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 from China causes a 1.91% decline in consumer prices. This price response is driven by declining markups for domestically-produced goods, and is one order of magnitude larger than in standard trade models that abstract from strategic price-setting. 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.

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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 indicate 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 (2016a), 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? 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 United States 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 organize our analysis into three parts. First, we estimate the causal effect of increased trade with China on prices across detailed product categories in the 1990s and 2000s, using the instrumental variable approaches developed by Pierce and Schott (2016a) and Autor et al. (2014). We find large effects: on average, an increase in the import penetration rate from China of 1 percentage point leads to a fall in U.S. consumer prices of approximately 2%. Second, we investigate potential mechanisms and examine which trade models can account for the observed patterns. The estimated price response is about one order of magnitude larger than predicted by the large class of quantitative trade models characterized by Arkolakis et al. (2012). We find that the price response is driven by price changes for domestically-produced goods and is primarily explained by declining markups, rather than by falling domestic production costs. These findings highlight the importance of including endogenous markups and pro-competitive effects into quantitative trade models used for policy analysis. Third, we use the estimates to characterize the distributional effects of rising trade with China. We find that falling prices in product categories that are more exposed to trade with China increase consumer surplus by several hundreds of thousands of dollars for each displaced job, and that the price response is larger in product categories that cater to lower-income households.[1]

Estimating the causal effect of trade with China on U.S. consumer prices is challenging because of

[1] Our main analysis focuses on consumer prices, but producer prices are also used to investigate mechanisms. The internal Consumer Price Index Research Database of the BLS offers full coverage of the market basket of the representative consumer, with the exception of shelter, and keeps track of products' prices inclusive of retail margins, which are the relevant prices for consumers. The product-level micro data allows us to work at a fine level of disaggregation, to isolate the role of domestic products, and to build alternative price indexes (e.g., using "continued products" only so that the price index is immune to potential changes in composition). The sample frame has a fixed number of products and makes it impossible to measure the potential increase in product variety that is likely to be induced by trade. Because consumers value increasing product variety, our estimates are likely to be a lower bound for the impact of trade with China on U.S. consumer prices.

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 by Pierce and Schott (2016a) and Autor et al. (2014), who study the consequences of trade with China on employment across U.S. industries.[2] Pierce and Schott (2016a) leverage a change in U.S. trade policy passed by Congress in October 2000, which eliminated potential tariff increases on Chinese imports. This research design uses transparent policy variation and lends itself to sharp tests for pre-trends, but the effects of changes in policy uncertainty may differ from those of more common permanent changes in tariffs (e.g., Handley and Limão (2017)). To gauge the stability and 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 across U.S. industries with contemporaneous changes observed in eight comparable economies.[3]

To assess the plausibility of a causal interpretation of our estimates, we implement several falsification and robustness tests. The results all support the validity of the exclusion restrictions. First, for each of the two instruments, we implement pre-trend tests and consider alternative specification choices, with different sets of fixed effects, time-varying controls and sample restrictions. There are no pre-trends and the estimated price effect is stable across specifications. Second, we study the sensitivity of our baseline estimate to aggregation choices by aggregating our data to the level of broader industries (as defined by the BEA's input-output table), and we use alternative measures of changes in import penetration from China (including or excluding retail margins, and accounting for changes in trade with trading partners of the U.S. other than China). We find that the estimated price response remains stable. Third, with the instrument from Pierce and Schott (2016a), 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. Finally, using both instruments jointly, we run the test of over-identifying restrictions of Hansen (1982) and cannot reject that the restrictions are valid.

Our IV estimates indicate that the price effects of increasing trade with China are large. With the instrument from Pierce and Schott (2016a), a one percentage point increase in the import penetration rate from China causes a fall in inflation of 2.23 percentage points (s.e. 0.47). Put another way, the consumer price index falls by 2.23%. With the instrument from Autor et al. (2014), the corresponding fall in consumer prices is 1.44% (s.e. 0.45). With both instruments jointly, the IV coefficient is -1.91 (s.e. 0.38). The J test of over-identifying restrictions indicates that the two instruments are statistically

[2] We estimate the price effects of trade across product categories that are differentially exposed to rising trade with China in the 1990s and 2000s, which characterizes the average impact on U.S. consumers at the *national* level. With suitable data on *local* prices (in particular, housing prices), it would be instructive to estimate the price effects across local labor markets in future work (e.g., for comparison with Autor et al. (2013)'s estimates of the local employment effects of trade).

[3] The eight comparable developed economies are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. This research design addresses threats to identification that stem from U.S.-specific supply or demand patterns, i.e. changes in U.S. supply or U.S. demand across industries that are not correlated with supply or demand changes in the group of eight comparable economies.

indistinguishable.[4]

In the second part of the paper, we investigate a series of potential mechanisms that could account for the estimated price effect of trade with China across product categories. We start by showing 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 wide set of trade models characterized by Arkolakis et al. (2012), the price response is predicted to be equal to the inverse of the trade elasticity. We find that the estimated price effect is about one order of magnitude larger than predicted by these standard models. To account for the observed effect, this class of trade models requires an implausibly small trade elasticity, around -0.3, while common estimates are around -4 (cf. Simonovska and Waugh (2014)).

To uncover the mechanisms that might explain the effect, we start by documenting which products drive the price response. 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.[5] 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 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.[6] 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

[4] Our main specifications implement the diff-in-diff IV using long differences over two periods, 1991-2000 and 2000-2007, as in Acemoglu et al. (2016).

[5] For each product in the CPI, specification checklist files record characteristics like country of origin. We identify the subsample of U.S. products and repeat our IV specification.

[6] 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.

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.

Having established that changes in domestic production costs are unlikely to drive the price effects, we turn to the potential relevance of markups. We examine theoretically whether endogenous markups arising from strategic interaction can match the estimated price response. To do so without committing to a specific model of demand, market structure, price setting or production, we use the theoretical framework of Amiti et al. (2018b), which only requires mild assumptions about demand.

We find 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 of the fall in U.S. prices, U.S. consumers do not substitute as much toward the products from China, i.e. 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, we can obtain a large reduced-form relationship between changes in import penetration and price changes across product categories (which is our IV coefficient). Setting markup elasticities to match the estimates of Amiti et al. (2018b), we find that the price response across industries predicted by this class of models is close to our IV estimate.

Next, we conduct empirical tests of the markup channel. We start by examining the response of estimated markups for publicly-listed firms in Compustat, following the methodology of De Loecker et al. (2017) 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 1.75 percentage points (s.e. 0.848). 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 *across* product categories is also 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; conversely, there is less room for China to disrupt market power in a product category where it already has a high market share. These findings hold in both the CPI and PPI samples. Overall, the data point to markup responses as an important explanatory mechanism.

In the final part of the paper, 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.[7] These large magnitudes suggest that it may be possible to compensate those who suffer from the labor market impacts of trade shocks. In contrast, using the predicted price effects from 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.[8]

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), Borusyak and Jaravel (2018) and Carroll and Hur (2019) examine differences in spending shares on imports, and Hottman and Monarch (2018) document differences in import price inflation across income groups).

This paper relates and contributes to several literatures. First, a growing literature examines the reduced-form impact of changes in trade on prices, but no paper uses comprehensive data on consumer prices as we do. Amiti et al. (2019), Cavallo et al. (2019), Fajgelbaum et al. (2019) and Flaaen et al. (2019) 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. The price effects of the China shock are also studied by Bai and Stumpner (2018) for consumer packaged goods, and by Amiti et al. (2018a) for producer prices in manufacturing. Our findings advance the literature by leveraging a comprehensive data set, which is representative of the market basket of U.S. consumers and allows for an in-depth investigation of the identifying assumptions (e.g., with pre-trend tests) and mechanisms (e.g., isolating

[7] These calculations reflect partial-equilibrium differences across industries with different levels of exposure to rising import penetration from China. General equilibrium effects induced by the China shock could affect all industries simultaneously. If displaced manufacturing jobs lead to more job creation in other industries, then the increase in consumer surplus per "destroyed" job at the aggregate level (rather than per displaced jobs across industries) would be larger. In a related analysis assuming no GE effects affecting prices in all product categories, 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.

[8] Our large estimates of consumer surplus per displaced job are explained by our large estimated price effects, but also by the fact that the product categories exposed to rising trade with China are not very labor intensive. Since they account for relatively few jobs but for substantial consumption expenditures, a large amount of consumer surplus can be created per displaced job.

the response of domestically-produced goods and markups).[9]

Second, 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 (2016a) and Bloom et al. (2019)), mortality (Pierce and Schott (2016b)), marriage, fertility and children's living circumstances (Autor et al. (2018)), domestic innovation and investment (Pierce and Schott (2018) and Autor et al. (2019)), and political polarization (Autor et al. (2016)). Third, 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 estimated the empirical relationship between international trade and markups (e.g., Levinsohn (1993), Krishna and Mitra (1998), Nakamura and Zerom (2010), Feenstra and Weinstein (2017), Arkolakis et al. (2018), Auer et al. (2018) and Amiti et al. (2018b)) and that has examined the extent to which opening up to trade may reduce markup distortions (e.g., Brander and Krugman (1983), Atkeson and Burstein (2008), Epifani and Gancia (2011), Edmond et al. (2015), Feenstra (2018), and Impullitti and Licandro (2018)). Finally, our findings speak to a growing literature on the distributional effects of trade via the expenditure channel (e.g., Porto (2006) and He (2018), and the aforementioned studies).

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. Additional results are reported in the Online Appendix.

