2000-2007}ChinaIP$); (b) the IV estimates for the price response (β); and (c) average household spending on tradable product categories in 2007, which we measure in the 2007 Consumer Expenditure Survey (denoted C_{2007}). A product of these three ingredients gives a first-order approximation to the annual consumer surplus created by falling prices from increase trade with China: $CS = \frac{-\beta}{100} \cdot \Delta_{2000-2007}ChinaIP \cdot C_{2007}$. The three columns of the table consider different estimates for the price response, which we apply to the observed cumulative change in import penetration from China between 2000 and 2007 (equal to 6.15 percentage points within the set of tradable product categories). In Column (1), using the IV estimate from the NTR gap instrument, we obtain an increase in consumer surplus per household of \$1,711 ($= \frac{-2.23}{100} \cdot 6.15 \cdot 12479$). Columns (2) and (3) report the results using alternative instruments for the price effects. The increase in consumer surprlus is \$1,105 per U.S. household using the change in trade with China in other developed economies (Column (2)), and \$1,466 using both instruments jointly (Column (3)). These estimates are much larger than predicted by the class of trade models nested by Arkolakis et al. (2012). Using a standard trade elasticty of $\theta = -4$, the predicted price effect in these models is $\beta = \frac{1}{\theta} = -0.25$, implying an increase in consumer surplus of \$192 per U.S. household ($= \frac{-0.25}{100} \cdot 6.15 \cdot 12479$). In robustness checks, we find that these results are similar (i) when we use the BEA's measure of average personal consumption expenditures on tradable goods in 2007 (equal to \$11,153) instead of the estimates from the CEX, as well as (ii) when we use an adjusted measure for the change in trade with China as in Acemoglu et al. (2016) (they attempt to isolate the share of the observed increase in trade with China that was caused by increased productivity in China, rather than by other factors such as a fall in productivity in the U.S.). The calculations underlying this table rest on two simplifying assumption that may understate the magnitude of the gains to U.S. consumers: (1) the first-order approximation does not allow U.S. consumers to reallocate their expenditures toward product categories that become relatively cheaper – including these second-order gains would further increase consumer surplus; (2) we assumed away GE effects affecting all product categories, but if increasing import penetration induces an overall fall in domestic prices to restore trade balance, then the increase in purchasing power for U.S. consumers would increase further.

Table A10: Summary Statistics for CPI and PPI samples

Panel A: CPI Sample

	Mean	S.D.	p10	p50	p90	Observations	
						N	Aggreg. Level
Inflation, continued products (%)	-3.77	10.75	-19.04	1.18	7.36	3,774	ELI-by-year

Panel B: PPI Sample

	Mean	S.D.	p10	p50	p90	Observations	
						N	Aggregation Level
Inflation, all (%)	0.04	10.19	-7.19	0.84	7.28	1,044	NAICS6-by-period
ΔChina IP in U.S., direct	0.39	0.69	0.00	0.11	1.04		
NTR Gap	0.24	0.19	0.00	0.29	0.45	522	NAICS6

Notes: Panel A presents summary statistics for inflation for continued products in the CPI sample. Panel B presents summary statistics for the PPI sample, which is described in Section II.A and Online Appendix A.E. The sample extends between 1991 and 2007 and is divided into two periods, 1991-1999 and 2000-2007.

Table A11: Testing for Pre-trends in the Extended CPI Sample (1977-1986)

	Annual U.S. CPI Inflation	
	(1)	(2)
NTR Gap	1.798	
	(2.285)	
Δ China IP Other		-0.2863
		(0.5016)
N	156	156

Notes: This table reports the reduced-form specifications in the extended CPI sample. The level of observation is an ELI and heteroeksedasticty-robust standard errors are reported in parentheses. The corresponding binned scatter plots are shown in Panel B of Figure 1 in the main text. The extended CPI sample is described in Online Appendix A.B.