II Data

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

II.A Data Sources, Samples and Variable Definitions

Our main analysis relies on three data sources: inflation data from the Bureau of Labor Statistics; trade data from Acemoglu et al. (2016); and instruments for trade with China from Pierce and Schott (2016a) and Autor et al. (2014). For robustness analyzes and extensions we use additional data sets, which are also introduced below.

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,

[9] For our purposes, scanner data such as those used by Bai and Stumpner (2018) suffer from certain drawbacks: (a) the sample covers consumer packaged goods (about 10% of total expenditures) and is not representative of several important product categories for trade with China (e.g., apparel, consumer electronics and small appliances); (b) the sample starts in 2004, making it impossible to test for pre-trends prior to the "China shock."

excluding shelter.[10] A product is defined as a specific item available in a specific store, such as a 500 ml bottle of Coca-Cola Sparkling on the shelf of a specific Whole Foods Market store in Washington D.C. 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 Online Appendix A.A.[11] 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."[12]

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.[13]

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

[10]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.

[11]The BLS weighting procedure for aggregation has two components: (a) the main weighting is performed by BLS through probability sampling, i.e. through the selection of retail outlets and individual products within those outlets; (b) the CPI-RDB provides additional weights for each product-level price that correct for sampling error.

[12]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. See Online Appendix A.A for a complete discussion.

[13]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.

market basket almost comprehensively. This allows us to implement stringent tests for "pre-trends" and assess the plausibility of a causal interpretation of our IV estimates.[14] 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.[15]

Despite these advantages, our price data set also has some limitations. 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. A well-established literature has shown both theoretically and empirically that increased trade tends to increase product variety, which lowers consumers' effective price index through love of variety (e.g., Feenstra (1994), Broda and Weinstein (2006), Feenstra and Weinstein (2017), Bai and Stumpner (2018), Amiti et al. (2018a)). In this sense, our estimates are likely to be a lower bound for the impact of increased trade with China on U.S. consumer prices. Although we cannot measure changes in product variety in the CPI sample, we can study product turnover, using as a proxy the frequency of "product substitutions" (instances when the data collector cannot find the same item on the shelf from one period to the next).

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.[16] 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. We work with the annualized change in Chinese import penetration, in percentage points, for each of these two periods.[17]

[14] 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)).

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

[16] In prior work, Autor et al. (2013) measured labor market exposure to import competition from China as the "change in Chinese import exposure per worker". We don't adopt this measure because in standard trade models price effects are related to the ratio of imports over absorption (as in equation (1)), not to exposure per worker.

[17] Acemoglu et al. (2016) follow the definition in equation (1) using imports and exports trade data reported under Harmonized System product codes, which they match to domestic production data at the level of more aggregated SIC industries in the NBER-CES Manufacturing Industry database. Acemoglu et al. (2016) keep the denominator in (1) fixed to its value in 1991, implying that changes in import penetration from China over time result from changes in the numerator. This approach could potentially conflate increased Chinese import penetration with overall industry growth. In a robustness

Although our baseline trade exposure measure facilitates the comparison with prior work, it could suffer from potential limitations, which we relax in various extensions. In standard trade models, the price effects of trade are related to changes in the overall import penetration rate (not just from China), sometimes with a specific functional form (e.g., the log change in the domestic expenditure share in Arkolakis et al. (2012)). We compute these alternative measures by matching trade data recorded under Harmonized System (HS) codes (from China and from the rest of the world) to domestic production data from the NBER-CES Manufacturing database, using the concordance of Pierce and Schott (2012).

Another potential concern with respect to our baseline import penetration measure is that distribution margins (i.e., retail and transportation costs and profits) sometimes account for a significant fraction of a product's consumer price. In the import penetration measure of Acemoglu et al. (2016), the denominator does not include these margins, therefore the change in Chinese import penetration is potentially over-estimated from the perspective of consumers. In a robustness test, we adjust the denominator in equation (1) for 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.[18]

Instruments for Trade with China. To instrument for the patterns of trade with China, we rely on two complementary identification strategies, from Autor et al. (2014) and Pierce and Schott (2016a). Autor et al. (2014) instrument changes in China import penetration in the U.S. by changes in China import penetration across industries in developed economies comparable to the U.S. Their instrument follows equation (1), except that the numerator is measured in developed economies other than the U.S.[19] Pierce and Schott (2016a) use a policy change reducing uncertainty over import tariffs applied to China, when the U.S. Congress granted China "Permanent Normal Trade Relations" in 2000. Pierce and Schott (2016a)'s instrument is the "Normal Trade Relations (NTR) gap," defined as the jump in tariffs that could have occurred without this policy change. The NTR gap is measured at the level of 6-digit NAICS industries. Section III details the research designs that leverage these instruments.

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 (2016a)). 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. The crosswalks are built by hand and are described in Online Appendix A.C.

check, we re-build the import penetration measure following equation (1) in each year, i.e. allowing the denominator to change over time (see Section III). In an additional robustness check, to alleviate potential measurement concerns, we check that our import penetration measure is closely aligned with the import penetration rates published by the Bureau of Economic Analysis for the detailed industries of the 2007 input-output table (Online Appendix Figure A1).

[18] For this analysis, we aggregate the data to the level of the 6-digit industries of the input-output table (see Section III).

[19] These countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland, which represent all high-income countries for which Autor et al. (2014) and the previous study by Autor et al. (2013) could obtain disaggregated bilateral trade data at the HS level back to 1991.

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, with 170 industries relevant for final consumption. We build by hand a many-to-one match from ELI categories to these industries and then aggregate the data.[20] We refer to this linked data set as the input-output sample, which we use to investigate whether the estimated price effects are stable across levels of aggregation as well as to investigate potential mechanisms. For example, we examine whether the estimated price effects result from indirect exposure to trade with China, via intermediate inputs. 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' Producer Price Index (PPI) dataset, which tracks producer prices for products manufactured in the United States. As we did with the CPI, we aggregate the product-level price changes into category-level price changes. The PPI database allows us to work with 6-digit NAICS codes, which are more disaggregated than ELIs. Our baseline category-level PPI inflation rate follows the BLS' procedure to compute official aggregate PPI inflation statistics. We also build alternative measures, for instance using only the subset of "continued products" for which no quality adjustment is required. We then link the trade data and instruments to the PPI inflation outcomes; in the remainder of the paper, we refer to the linked data set as the PPI sample.[21] Online Appendix A.E describes the PPI data set and the computation of price indices.

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), demand-side variables from the public-use Consumer Expenditure Survey,[22] and several supply-side variables from Broda and Weinstein (2006), the NBER-CES Manufacturing Database and the U.S. Census (e.g., trade elasticities, average wages, capital intensity, total factor productivity, and market concentration). We also use data from the French CPI to implement placebo tests and Compustat data to measure markups following De Loecker et al. (2017). These variables are introduced when relevant in subsequent sections.

[20] 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.

[21] The level of aggregation is 6-digit NAICS industries: PPI inflation is available across 6-digit NAICS industries; Pierce and Schott (2016a)'s instrument can be directly matched to those industries; and we use a crosswalk from SIC to NAICS codes to link the trade data and Autor et al. (2014)'s instrument. While the main analysis sample only covers final products, the PPI sample also cover intermediate products.

[22] We use the Consumer Expenditure Survey dataset as processed by Borusyak and Jaravel (2018). 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.

II.B Summary Statistics

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

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. We use changes in the share of unavailable products over time as a proxy for changes in product turnover.[23]

Rows four and five of Table 1 describe the changes in import penetration rates from China. As previously discussed, we consider changes in import penetration over two periods, 1991-1999 and 2000-2007. 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, which we will leverage to estimate the price effects of trade. Online Appendix Figure A2 documents the increase in Chinese import penetration over time in greater detail.[24] The change in import penetration from China in developed economies comparable to the United States features similar properties.

The remainder of Table 1 reports summary statistics for several variables defined at the ELI level. The NTR gap from Pierce and Schott (2016a) is on average 21% and exhibits large variation across ELIs, which provides another source of variation to estimate the price effects of trade. The table also reports various indicators for product categories, showing the fraction of goods, apparel products, high-tech products, and a set of durable goods with particularly low inflation rates as defined in Bils (2009).[25] We use these variables, along with others such as contract intensity from Pierce and Schott (2016a), to assess whether the estimated price effects may be confounded by omitted variables biases. Finally, we use a range of ELI-level variables characterizing consumers' income levels: the expenditure elasticity and the shares of sales to college graduates and to households across income brackets. We use them to estimate

[23]The BLS data collectors sometimes start pricing a different item even when the initial item is still available, a case known as a "planned rotation". Planned rotations, forced substitutions (when the initial item becomes unavailable) and continued products account for all items in the CPI's sample frame.

[24]In manufacturing as a whole, the import penetration rate from China increased by approximately 5 percentage points cumulatively from 1991 to 2007, with a faster increase after 2000. However, the increase varied drastically across industries. Certain industries experienced a continuous increase in import penetration throughout the sample (e.g., footwear), while for others the increase occurred only after 2000 (e.g., computers), and while certain categories remained entirely unaffected by China (e.g., breakfast cereals).

[25]See Online Appendix A.A for a discussion of the set of durables defined in Bils (2009). In our baseline analysis, we keep the full sample of ELIs, including services, because (a) the instrument of Pierce and Schott (2016a) is non-zero for some product categories within services that are traded, and (b) services can be exposed to trade indirectly via input-output linkages. As described in section III.C, our specifications include controls so that differences between services and manufacturing do not contribute to the identifying variation. The results are very similar when only ELIs within goods are kept in the sample.

heterogeneity in the treatment effect for consumers across the income distribution and assess the potential distributional effects of trade.

Online Appendix Tables A1 and A2 report similar summary statistics for the input-output sample and the PPI sample.

III Estimating the Impact of Trade with China on 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. After presenting our research design, we report an analysis of pre-trends to assess the plausibility of the exclusion restrictions. We then report the baseline IV estimates and document their robustness to a variety of potential concerns.

III.A Research Design

Estimating the causal effect of trade with China on U.S. consumer prices poses several challenges. To understand the main threats to identification, suppose we were to estimate a simple regression of the change in U.S. consumer prices (inflation) on the change in import penetration from China across U.S. product categories over time. A causal interpretation of the OLS estimate from this specification could be misleading for two main reasons.

First, there could be reverse causality. 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). Alternatively, China may decide to enter product categories where U.S. demand is growing (implying higher U.S. inflation if the marginal cost of U.S. producers is upward-sloping, hence another upward bias of the OLS estimate).

Second, there may be omitted variable biases given that China has a comparative advantage in specific product categories, which may be on different inflation trends compared with other product categories. For instance, trade with China is 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,[26] these categories are characterized by low inflation (implying lower U.S. inflation in these product categories and a downward bias for the OLS estimate).

Given these identification challenges, we use two complementary research designs borrowed from recent work by Pierce and Schott (2016a) and Autor et al. (2014). They study the consequences of trade with China on employment across U.S. industries by leveraging different sources of variation.

Variation in the NTR Gap. Pierce and Schott (2016a) focus on a specific change in U.S. trade policy passed by Congress in October 2000, which eliminated potential tariff increases on Chinese imports.[27]

[26] Apparel products exhibit large price declines the longer they remain on the shelf.

[27] The change became effective when China joined the World Trade Organization 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. Indeed, before China was granted PNTR, U.S. import tariffs on Chinese goods needed to be renewed by Congress.

As explained by Pierce and Schott (2016a), 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. The fall in uncertainty over tariff increases can generate an increase in trade with China is theoretically plausible (e.g., Handley and Limão (2017)) and can be directly assessed in the data (with the "first-stage" specification described below).

The advantage of this research design is that the policy variation is transparent and lends itself to sharp tests for pre-trends. The main limitation is that using a change in uncertainty over import tariffs as an instrument for trade flows may potentially yield estimates with low external validity, because changes in policy uncertainty may have different effects from more common permanent changes in tariffs (e.g., Handley and Limão (2017)).

Variation in Import Penetration from China in Other Countries. To assess the stability and generalizability of our estimates, we also use the empirical strategy of Autor et al. (2014), who instrument for the change in import penetration from China across U.S. industries with changes in import penetration from China across industries in eight comparable developed economies. 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.

A potential limitation of this approach is that reverse causality or omitted variable bias could in principle stem from supply and demand changes that are in fact common to both the U.S. and the other developed economies. Testing for pre-trends can help alleviate this concern. Pre-trend tests for Autor et al. (2014)'s strategy are not possible in our baseline sample because trade with China increases throughout this period; instead, we implement pre-trend tests in our extended CPI sample, going back to 1977.

In sum, we leverage the strategies of both Pierce and Schott (2016a) and Autor et al. (2014) and assess whether they paint a consistent picture of the effect of trade with China on U.S. consumer prices. We treat the instrument from Pierce and Schott (2016a) as our benchmark, because it allows for more stringent falsification tests, including year-specific pre-trend tests and a triple-difference test discussed below (in practice, both instruments yield similar results).

The next subsections describe our statistical specifications and present the results. We first focus on reduced-form specifications that test for pre-trends, reported in Subsection III.B. We then turn to our baseline IV estimates (Subsection III.C) and we assess their robustness in multiple ways (Subsection

III.D).

III.B Pre-Trends Analysis

To assess the plausibility of the exclusion restrictions, we implement pre-trend tests. We examine the relationship between the instruments and inflation in periods when we would expect to find none if the identification conditions hold.

With the NTR gap of Pierce and Schott (2016a), 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 as far as possible, until 1988. We then run a flexible "event-study" specification across ELIs:

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

where t indexes year, i ELI categories, π_{it} is the CPI inflation rate, $1_{\{k=t\}}$ is an indicator variable for year t, X_{it} denotes a set of controls, and δ_t is year fixed effects. In the baseline specification, X_{it} includes two "fixed effects", i.e. two separate indicator variables corresponding to the set of ELIs within apparel and to the set of ELIs within durable goods categories (see Bils (2009) and the discussion in Section II.B). The inclusion of these controls is motivated by the fact that these product categories are known to have low inflation rates and are more exposed to trade.[28]

The path of the year-specific reduced-form coefficients, denoted $\{\beta_k\}_{t=1988}^{2007}$ in equation (2), is informative about the plausibility of the identification condition. The exclusion restriction, $\mathbb{E}\left[NTR\,Gap_i \cdot \varepsilon_{it} | X_{it}, t\right] \xrightarrow{p} 0$, 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 markedly 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 with a placebo test using French CPI data in Subsection III.D.

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 sharp 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

[28] Likewise, when studying a variety of outcomes other than inflation, Autor et al. (2019), Fort et al. (2018), Pierce and Schott (2016a) and Autor et al. (2014) highlight the importance of controlling for broad sectoral trends.

sample and inflation in the 1980s. We conduct this analysis using the extended CPI sample described in Online Appendix A.B.

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 (2016a) (subfigure (b)).[29] With both instruments, there is no relationship with inflation. These patterns strengthen the plausibility of the identification conditions.

The Online Appendix reports additional results about the analysis of pre-trends. Online Appendix Figure A4 repeats the estimation of equation (2), but without fixed effects for apparel or durable goods. Without these fixed effects, the figures exhibits pre-trends: ELI categories with a higher NTR gap had lower inflation even prior to 2000. This result indicates that including fixed effects for apparel and durable goods is important to ensure that a causal interpretation of the estimates is plausible.[30] Online Appendix Figure A5 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.

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 to obtain estimates of the impact of increased trade with China on U.S. consumer prices.

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.[31] This approach is natural for both of the instruments we use: the policy change making the NTR gap relevant occurs in 2000; and the increase in the import penetration from China in the other developed economies becomes more pronounced in the

[29] 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 $\Delta ChinaOther_i$ 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. Online Appendix Table A3 reports the regression results. Online Appendix Figure A3 reports the year-specific reduced-form coefficients by running the event-study specification (2) in the extended CPI sample (the results are similar).

[30] The validity of the research design would be doubtful if changing the set of controls in (2) had a large impact on pre-trends. However, we find that once fixed effects for apparel and durable goods are included, the estimated coefficients are stable and do not exhibit pre-trends, even when we add additional controls. We demonstrate the robustness of our estimates to this type of concerns in the remainder of this section by considering alternative sets of controls, including demanding specifications with ELI fixed effects.

[31] For a recent discussion of the identification challenges posed by dynamic causal effects in IV designs, see Jaeger et al. (2018).

early 2000s, as China joins the WTO. The variables are averaged within periods, such that we can study the relationship between the average annual change in import penetration from China and the average annual inflation rate across ELIs and periods.

We introduce ELI fixed effects in our baseline IV specification. These fixed effects help reduce noise and can address any potential omitted variable biases that remain unchanged over time. The analysis of pre-trends in Subsection III.B established that fixed effects for apparel and durable goods are sufficient to eliminate pre-trends. ELI fixed effects subsume these fixed effects and are more demanding, as they allow for each detailed 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 instruments from Pierce and Schott (2016a) and Autor et al. (2014) to obtain variation in trade with China. Our baseline specification uses the most detailed product categories and the most demanding set of fixed effects, but we then show that the results are stable across alternative sets of fixed effects and when aggregating the data further.

Formally, the structural equation and first stage in our IV specifications are as follows:

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

where i indexes ELIs, t the period (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. $\mathbf{Z_{it}}$ is a vector of instruments, which varies across specifications. Under the identification condition $\mathbb{E}\left[\mathbf{Z_{it}} \cdot \varepsilon_{it} | X_{it}, i, t\right] \xrightarrow{p} 0$ 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 causal effect of a 1 percentage point increase in the import penetration rate from China in an ELI on the level of inflation faced by U.S. consumers in that product category. All specifications use consumption weights.[32]

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. The two instruments are only weakly correlated and offer independent sources of variation. 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, which allows us to increase power and to run a Hansen overidentification test.

[32]In our baseline specification, the only time-varying control included in X_{it} is goods-by-period fixed effects. We include the full set of ELIs in the sample because the NTR gap instrument is defined for some ELIs within services. The results are identical when we restrict the sample to goods only. When services are included in the sample, goods-by-period fixed effects must be included so that differences in price trends between goods and services over time do not contribute to the identifying variation.

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 a strong first stage: the larger the NTR gap, the larger the increase in import penetration from China. As shown in Panel B, the reduced-form relationship is striking: the CPI inflation rate is significantly lower in ELIs with a higher NTR gap. These binned scatter plots offer a non-parametric representation of the conditional expectation functions for the first stage and the reduced form: in both panels, the linear approximation by OLS appears to be an excellent fit of the underlying data, and outliers appear to play no role for the magnitudes of the estimated slopes.

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 depicted in Figure 2 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 (as reported in Table 1, the mean and standard deviation of the NTR gap are both around 21 basis points).

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 (put another way, the consumer price index falls by 2.23%). 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 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 the usefulness of the full sample with ELI fixed effects to gain power.