Table A12: Placebo First-stage with French Trade Data

	Δ China IP (in France, pp)
	OLS
	(1)
NTR Gap	0.63
	(0.82)
COICOP F.E.	✓
Period-specific Goods F.E.	✓
N	264

Notes: The level of observation is a COICOP-by-period cell. Standard errors are clustered by COICOPs.*** denotes statistical significance at the 1% level, ** at the 5% level.

Table A13: First Stage for Panel Specification with Additional Periods

	Δ China IP (pp)					
	$\gamma_{1991-1993}$	$\gamma_{1994-1996}$	$\gamma_{1997-1999}$	$\gamma_{2000-2002}$	$\gamma_{2003-2005}$	$\gamma_{2006-2007}$
NTR Gap	0.61	-0.13	0.43	2.65^{***}	3.23^{***}	3.73^{***}
	(0.51)	(0.67)	(0.54)	(0.56)	(0.64)	(0.71)
ELI F.E.			✓			
Period-specific Goods F.E.			✓			
N			1332			

Notes: The level of observation is an ELI-by-period cell. The periods are indexed by t, with $t \in \{1991-1993\}, \{1994-1996\}, \{1997-1999\}, \{2000-2002\}, \{2003-2005\}, \{2006-2007\}$. The IV specification is:

$$\pi_{it} = \sum_{k=1991-1993}^{2006-2007} \beta_k \Delta ChinaIP_{it} \cdot 1_{\{k=t\}} + \delta_i + \delta_t + \varepsilon_{it},$$

$$\Delta ChinaIP_{it} = \sum_{k=1991-1993}^{2006-2007} \gamma_k \mathbf{Z_{it}} \cdot 1_{\{k=t\}} + \tilde{\delta}_i + \tilde{\delta}_t + \eta_{it},$$

The table reports the first-stage estimates γ_k. Standard errors are clustered by ELIs. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table A14: IV Estimates with NTR Gap Instrument and Additional Controls

	U.S. CPI Inflation (pp)	
	IV	IV
	(1)	(2)
Δ China IP (pp)	-2.10^{***}	-2.03^{***}
	(0.62)	(0.58)
First-stage F	23.19	19.42
ELI F.E.	✓	✓
Period-specific Goods F.E.	✓	✓
Time-varying controls for High-tech, Contract intensity and Union membership	✓	✓
Controls for MFA quota reductions, Chinese import tariffs, export licensing requirements, and Chinese production subsidies		✓
Instrument: NTR Gap	✓	✓
N	444	444

Notes: This tables is similar to Table 3 in the main text, but follows Pierce and Schott (2016) by including additional controls in Column (2): exposure to MFA quota reductions, Chinese import taris from Brandt et al. (2012), data on export licensing requirements from Krishna, Bai, and Ma (2015), and data on production subsidies from China's National Bureau of Statistics. The level of observation is an ELI-by-period cell. Standard errors are clustered by ELIs.*** denotes statistical significance at the 1% level, ** at the 5% level.

Table A15: IV Results with Controls for Exports

	U.S. CPI Inflation	
	IV	IV
	(1)	(2)
Δ China IP	-1.805^{***}	-1.447^{***}
	(0.474)	(0.3358)
First-stage F	25.628	205.028
Controls:		
Change in exports to China, 1991-1999	✓	✓
Exports to China in 1992	✓	✓
Instruments:		
NTR Gap	✓	
Δ China IP Other		✓
N	306	306

Notes: This table reports the IV estimates with specifications similar to Section III.C but including controls for exports from the U.S. to China across product categories. Exports to China are measured in trade data recorded under HS codes (which we link to NAICS industries and to ELIs using the crosswalks from Online Appendix A.C). The controls include the log change in exports to China from 1991 to 1999, as well as the level of exports to China in 1992. The results are similar when repeating the anlaysis in subsamples (above vs. below median of exports), when including controls in level and changes for exports to China for other years, and when including all exports instead of exports to China specifically (not reported). These results indicate that the baseline IV estimates are not confounded by differences in export dynamics across product categories. The level of observation is an ELI-by-period cell. Standard errors are clustered by ELIs. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table A16: A Test of the Uncertainty Channel — First-stage Heterogeneity by Capital Intensity