Figure 3 and Panel B of Table 2 present the results using as an instrument the change in trade with China in other developed economies. Figure 3 shows a clear positive first-stage (panel A) and a strong negative reduced-form (panel B).[33] Column (1) of Table 2 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

[33]The binned scatter plots in Figure 3 feature somewhat dispersed observations, suggesting that the linear specifications based on trade in the other developed economies are potentially sensitive to outliers (more so than when using the NTR gap instrument, cf. Figure 2). The reason is the inclusion of ELI fixed effects, which absorb a lot of the variation in the data. With fixed effects at higher level of aggregation (e.g., for apparel and durable goods only), the binned scatter plot feature less dispersion and the estimated regression coefficients remain similar (not reported).

remains similar, equal to -1.27. These coefficients are precisely estimated and the F statistics are strong.

Column (3) of Table 2 reports the IV results 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. This finding bolsters the plausibility of a causal interpretation of our estimates.

III.D Robustness and Falsification Tests

We run a series of tests to establish the robustness of our baseline IV estimates: (a) we consider alternative specification choices, with different sets of fixed effects, time-varying controls and sample restrictions; (b) we repeat the analysis after aggregating the data at a higher level, from ELIs to 6-digit industries from the IO table; (c) we implement the IV design with alternative measures of changes in import penetration; (d) we implement falsification tests using French CPI data. Additional robustness checks are reported and described in the Online Appendix.

Robustness to specification choices. In Columns (1) through (4) of Panel A of Table 3, we examine whether the estimates remains 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. Columns (1) repeat 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. Column (4) repeats the specification after including the period-specific controls used by Pierce and Schott (2016a) (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.

Across all specifications, the estimated effects are statistically significant at the 1% level and the first-stage F statistic remains high. These results suggest that omitted variable biases are unlikely to drive the effects we document. Online Appendix Table A4 shows that the results are similar when the instrument is the change in import penetration in other developed economies.

Robustness to aggregation choices. The level at which we define an "industry" may matter for the magnitude of the estimates. On the one hand, if we consider coarse industry categories, the elasticity of substitution between domestic goods and Chinese goods may be artificially low because we are effectively lumping together very different goods. On the other hand, if we consider extremely detailed categories, it becomes difficult to accurately measure trade flows, thus generating attenuation bias. We assess the robustness 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. These industries are the most detailed industries available from the IO table, but they are considerably more aggregated than ELIs: the sample size fall from 444 industry-by-period observations to 170.

Column (5) of Panel A of Table 3 reports the results across 6-digit IO industries. The specification is similar to equation (3) but we now use fixed effects for 6-digit IO industries in the aggregated IO sample. Using the NTR gap instrument, the IV coefficient is -2.94 and is significant at the 5% level. The first stage F statistic falls to 9.54, suggesting that the instrument may become weak. However, we obtain a similar IV coefficient of -1.78 (s.e. 0.65) with the change in import penetration in other developed economies as the instrument, with a strong F statistic of 48.07 (Online Appendix Table A4). These results indicate that the large price effects of trade are not an artifact of the level of aggregation we choose.[34]

Robustness to alternative measures of import penetration. The estimated effects 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 (and our IV estimate would be artificially large). 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, which is a substantial displacement effect.[35]

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, are significant at the 5% level, and as previously are stable across specifications. As discussed in Section IV, the IV coefficient based on the overall change in import penetration is more informative for standard quantitative trade models than the change in import penetration from China alone.[36]

In another robustness check, we adjust our measure of import penetration from China to account for

[34] When we do not include 6-digit IO fixed effects, the NTR gap instrument recovers its strength. The F statistic increases above 20 and the IV coefficient remains stable. We obtain similar estimates with LIML, which also suggests that our results are not affected by a potential bias from weak instruments. We have also checked that there is no pre-trend in the sample aggregated to the level of 6-digit IO industries (not reported).

[35] Our measure of overall import penetration is based on trade flows across HS codes matched to domestic production data across 6-digit NAICS codes from the NBER CES database, as explained in Section II.A.

[36] There are two potential interpretations for the displacement pattern observed in the data (i.e., overall trade increases less than trade with China across ELIs): (a) it could be viewed as the causal effect of China on other trading partners of the U.S.; or (b) it could be viewed as an omitted variable bias that attenuates our estimate of the effect of trade with China on U.S. consumer prices (i.e., for reasons independent of China, other trading partners may happen to reduce trade with the U.S. in the same product categories where China is expanding). The absence of pre-trends and the falsification tests using French CPI data discussed below support interpretation (a). If the displacement pattern is causal, then our baseline estimates from Table 2 are not biased and are the correct measure of the causal effects of increase trade with China on U.S. consumer prices.

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 A5. 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.

Placebo reduced-form and triple-diff IV using French CPI data. The series of robustness checks discussed so far strengthens the plausibility of the identification conditions, but one potential confounding factor remains unaddressed. In principle, 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 (Online Appendix A.C), 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.[37]

Panel A of Figure 4 reports the placebo reduced-form. There is no relationship between the NTR gap and inflation across product categories in France, which provides another justification of the research design. Panel A for Table 4 reports the result: the first-stage in Column (1) is similar to before, except that we now run the regression across COICOP categories rather than ELIs. Columns (2) shows that the reduced form is not significant, and Column (3) reports a precisely estimated null IV coefficient with the baseline coefficient, at -0.074 (s.e. 0.38). The coefficient remains small and insignificant with the alternative specification in Column (4).[38]

Table 3 and Figure 4 also report the results from a triple-difference IV specification. 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

[37]We work with French CPI data because it is the public data source we found with the most detailed categories with a consistent definition over a long time series.

[38]The change in import penetration in other developed economies is naturally not suitable for this falsification test, given that it should also have an impact in France, while the NTR gap corresponds to a U.S.-specific policy change. The policy change in the U.S. could potentially have an impact in France if the fall in uncertainty induces China to make investments that increase exports not only to the U.S. but also to other destination markets. We have checked that the placebo reduced-form is still zero in a subset of product categories where the United States accounts for a small share of China's overall exports, and for which it is therefore unlikely that spillover effects exist (not reported).

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 4 depicts the reduced-form with this differenced outcome, which is clearly negative. Column (2) of Panel B of Table 3 reports the corresponding coefficient. The IV coefficients in Columns (3) and (4) are very 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.

Additional robustness checks. The Online Appendix reports and discusses additional robustness checks. We first 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 A6 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.

Furthermore, Online Appendix Table A7 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. Finally, using the estimated elasticities from Broda and Weinstein (2006), Online Appendix Table A8 reports that the IV coefficient is stable across subsamples with different trade elasticities.

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 Conceptual Framework

In this subsection, we discuss how to compare the IV coefficients from Section III to the predictions of standard trade models. The estimated price effect is a useful identified moment that can serve as a diagnostic tool to distinguish between classes of trade models, following Nakamura and Steinsson (2018). Using a first-order approximation, we first show that the magnitude of our IV estimate cannot be explained by a fall in the prices of products from China alone. We then show that standard trade models nested by Arkolakis et al. (2012) require an implausibly low trade elasticity to match our IV estimate.

First-order price effects. Suppose there are $j = 1, \ldots, J$ product categories in the domestic U.S. economy. In each product category, suppose there are two competing suppliers, China and the United States, with market shares S_j^{China} and $1 - S_j^{China}$, respectively.[39] Let $\sigma_j > 1$ denote the demand elasticity of substitution between imported Chinese products and domestically produced U.S. products within product category j. Suppose that the economy is perturbed by an unanticipated productivity shock in China (which can be heterogeneous across industries). By Roy's identity, the first-order impact on π_j, the price index of the representative U.S. consumer for industry j, is:

$$\pi_j = S_j^{China} \pi_j^{China} + (1 - S_j^{China}) \pi_j^{US}, \tag{4}$$

where π_j^i is the inflation rate for product category j supplied by country i. If the productivity shock in China only causes a price response for the Chinese product, then we know that $\pi_j^{US} = 0 \, \forall \, j$, and we can then re-write equation (4) in terms of the observed change in the import penetration rate from China in product category j, $\Delta ChinaIP_j$:[40]

$$\pi_j = -\frac{1}{(\sigma_j - 1)\left(1 - S_j^{China}\right)} \Delta ChinaIP_j. \tag{5}$$

Intuitively, when the price of the Chinese product falls (relative to the U.S. price), consumers reallocate their spending toward that product. Under the assumptions that U.S. prices do not respond, if we know the strength of consumers' substitution patterns (σ_j) we can infer the (unobserved) change in prices for the Chinese product from the (observed) change in import penetration from China.

Accordingly, our IV specifications should recover a weighted average of the terms $-\frac{1}{(\sigma_j - 1)\left(1 - S_j^{China}\right)}$ across industries. With an average elasticity of substitution of 5 (e.g., Simonovska and Waugh (2014)) and an average value $S^{China} = 0.0452$ (from Acemoglu et al. (2016), for 1999), we would expect to find an estimate of $\beta = -0.26$, i.e. a fall in prices of 26 basis points. However, our estimate is about one order of magnitude larger, equal to -1.91 percentage points (Table 2, using the two instruments jointly). The elasticity of substitution that would be necessary to reconcile our IV estimate with the comparative static exercise in Equation (5) is $\hat{\sigma} = 1 - \frac{1}{\beta \cdot (1 - S^{China})} = 1.54$, which is significantly lower than standard estimates.

The first-order approximation shows that the estimated price effect is too large to be entirely explained by a fall in the price of products from China alone. Next, we show that this conclusion still applies when accounting for general equilibrium effects in the standard class of trade models nested by Arkolakis et al. (2012).

Connecting the IV specification to quantitative trade models. In an influential paper, Arkolakis et al.

[39] The results readily extend to a setting with additional suppliers.

[40] See Online Appendix B.A for a derivation of Equation (5). The term $(1 - S_j^{China})$ in (5) is a normalization term: by definition of σ_j, the relevant substitution effect is given by the change in Chinese import penetration relative to the market share of the U.S. product, $\frac{\Delta ChinaIP_j}{\left(1 - S_j^{China}\right)}$.

(2012) show that in a wide set of trade models (including Armington (1969), Krugman (1980), Eaton and Kortum (2002), Melitz (2003) and Chaney (2008)) the gains from trade can be expressed as a simple function of two sufficient statistics: the change in the domestic expenditure share λ, and the trade elasticity θ. The parameter $\theta < 0$ is the elasticity of relative imports with respect to variable trade costs and governs how trade flows change in response to changes in trade costs. For example, in a one-sector Armington model, we have $\theta \equiv 1 - \sigma < 0$, where $\sigma > 1$ the elasticity of substitution between foreign and domestic goods.

In the class of trade model examined by Arkolakis et al. (2012), it can be shown that

$$\Delta \log(W_{US}) = \frac{1}{\theta} \Delta \log(\lambda_{US}), \tag{6}$$

where $\Delta \log(W_{US})$ is the change in welfare in the U.S. and $\Delta \log(\lambda_{US})$ is the change in the domestic expenditure share, i.e. the U.S. spending share on domestically produced U.S. goods and services.

Our empirical work departs from the baseline model of Arkolakis et al. (2012) because we run a regression across detailed product categories, while Equation (6) is a statement about the entire (one-sector) economy. However, it is straightforward to consider the multi-industry variant of Arkolakis et al. (2012) to derive predictions about price changes across industries when import penetration varies across industries. In Online Appendix B.B we derive our IV specification (3) from the multi-industry version of Arkolakis et al. (2012).

With many industries, the model predicts a cross-industry relationship between the domestic expenditure share and consumer prices similar to Equation (6), with prices instead of welfare on the left-hand side. With the log change in the domestic expenditure share as the endogenous variable, the model predicts that our IV specification should yield an estimate related to the inverse of the trade elasticity: $\widehat{\beta} = -\frac{1}{\theta}$.[41] When the trade elasticity varies across product categories, our IV estimator recovers a weighted average of the trade elasticities.[42]

While the formula from Arkolakis et al. (2012) nests a variety of trade models, it is well understood that different models require different estimation strategies for the trade elasticity (e.g., Melitz and Redding (2015)). In practice, these estimation strategies tend to yield relatively similar estimates for the trade elasticity around a value of $\theta \approx -4$ (c.f. Simonovska and Waugh (2014)). Therefore, using the log change in the domestic expenditure share as the endogenous variable, standard trade model models predict an IV coefficient of $\widehat{\beta} = -\frac{1}{\theta} \approx 0.25$.

Following the multi-sector variant of Equation (6), we implement our IV specification with the log

[41] There is a minus sign because when the endogenous variable is the log domestic expenditure share, rather than import penetration from China, the IV coefficient is larger than zero. When the log domestic expenditure share increases, overall import penetration decreases and prices are predicted to increase. With our baseline endogenous variable, the change in import penetration from China, the model predicts $\widehat{\beta} \approx \frac{1}{\theta} < 0$.

[42] These predictions are based on a model featuring a single domestic factor of production, perfectly mobile across domestic industries, which rules out the possibility that changes in factor prices could differentially affect domestic production costs across industries. We relax these assumptionss in Section IV.C but we do not find support for the hypothesis that potential changes in domestic production costs could help match our IV coefficient.

change in the domestic expenditure share as the endogenous variable. The estimates are reported in Online Appendix Table A9 and are large in magnitude: 2.57 (s.e. 0.96) with the instrument from Pierce and Schott (2016a), 3.46 (s.e. 1.41) with the instrument from Autor et al. (2014), and 3.10 (s.e. 0.96) with both instruments.[43] 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 below -1 and generally closer to -4. These results show that standard quantitative trade models do not match the estimated price response.[44]

Investigating potential mechanisms. What drives the price effects we find in the data? We have shown that the large price effects cannot be easily reconciled with consumer optimization if there is no response of U.S. prices (equation (5)) or with the predictions of standard quantitative trade models (equation (6)). Next, we empirically document that U.S. prices respond to increased import penetration from China (Subsection IV.B). We find no evidence supporting the hypothesis that domestic price changes resulted from changes in domestic production costs (Subsection IV.C). But we document that domestic markups fell and show that models with endogenous markups can match the estimated price effects (Subsection IV.D).[45]

IV.B The Roles of Continued and Domestic Products

We start our empirical investigation of potential mechanisms with a simple statistical decomposition to isolate the roles of continued products and products that were made in the U.S. We first describe the statistical decompositions, then the variables we use, and finally the results.

Statistical decompositions. We are interested in decomposing the overall prices effect into effects arising from subsets of products. Denote 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

$$\pi_i = \underbrace{s_i^A \pi_i^A}_{\equiv \tilde{\pi}_i^A} + \underbrace{s_i^B \pi_i^B}_{\equiv \tilde{\pi}_i^B}, \tag{7}$$

[43] As expected, these IV coefficients are larger (in absolute value) than with the change in import penetration from China (Table 2), because China tends to displace other trading partners (Table 3)

[44] As noted by Arkolakis et al. (2011), the trade literature and the international macro literature don't 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. In the remainder of this section, we provide direct evidence for the pro-competitive effects of trade by documenting the response of domestic prices and markups (i.e., the patterns in the data could not be fully explained simply by setting a θ above minus one).

[45] Endogenous markups resulting from strategic interactions fall outside of the class of trade models nested by Arkolakis et al. (2012). Intuitively, because of the threat of competition from China, U.S. producers may endogenously lower their markups, even without much substitution toward imported Chinese goods in equilibrium.

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 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.[46]

Because we have established that the two instruments from Pierce and Schott (2016a) and Autor et al. (2014) behave similarly (Table 2), and because more stringent pre-trend and falsification tests could be implemented with the NTR gap instrument (Section III.D), 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 (see Online Appendix Table A10).

The Role of Continued Products. Panel A of Table 5 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).[47] 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 (7), Columns (3) and (4) show that continued products account for approximately 70% of the overall price effects from Table 2.

The Online Appendix reports additional results. Online Appendix Table A11 focuses on the subset of goods that existed prior to the "China shock" (specifically, there were available as of 2000). We still find a large response of continued products inflation, which shows that pre-existing varieties are affected

[46]Since the first-stage regressions are identical, this can be seen immediately from the reduced-form regressions in our IV setup: we run $\pi_{ip} = \beta \mathbf{Z_{ip}} + \nu X_{it} + \delta_i + \delta_p + \varepsilon_{it}$, $\widetilde{\pi}_i^A = \beta^A \mathbf{Z_{ip}} + \nu X_{it} + \delta_i + \delta_p + \varepsilon_{it}$, and $\widetilde{\pi}_i^B = \beta^B \mathbf{Z_{ip}} + \nu X_{it} + \delta_i + \delta_p + \varepsilon_{it}$. Because $\pi_i = \widetilde{\pi}_{i,A} + \widetilde{\pi}_{i,\bar{A}}$, we obtain the convenient decomposition $\beta = \beta^A + \beta^B$.

[47]Moreover, using "continued products" only ensures that the price index is immune to potential changes in composition.

by Chinese import competition. This result shows that the patterns of lower continued products inflation in Panel A of Table 5 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 A12 documents that trade with China led to increased product turnover, consistent with the notion that Chinese products displace domestic varieties.

The Role of Domestic Products. Having established that continued products play an important role in the overall price effects, 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 populates with text (e.g., "Write in the country in which the product was made."). Online Appendix A.A describes the specification checklists and the parsing algorithms we use to retrieve countries of origin from text entries. Online Appendix Table A13 reports summary statistics on the number of product categories with explicit flags for country of origin.

Panel B of Table 5 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., and therefore it is an ideal data set to test whether the price effects we document are driven by U.S. products.

We run an IV specification identical to (3), except that the outcome variable is now the PPI inflation rate, measured from micro data underlying the Producer Price Index of the BLS, and that the level of observation is a 6-digit NAICS code. The PPI methodology is described in Online Appendix A.E: we aggregate item-level price changes at the level 6-digit NAICS industries using weights derived from the Census' data on value of shipments.

Panel C of Table 5 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 -2.10 to -2.60 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 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 previous results show that there is a large response of domestic prices to trade with China. Conceptually, this response could result from two types of effects of increased trade with China: changes in production cost for U.S. manufacturers, or changes in markups. In this section, we examine several potential channels through which production costs for U.S. producers might change across industries due to trade with China.

Accounting framework. A simple accounting framework helps organize the analysis of changes in markups and costs. The change in prices for industry i can be decomposed into

$$\Delta \log(p_i) = \Delta \log(\mu_i) + \Delta \log(c_i),$$

where μ_i is the gross markup and c_i is the marginal cost of production. Assume domestic firms have access to a Cobb-Douglas production technology that transforms intermediate inputs I, labor L, and capital K into output of item i such that,

$$Y_i = A_i K_i^{\alpha_i^K} L_i^{\alpha_i^L} I_i^{\alpha_i^I},$$

where A_i is total factor productivity and factor shares $\alpha_i^K, \alpha_i^L, \alpha_i^I < 1$ sum to one. Cost minimization yields the change in the domestic production cost,

$$\Delta \log(c_i) = -\Delta \log(A_i) + \alpha_i^K \Delta \log(r_i) + \alpha_i^L \Delta \log(w_i) + \alpha_i^I \Delta \log(p_{I,i}). \tag{8}$$

where 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 (8).