	ΔChina IP	
	OLS	OLS
	(1)	(2)
Δ NTR Gap	3.861***	
	(1.361)	
Δ NTR Gap × Capital Intensity	4.786**	
	(2.308)	
Δ China IP Other		1.353***
		(0.331)
Δ China IP Other × Capital Intensity		−0.249
		(0.357)
N	306	306

Notes: This table reports the results from first-stage regressions with interaction terms for capital intensity. The interaction term is the only difference with the specifications described in Section III.C. Capital intensity is measured in the NBER-CES database. The sample is restricted to ELIs that can be matched to this data set; the crosswalk is described in Online Appendix A.C. The NTR gap instrument corresponds to a fall in uncertainty over import tariffs applied by the U.S. to China. In a situation of uncertainty, standard models generate a region of inaction in investment space due to nonconvex adjustment costs (e.g., Dixit and Pindyck (1994)). If the relevance of the NTR gap instrument is driven by the uncertainty channel, we expect the first stage to be stronger in product categories that are more capital intensive. Column (1) confirm that this is the case in the data. Column (2) reports a placebo test and shows that the first stage features no heterogeneity by capital intensity when the instrument is the change in import penetration from China in the set of developed economies other than the United States. The level of observation is an ELI-by-period cell. Standard errors are clustered by ELIs. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table A17: Alternative IV Specifications with the Change in Import Penetration in Other Developed Economies

	U.S. CPI Inflation			
	(1)	(2)	(3)	(4)
Δ China IP	-1.43^{***}	-1.43^{**}	-1.58^{***}	-1.78^{***}
	(0.34)	(0.61)	(0.48)	(0.65)
First-stage F	357.70	14.84	21.50	48.07
Major Category F.E.	✓			
ELI F.E.		✓	✓	
Period-specific Goods F.E.	✓	✓	✓	✓
Durables & Apparel Time-Varying F.E.		✓		
Excluding Deflationary ELIs			✓	
6-digit IO industry F.E.				✓
Instrument: Δ China IP Other	✓	✓	✓	✓
N	444	444	444	170

Notes: The specifications reported in this table are described in Section III.C. They are identical to Panel A of Figure 3 in the main text, except that we use the change in import penetration from China in other developed economies as the instrument, instead of the NTR gap. The level of observation is an ELI-by-period cell and the sample includes all ELIs from 1991 to 2007, with variables averaged over two periods, 1991-1999 and 2000-2007. Column (4) of Panel A is an exception: the data is aggregated from ELIs to 6-digit industries defined in the BEA's IO table. Consumption weights are used. Standard errors are clustered by ELIs or 6-digit IO industries. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table A18: IV Results with Purchaser vs. Producer Pricers

	U.S. CPI Inflation	
	IV	IV
	(1)	(2)
Δ China IP, Producer Prices	-2.44^{***}	
	(0.431)	
Δ China IP, Purchaser Prices		-4.37^{***}
		(0.852)
First-stage F	111.71	31.56
Hansen J	0.881	0.459
Instruments: NTR Gap & Δ China IP Other	✓	✓
N	170	170

Notes: The specifications reported in this table are described in Section III.C, except that the data is aggregated from ELIs to 6-digit industries defined in the BEA's IO table. Column (1) uses the baseline definition for the change in import penetration rate from China (defined in Section II.A). Column (2) adjusts this definition by accounting for distribution margins. Distribution margins correspond to the costs associated with transportation and retail, which inflate the denominator in the definition of China IP in equation (1) in the main text. For each 6-digit IO industry, we estimate distribution margins as the ratio of purchaser prices to producer prices observed in the BEA's 2007 IO table. When accounting for distribution margins, the change in the import penetration rate from China decreases, and accordingly the IV coefficient is larger in Column (2) than in Column (1). These IV specifications use both instruments jointly (the NTR gap and the change in import penetration from China in other developed economies). The Hansen J statistics indicate that we cannot reject the over-identification restrictions. The results are similar when using the 1992 IO table, where the available industries are more aggregated (not reported). The level of observation is a 6-digit IO industry-by-period cell. Standard errors are clustered by 6-digit IO industries. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table A19: IV Estimates for Continued Goods in Balanced Sample