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.[48]

[48]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)).

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. Online Appendix Table A.D describes the data construction steps for these IO-adjusted variables, as well as other variables used for robustness tests.[49]

Panel A of Table 6 reports the correlations between direct and indirect exposure to trade with China. Column (1) shows the raw relationship without any controls, which is also depicted graphically in Panel A of Figure 5. 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. Panel B of Figure 5 depicts this relationship. 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.

In Panel B of Table 6, 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).

The Online Appendix reports additional results. Table A14 shows that the patterns are the same when accounting for higher-order I-O linkages. Table A15 and Figure A6 report similar results in an augmented IV framework, where we instrument for direct and indirect exposure measures simultaneously.

Offshoring. The previous results indicate that upstream and downstream changes in trade with China

[49] We report the main results using IO-adjusted variables based on first-order linkages in the IO table. The Online Appendix repeats the analysis with higher-order IO linkages, using the Leontieff inverse.

do not help explain the estimated price effects. However, 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, 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 does not correspond to intensified import competition, but rather to an increase in trade between related parties, i.e. our measure of changes in trade flows may reflect offshoring.

We examine the importance of this potential channel using the related-party trade database of the U.S. Census Bureau (as in, e.g., Antràs and Chor (2013)).[50] Related-party trade includes trade by U.S. 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. In fact, the share of trade with China occurring between related parties is very low during the period we study, with a median of 4% (Online Appendix Table A16; related-party trade is significantly more important with other trading partners).

Although 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 A 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. Similar results are obtained with other thresholds and a linear interaction term (not reported). Overall, the data indicate that changes in domestic production costs via imported inputs or offshoring cannot account for the estimated price effects.

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 5 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-

[50] For the remainder of this subsection, we work with our main analysis sample restricted to the ELI categories for manufactured goods, which we match to the Census' related-party trade database and to the NBER-CES Manufacturing database.

specific factors and endogenous changes in technology. If an industry relies on industry-specific (hence "fixed") factors, then a fall in production could lead to a substantial fall in production costs, because the supply curve is inelastic (vertical) 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 (8), this effect should be particularly important for capital-intensive industries (through the term $\alpha_i^K \Delta \log(r_i)$ in equation (8)).

In Column (2) of Panel A 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. Similar results are obtained with other thresholds and a linear interaction term (not reported). This finding suggests that decreasing returns through industry-specific capital do not drive the domestic price effects.

Another possibility is that import competition may affect productivity through endogenous technology choices. If increased competition spurs domestic firms to adopt or invent cost-reducing technologies (e.g., Bustos (2011), Bloom et al. (2016) and Aghion et al. (2018)), then change in productivity could rationalize our results, through the term $\Delta \log(A_i)$ in equation (8). 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. (2019)).

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. Becker et al. (2013) describe these TFP measures, which use either four or five factors of production.[51] In Panel B 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. (2019) using patent data. Online Appendix Figure A7 reports the event study of TFP growth by exposure to the instruments.

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. But the patterns indicate that the price effects are unlikely to be driven by increases in productivity for domestic firms. If anything, productivity is falling.

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 (8)). 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

[51] The 5-factor TFP measures uses non-production workers, production workers, energy, materials and capital. The 4-factor TFP measur is calculated similarly, but using total materials cost spending rather than separating it into energy and non-energy materials.

output is only 10.9%, because these industries use intermediate inputs intensively.[52] In other words, when a consumer spends $1 on a domestically-produced good, on average only 10.9 cents accrue to domestic workers. Therefore, 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%.[53]

Both public data and high-quality administrative data (used in prior studies) indicate that the wage effects are much smaller than would be needed to explain the price effects. First, evidence using worker-level administrative data is provided by Autor et al. (2014), who 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). Second, using public data from the NBER-CES and County Business Patterns databases, Acemoglu et al. (2016) find no significant fall in average wages, and they also document a 24 basis point increase for production workers (their Table V).[54] In Panel B of Table 7, we use the same outcome variables in our IV specification and 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)). Online Appendix Figure A7 reports the event study of wage growth by exposure to the instruments. 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.[55]

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. First, we show theoretically that endogenous markups arising from strategic interaction can rationalize the evidence. Second, empirically we find that estimated markups for domestic firms (within Compustat) fall in response to increased trade with China. Finally, consistent with theoretical predictions, we document that the price effects are larger in industries where domestic market concentration is higher and China's initial market share is lower.

Connecting the IV specification to models with endogenous markups. We start with a simple theoretical exercise: could changes in markups plausibly explain the observed domestic price response, or are the observed price effects too large? To answer this question without committing to a specific model of demand, market structure, price setting or production technology, we consider the theoretical framework

[52] These figures are reported in Panel A of Table 10, which we discuss further in Section V.

[53] Note that indirect exposure to China via input-output linkages is not correlated with direct exposure (Table 6). Therefore, to assess whether wage changes can account for the price response to increased import penetration from China, we only need to measure the direct contribution of labor in domestic output (without accounting for labor inputs that are indirectly used through input-output linkages).

[54] As they note, this finding can be reconciled with Autor et al. (2014) because public data sources are likely to suffer from composition effects: if lower-paid workers are more likely to be laid off, the measured wage may increase.

[55] Autor et al. (2013) also investigate wage effects, but they focus on commuting zones as the level of analysis. They find that increased exposure to trade with China (a) has no significant effect on manufacturing wages across CZs; (b) leads to a fall in non-manufacturing wages across CZs (their Table VII). For our cross-industry regression, manufacturing wages are relevant.

in Amiti et al. (2018b) which only requires mild conditions on demand.

In order to starkly illustrate the mechanisms at play, we return to the stylized economic environment from Section IV.A in which one U.S. producer and one Chinese producer compete in each industry. We will now introduce price dynamics that depend on the strategic interaction between producers within each industry. We derive our IV specification in this model, and then discuss testable implications from a more general setting with multiple, heterogeneous firms.

Economic environment. There are $j = 1, \ldots, J$ industries. In each industry, there are two producers: a domestic U.S. producer and a foreign Chinese producer that exports its product. The two producers produce and sell differentiated products to a representative U.S. consumer who has an elasticity of substitution between industry j's varieties of σ_j and Cobb-Douglas preferences across industries. Let p_j^i, S_j^i, c_j^i and μ_j^i denote respectively the price, market share, marginal cost of production and markup of producer $i \in US, China$ in industry j, and let p_j denote the industry price index.

Amiti et al. (2018b) show that for any invertible demand system each firm i's profit-maximizing price can be expressed as the solution to a fixed point equation:

$$\log\left(p_j^i\right) = \log\left(c_j^i\right) + \log\left(\mathcal{M}_j^i\left(p_j^i, p_j^{-i}\right)\right)$$

where $\mathcal{M}_j^i\left(p_j^i, p_j^{-i}\right)$ is the equilibrium markup as a function of firm i's own price choice and the price choice of the other firm, p_j^{-i}. Total differentiation of the fixed-point equation yields an instructive decomposition, which characterizes the role of strategic pricing for the observed price effects (see Online Appendix B.C for derivations). To a first order, a firm's optimal price change can be decomposed to into its own change in marginal cost ($d\log(c_j^i)$) and its competitor's price change ($d\log(p_j^{-i})$). A change in a firm's marginal cost passes-through into its own price at a rate given by $\frac{1}{1+\Gamma_j^i}$, where $\Gamma_j^i \equiv -\frac{\partial \log\left(\mathcal{M}_j^i(.)\right)}{\partial \log\left(p_j^i\right)}$ is the firm's "own-price markup elasticity". Furthermore, the pass-through rate of a change in the competitor's price is given by $\frac{\Gamma_j^{-i}}{1+\Gamma_j^i}$, where $\Gamma_j^{-i} = \frac{\partial \log\left(\mathcal{M}_j^i(.)\right)}{\partial \log\left(p_j^{-i}\right)}$ is the "competitor-price markup elasticity".

With constant markups, the markup is inelastic and we obtain that $\Gamma_j^i = \Gamma_j^{-i} = 0$. With oligopolistic competition (e.g., Krugman (1979) and Atkeson and Burstein (2008)), Γ^i and Γ^{-i} are increasing in the firm's market share. Under relatively mild assumptions about the demand system, Amiti et al. (2018b) show that $\Gamma_j^i = \Gamma_j^{-i}$.[56] Empirically, using idiosyncratic variation in the cost of intermediate inputs as an instrument for prices at the firm level, Amiti et al. (2018b) cannot reject that $\Gamma_j^i = \Gamma_j^{-i}$; their results indicate that the markup elasticity Γ_j is increasing in firm size and is about 0.6 on average.

Our goal is to assess whether our estimated price effects can be matched in a setting with endogenous markups and a plausible markup elasticity. To do so, we perturb the equilibrium with a change in China's marginal production costs, which can be heterogeneous across industries.[57] We assume that U.S.

[56] This condition is satisfied if the firm perceives that the demand elasticity is a function of the firm's price relative to the industry expenditure function. This property holds exactly for a nested-CES demand structure as well as a first-order approximation for a broad class of models with symmetric preferences.

[57] See Online Appendix B.C for proofs and derivations for the remainder of this section.

production costs remain unchanged, in line with Section IV.C), so that U.S. prices respond only through changes in markups. A first-order approximation to the equilibrium perturbation is given by (i) the overall change in the industry's price index,

$$d\log(p_j) = S_j^{China} d\log\left(p_j^{China}\right) + \left(1 - S_j^{China}\right) d\log\left(p_j^{US}\right),$$

(ii) the change in the domestic U.S. producer's price with respect to its Chinese competitor's price change, under the assumption of no change in own-costs,

$$d\log\left(p_j^{US}\right) = \frac{\Gamma_j}{1+\Gamma_j} d\log\left(p_j^{China}\right), \tag{9}$$

(iii) the change in the foreign Chinese producer's price with respect to the marginal cost shock and the change in its U.S. competitor's price,

$$d\log\left(p_j^{China}\right) = \frac{1}{1+\Gamma_j} d\log\left(c_j^{China}\right) + \frac{\Gamma_j}{1+\Gamma_j} d\log\left(p_j^{US}\right), \tag{10}$$

and, finally, (iv) the substitution between U.S. produced and Chinese produced goods given the change in the relative price of Chinese goods and the elasticity of substitution σ_j,

$$d\log\left(S_j^{China}\right) = (1-\sigma_j)\left(1 - S_j^{China}\right)\left(d\log\left(p_j^{China}/p_j^{US}\right)\right). \tag{11}$$

Solving the system of equation and re-arranging terms, we obtain a first-order approximation to the cross-industry relationship between inflation and changes in the import penetration rate from China:[58]

$$\pi_j = -\frac{1+\Gamma_j/S_j^{China}}{(\sigma_j - 1)\left(1 - S_j^{China}\right)} \Delta ChinaIP_j. \tag{12}$$

With strategic interactions, our IV specification should recover a weighted average of the terms $-\frac{1+\Gamma_j/S_j^{China}}{(\sigma_j-1)\left(1-S_j^{China}\right)}$ across industries. With the benchmark estimates $\Gamma_j = 0.6$ (Amiti et al. (2018b)), $\sigma_j = 5$ (Head and Mayer (2014), Simonovska and Waugh (2014)) and $S_j^{China} = 0.0452$ (Acemoglu et al. (2016), for 1999), we expect to find $\beta = -3.74$. This benchmarking exercise establishes that, with strategic interactions, the magnitude of the reduced-form relationship we estimate is expected to be one order of magnitude larger than with no domestic price responses (equation (5)) or than from the class of trade models nested by Arkolakis et al. (2012) (equation (6)).

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

[58] Absent strategic interations ($\Gamma_j = 0$), equation (12) reduces to the price change expression we derived under the assumption of zero domestic price change in equation (5).

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 equations(9) and (10) as $\frac{\Gamma_j}{1+\Gamma_j} \to 1$. Because the relative price of the two producers remains almost unchanged, the import penetration rate from China barely changes (equation (11)). 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.

Having established theoretically that the markup channel can plausibly explain large price effects, we now conduct specific tests to assess its empirical relevance more directly.

The Response of Estimated Markups. To test the theoretical framework above as directly as possible, 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. (2017) and estimate markups for publicly-listed firms in Compustat. In this sample, indexing firms by i and years by t, the gross markup can be written

$$\mu_{it} = \theta^v \cdot \frac{SALES_{it}}{COGS_{it}}, \tag{13}$$

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.[59] We then aggregate the firm-level data to 6-digit NAICS codes, using sales weights. We will consider in turn the response of the average markup or of certain quantiles of the markup distribution (where the average and quantiles are computed within each 6-digit NAICS industry). Summary statistics are reported in Online Appendix Figure A8.

Estimated markups from the Compustat sample can be used to test two predictions from the theoretical framework introduced above. First, 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? The first test is directly implied by equation (9) with $\Gamma_j \neq 0$. The second test is intuitive: a domestic producer with a large markup has more market power, therefore it should respond more strongly when rising import penetration from China disrupts domestic market power. Formally, in standard models firms with larger markups also have a higher markup elasticity Γ_j^i, as shown by Amiti et al. (2018b).

Figure 6 and Table 8 present the results of the analysis with estimated markups as the outcome. We

[59] Online Appendix A.F derives equation (13) and describes the Compustat sample. Total sales and the cost of goods sold are reported in firms' financial statements. We use the time-invariant and sector-invariant elasticity $\theta^v = 0.85$ from De Loecker et al. (2017), who show that changes in markups over time are driven by changes in the ratio of sales to cogs (rather than by changes in the output elasticity). The results are similar when we estimate time-varying elasticities as in De Loecker et al. (2017) (not reported). Although the production approach to markup estimation has well-known limitations (e.g., Raval (2019)), it provides an instructive test for our purposes.

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 $\tilde{\mu}_{it} = (\mu_{it} - 1) \cdot 100$.[60]

Panel (a) of Figure 6 reports a clear negative reduced-form relationship for the average markup. The binned scatter plot shows that the linear fit is a good approximation to the underlying data. Panel A of Table 8 reports the point estimates. Column (1) shows that the first stage remains strong in the Compustat sample, with statistical significance at the 1% level (Online Appendix Figure A9 depicts the first stage). Columns (2) reports the reduced-form coefficient, which is also precisely estimated. 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). The IV estimate is large in magnitude and statistically indistinguishable from the IV coefficients for the response of domestic prices (from Table 5: -2.73 for CPI, and -2.10 for PPI). This result indicates that changes in domestic markup can account for much of the observed price effects.

Panels (b), (c) and (d) of Figure 6 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)). Panel B of Table 8 reports the corresponding reduced-form coefficients. 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.

As a robustness check, we also 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 (13) does not use information about fixed costs). Online Appendix A.F describes these measures, and Online Appendix Figure A8 reports summary statistics. Panels (e) and (f) of Figure 6 show that profitability ratios deteriorate in industries that are more exposed to trade with China. Columns (4) and (5) of Table 8 report the corresponding point estimates, which are statistically significant at the 1% level.[61] Finally, the Online Appendix reports additional results on the role of between-firm reallocation effects (Online

[60] The results are similar with the log change in the gross markup, which is closely relate to the (level) change in the net markup: $\Delta log(\mu) \approx \Delta\tilde{\mu}/100$.

[61] These results are consistent with the findings of Autor et al. (2019), 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 deterioriates 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.

Appendix Table A17 and Online Appendix Figure A10).[62]

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. Using the predictions from equation (12), we can (indirectly) test for the relevance of the markup channel by studying heterogeneity in the IV estimates across subsamples.

First, the predicted effect $\hat{\beta} = -\frac{1+\Gamma_j/S_j^{China}}{(\sigma_j-1)\left(1-S_j^{China}\right)}$ is increasing in the markup elasticity Γ_j. The markup elasticity depends on market structure and can therefore vary across industries. In Online Appendix B.C, we extend the model to accommodate multiple domestic firms and show that Γ_j 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 predicted effect $\hat{\beta}$ shows that the magnitude of the effect is decreasing in China's initial market share, S_j^{China} (starting from an equilibrium with a small spending share on Chinese goods, as in the data). Intuitively, if China has a larger initial market share in an industry, by increasing its market share by one percentage point China does not disrupt domestic U.S. producers as much as in another industry where the initial import penetration rate from China is low. Put another way, there is less room for China to disrupt market power (at the margin) in an industry where it already has a high market share.[63]

Next, we take these predictions to the data. 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 ELI sample from the CPI micro data. 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 with interaction terms, interacting the indicator variables with the endogenous variable and the instrument.[64]

[62]The recent literature documents that trends of rising markups and falling labor share are driven by reallocation of spending. In contrast, trade-induced competition predicts that markups should fall *within* firms. We test and find support for this prediction by introducing firm fixed effects into our research design. Naturally, our results are not inconsistent with the literature documenting a rise in the aggregate markup and profitability in the U.S. (e.g., Autor et al. (2017), Baqaee and Farhi (2017), De Loecker et al. (2017)). We find that increase trade with China leads to a fall in U.S. markups, but there could be many other channels leading to a rise in U.S. markups in the aggregate.

[63]Online Appendix B.C discusses the predicted heterogeneity in treatment effect in greater detail. The model with multiple firms shows that the heterogeneous effects are non-linear, which motivates the use of specifications with "threshold" interaction terms, as we do below, rather than linear interaction.

[64]For this analysis, the sample is restricted to 153 ELIs that can be matched to the concentration statistics from the Census, which are publicly available for most industries producing goods. In the matched sample, the implied number of "equally-sized firms" that should operate in the domestic market to be consistent with the median Herfindahl index (H) is $N = \frac{10{,}000}{H} = 19$. This calculation helps fix ideas about the degree of domestic market concentration for the median U.S. industry. The 75th percentile of the import penetration rate from China (in 1999) is computed for the restricted sample and is about 10%. The choice of these thresholds for the indicator variables is guided by the non-linear heterogeneity predicted by the model (Online Appendix B.C). The results are similar with alternative thresholds, as well as when measuring

Panel A of Table 9 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.

Panel B of Table 9 repeats the analysis in the PPI sample. We proceed in the same way as for CPI, except that 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.

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). The PPI results confirm the patterns observed in our main CPI sample.[65]

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

V The Distributional Effects of the China Shock

The previous analysis shows that there is a large price response to increased trade with China, and that this response includes a substantial response from domestic products, which can be accounted for by an endogenous fall in domestic markups. In this section, we discuss how our estimates help shed light on the distributional effects of the China shock.

We first characterize distributional effects between consumers and workers, benchmarking our esti-

concentration and trade with China in earlier years (not reported).