	2000-2003 CPI Infl. for Contined Goods		2000-2005 CPI Infl. for Contined Goods	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Δ China IP	-1.98^{***}	-2.63^{***}	-2.00^{***}	-2.66^{***}
	(0.71)	(0.98)	(0.72)	(1.01)
First-stage F		215.40		214.06
2000-2007 only	✓	✓	✓	✓
Goods, Durables & Apparel F.E.	✓	✓	✓	✓
N	222	222	222	222

Notes: This table reports OLS and IV estimates using inflation for continued products as the outcome variable. We consider a balanced sample of products that are continuously available from 2000 to 2003 (Columns (1) and (2)) or from 2000 to 2005 (Columns (3) and (4)). The NTR gap is used as an instrument. The price effects are not sensitive to the period we choose for the balanced sample. The magnitudes are similar to the estimates in Panel A of Table 6, which indicates that changes in composition do not drive our results for continued products. 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). The level of observation is an ELI-by-period and the standard errors are clustered by ELIs. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table A20: The Effect of Trade with China on Product Turnover

	Product Turnover (pp)	
	(1)	(2)
Δ China IP (pp)	1.72	1.45^{***}
	(1.533)	(0.403)
Instrument:		
NTR gap	✓	
Δ China IP Other		✓
N	444	444

Notes: This table 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). The table shows that product turnover increases substantially in response to trade with China, consistent with the notion that Chinese products displace domestic varieties. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table A21: Correlations between Direct and Indirect Exposure to Trade with China

	Δ China IP Supplier, First-order IO (pp)			Δ China IP Buyer, First-order IO (pp)		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ China IP (pp)	0.099***	0.073***	0.046***	0.018***	0.01241	−0.00081
	(0.014)	(0.0154)	(0.010)	(0.0062)	(0.0098)	(0.00191)
6-digit IO F.E.		✓	✓		✓	✓
Period-specific Goods F.E.		✓	✓		✓	✓
Excl. diagonal of IO Table			✓			✓
N	170	170	170	170	170	170

Notes: The specifications are described in Section IV.C. The level of observation is a 6-digit IO industry-by-period cell. The instrument is the NTR gap. Standard errors are clustered by IO industries. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table A22: The Role of Higher-Order Input-Output Linkages

Panel A: Direct and Indirect Higher-Order Exposure to Trade with China

	Δ China IP Supp, Higher-order IO			Δ China IP Buyer, Higher-order IO		
	(1)	(2)	(3)	(3)	(4)	(6)
Δ China IP (pp)	0.0567***	0.0394***	0.03607***	0.0163***	0.01127	−0.0013
	(0.0077)	(0.0097)	(0.0072)	(0.0061)	(0.0098)	(0.00149)
6-digit IO F.E.		✓	✓		✓	✓
Period-specific Goods F.E.		✓	✓		✓	✓
Excl. diagonal of IO Table			✓			✓
N	170	170	170	170	170	170

Panel B: IV Results Controlling for Indirect Higher-Order Exposure to Trade with China

	U.S. CPI Inflation		
	(1)	(2)	(3)
Δ China IP	−3.143**	−2.831**	−3.196**
	(1.451)	(1.383)	(1.515)
First-stage F	7.110	8.497	6.321
Controls:			
Δ China IP Supplier. Full IO	✓		✓
Δ China IP Buyer. Full IO		✓	✓
ELI F.E.	✓	✓	✓
Period-specific Goods F.E.	✓	✓	✓
N	170	170	170

Notes: The sample and specification are the same as in Panel A of Table 7 in the main text, except that the IO-adjusted measures including higher-order IO linkages instead of first-order linkages only. The level of observation is a 6-digit IO industry-by-period cell. The instrument is the NTR gap. Standard errors are clustered by IO industries. *** denotes statistical significance at the 1% level, ** at the 5% level.

Table A23: IV Estimates for Input-Output Effects

	U.S. CPI Inflation			
	First-order I-O Linkages		Higher-order I-O Linkages	
	(1)	(2)	(3)	(4)
Δ China IP	-1.454^{***}	-1.458^{***}	-1.441^{***}	-1.478^{***}
	(0.402)	(0.408)	(0.389)	(0.399)
Δ China IP Supplier	-4.602	-5.552	-8.688	-9.208^{*}
	(3.821)	(3.633)	(5.348)	(5.310)
Δ China IP Buyer	-4.868	-8.102	-0.383	-1.489
	(9.348)	(10.614)	(9.942)	(11.373)
First-stage F	45.773	40.567	45.773	40.567
Period-specific Goods F.E.	✓	✓	✓	✓
Tech-by-period F.E.	✓	✓	✓	✓
IO2 F.E.		✓		✓
N	170	170	170	170

Notes: This table reports IV estimates with three endogenous variable: direct trade exposure, indirect exposure via intermediate inputs ("supplier effect") and indirect exposure via domestic buyer industries ("buyer effect"). Columns (1) and (2) use first-order IO linkages only, while columns (3) and (4) use higher-order IO linkages. The supplier and buyer effects across specifications are computed as explained in Online Appendix A.D. We include alternative sets of fixed effects across specifications. With 6-digit IO fixed effects, the IV becomes weak (not reported). *** denotes statistical significance at the 1% level, ** at the 5% level.

Table A24: Markup Quantiles and Profitability Ratios

	U.S. Markups by Quantiles (pp)			Profitability	
	p90	p50	p10	Profits/Sales	Profits/Assets
	(1)	(2)	(3)	(4)	(5)
NTR Gap	-17.42^{**}	-7.97^{*}	-0.84	-7.47^{***}	-4.91^{***}
	(7.28)	(4.83)	(4.023)	(2.66)	(2.23)
NAICS F.E.	✓	✓	✓	✓	✓
Period-specific Goods F.E.	✓	✓	✓	✓	✓
N	796	796	796	796	796

Notes: The level of observation is a 6-digit NAICS-by-period cell. Standard errors are clustered by 6-digit NAICS industries.*** denotes statistical significance at the 1% level, ** at the 5% level, * at the 10% level. Source: Compustat North America Fundamentals Annual Data, (Wharton Research Data Services) and authors' calculations.

Table A25: Heterogeneity by Market Structure in CPI Sample

	U.S. CPI Inflation (pp)				
	Interacted Specs.	Subsample Specs.			
	(1)	(2)	(3)	(4)	(5)
Δ China IP (pp)	-0.70	-1.58^{***}	-0.34	-0.77^{**}	-1.61^{***}
	(0.53)	(0.40)	(0.48)	(0.35)	(0.33)
Δ China IP×High Concentration	-1.29^{**}				
	(0.53)				
Δ China IP×High China IP	1.50^{**}				
	(0.60)				
First-stage F	5.76	28.77	8.26	2.64	34.23
ELI F.E.	✓	✓	✓	✓	✓
Period-specific Goods F.E.	✓	✓	✓	✓	✓
Subsample	All	High Conc.	Low Conc.	High China IP	Low China IP

Notes: "High Concentration" product categories have a level of domestic market concentration above median in 1997 (resp. below for "Low Concentration"). "High China IP" product categories have an import penetration rate from China above the 75th percentile in 1999 (resp. below for "Low China IP"). The level of observation is an ELI-by-period cell. Standard errors are clustered by ELIs.*** denotes statistical significance at the 1% level, ** at the 5% level, * at the 10% level.