[65]The first-stage F statistics remain strong for all specifications for Panel B of Table 9, with the PPI data. However, the F statistics deteriorate in several specifications in Panel A, with the CPI data. For both panels, we have repeated the analysis using LIML and obtained similar points estimates (not reported). The fact that the results are similar for CPI and PPI, as well as with LIML, gives us confidence that the results are not confounded by weak instruments.

mates of the price effects to the estimates of employment effects from prior work. We find that falling prices in product categories that are more exposed to trade with China create hundreds of thousands of dollars in consumer surplus for each displaced job. Second, we investigate distributional effects across consumers and we find that the price response is larger in product categories that cater to lower-income households.[66]

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 (2016a)). 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. 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 fall in the number of 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

$$\frac{\Delta CS_j}{\Delta Jobs_j} = \frac{\beta_{price}}{\beta_{emp}} \cdot \frac{Cons_j}{Emp_j}. \tag{14}$$

This expression tells us that 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. Accordingly, in addition to the IV estimates we need to know the ratio $\frac{Cons_j}{Emp_j}$ across industries to characterize the tradeoff between jobs and consumer surplus.

Panel A of Table 10 reports informative summary statistics about the term $\frac{Cons_j}{Emp_j}$ in equation (14), focusing on the set of ELIs within goods only (for which we obtain data on domestic absorption and

[66] Our results indicate that the China shock led to a fall in markups for U.S. manufacturers. The implications of this finding for U.S. producer surplus are ambiguous: if markups reflect market power and economic profit, then producer surplus may have fallen in response to increased trade with China; but if markups merely offset fixed costs such that a zero-profit condition holds, then there is no change in producer surplus. A useful avenue for future research would be to characterize more comprehensively the effect of the China shock on producer surplus and on the owners of businesses and capital.

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 absorption per job is even higher, approximately \$390,000 per job (row 4).[67]

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. Online Appendix Table A18 reports the results. A one percentage point increase in import penetration from China leads to a fall in employment of 1.834% with the NTR gap instrument, 1.774% with the change in import penetration in other developed economies, and 1.815% with both instruments. 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 10 characterizes the tradeoffs between rising consumer surplus and displaced jobs across industries, using our IV estimates and equation (14). 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 10. They are slightly attenuated compared to the baseline but remain very large in magnitude, ranging from \$288,147 to \$433,565 across specifications.[68]

[67] The various columns in Panel A of Table 10 show that there is much heterogeneity across product categories: domestic absorption per job varies from \$150,591 at the 10th percentile to \$625,686 at the 90th percentile. It is everywhere significantly higher than average labor earnings.

[68] As indicated earlier, the calculations carried out in this section are partial-equilibrium differences across industries with different levels of exposure to rising import penetration from China. General equilibrium effects induced by the China shock could affect all industries simultaneously. As is well-known (e.g., Adao et al. (2019)), GE effects affecting all industries are not

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 (equation (6)) and would be on the order of $40,000 per displaced job, which is similar to average annual labor earnings in this sample.[69]

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 (2018), He (2018), and Hottman and Monarch (2018)). 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.[70]

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.[71]

The results are reported in Panel A of Table 11. 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

reflected in our cross-industry IV estimates as they are absorbed by fixed effects. The tradeoff between increasing consumer surplus and displaced jobs could be different at the aggregate level, once GE effects are accounted for. For example, jobs are likely to be created in other industries in the short to medium run, which would attenate the aggregate impact on jobs (e.g., Bloom et al. (2019)). For this reason, the increase in consumer surplus per "destroyed" job at the aggregate level (rather than per displaced jobs across industries) could be even larger than the estimates in Table 10.

[69] In Online Appendix Table A19, we compute the equivalent variation for increased trade with China from 2000 to 2007, for the average U.S. household. Assuming that there are no GE effects affecting prices in all product categories, the cross-industry IV estimates accurately capture the price effects. Using our baseline IV estimate, 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. The estimates range from $1,105 to $1,711 across specifications. 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% (in the CEX, average annual expenditures were $49,638 in 2007). In GE, increasing import penetration may induce an overall fall in domestic prices to restore trade balance; therefore the increase in purchasing power for domestic consumers could be larger after accounting for GE effects.

[70] In a sample of consumer packaged goods, Bai and Stumpner (2018) 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).

[71] We use the spending shares from the CEX for the year 2000, as processed by Borusyak and Jaravel (2018). We match the CEX consumption categories (UCCs) to ELI as explained in Online Appendix A.C.

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 slightly 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)). Online Appendix Table A20 reports similar results with interaction terms in a single specification, instead of repeating the analysis in subsamples.[72]

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 11) 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).[73]

Panel B of Table 11 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

[72] Because we split the sample, the first-stage F statistics in Panel A of Table 11 are low, raising concerns over weak instruments. The table reports the results with LIML, which yields very similar point estimates and alleviates the potential concerns. To maximize power, we use both instruments jointly in all specifications. The Hansen J statistics indicate that we can never reject the overidentifying restrictions, as in the baseline sample.

[73] 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.

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 (2018).

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 11. 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 11).

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 and complementary identification strategies from Autor et al. (2014) and Pierce and Schott (2016a). Most previous work on the "China shock" emphasized its detrimental consequences for U.S. employment. Our findings send 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. We showed that the large price response is accounted for by falling *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. (2017), De Loecker et al. (2017)), the pro-competitive effects of trade may be particularly valuable to U.S. consumers.

While the costs of 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.

References

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

Adao, Rodrigo, Costas Arkolakis, and Federico Esposito, "Spatial linkages, global shocks, and local labor markets: Theory and evidence," *National Bureau of Economic Research*, 2019.

Aghion, Philippe, Antonin Bergeaud, Matthieu Lequien, and Marc J Melitz, "The impact of exports on innovation: Theory and evidence," *Working Paper*, 2018.

Amiti, Mary, Mi Dai, Robert C Feenstra, and John Romalis, "How Did China's WTO Entry Benefit US Consumers?," *Working Paper*, 2018.

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

— , Stephen J Redding, and David Weinstein, "The Impact of the 2018 Trade War on US Prices and Welfare," *Working Paper*, 2019.

Antràs, Pol and Davin Chor, "Organizing the global value chain," *Econometrica*, 2013, *81* (6), 2127–2204.

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

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

— , Jonathan Eaton, and Samuel Kortum, "Staggered adjustment and trade dynamics," *Working Paper*, 2011.

Armington, Paul S, "A theory of demand for products distinguished by place of production," *Staff Papers*, 1969, *16* (1), 159–178.

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

Auer, Raphael, Ariel T Burstein, and Sarah M Lein, "Exchange rates and prices: evidence from the 2015 Swiss franc appreciation," *Working Paper*, 2018.

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

— , — , Gordon H Hanson, Gary P Pisano, and Pian Shu, "Foreign Competition and Domestic Innovation: Evidence from US Patents," *forthcoming American Economic Review: Insights*, 2019.

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

— , — , — , and Kaveh Majlesi, "Importing political polarization? The electoral consequences of rising trade exposure," *Working Paper*, 2016.

— , — , — et al., "When work disappears: Manufacturing decline and the falling marriage-market value of young men," *American Economic Review: Insights*, 2018.

— , — , Lawrence F Katz, Christina Patterson, and John Van Reenen, "The fall of the labor share and the rise of superstar firms," *Working Paper*, 2017.

Backus, David, Patrick J Kehoe, and Finn E Kydland, "International business cycles: theory and evidence," *NBER Working Paper*, 1993.

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

Baqaee, David Rezza and Emmanuel Farhi, "Productivity and Misallocation in General Equilibrium.," *Working Paper*, 2017.

Becker, Randy, Wayne Gray, and Jordan Marvakov, "NBER-CES manufacturing industry database: Technical notes," *NBER Working Paper*, 2013, *5809.*

Bils, Mark, "Do higher prices for new goods reflect quality growth or inflation?," *The Quarterly Journal of Economics*, 2009, *124* (2), 637–675.

— **and Peter J Klenow**, "Some evidence on the importance of sticky prices," *Journal of political economy*, 2004, *112* (5), 947–985.

— **, — , and Benjamin A Malin**, "Reset price inflation and the impact of monetary policy shocks," *American Economic Review*, 2012, *102* (6), 2798–2825.

Bloom, Nicholas, Kyle Handley, Andre Kurmann, and Philip Luck, "The Impact of Chinese Trade on US Employment: The Good, The Bad, and The Apocryphal," *Working Paper*, 2019.

— **, Mirko Draca, and John Van Reenen**, "Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity," *The Review of Economic Studies*, 2016, *83* (1), 87–117.

Borusyak, Kirill and Xavier Jaravel, "The Distributional Effects of Trade: Theory and Evidence from the United States," *Available at SSRN 3269579*, 2018.

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

Broda, Christian and David E Weinstein, "Globalization and the Gains from Variety," *The Quarterly journal of economics*, 2006, *121* (2), 541–585.

Bustos, Paula, "Trade liberalization, exports, and technology upgrading: Evidence on the impact of MERCOSUR on Argentinian firms," *American economic review*, 2011, *101* (1), 304–40.

Carroll, Daniel and Sewon Hur, "On the Heterogeneous Welfare Gains and Losses from Trade," *Working Paper*, 2019.

Cavallo, Alberto, Gita Gopinath, Brent Neiman, and Jenny Tang, "Tariff Passthrough at the Border and at the Store: Evidence from US Trade Policy," *Working Paper*, 2019.

Chaney, Thomas, "Distorted gravity: the intensive and extensive margins of international trade," *American Economic Review*, 2008, *98* (4), 1707–21.

Costinot, Arnaud, Dave Donaldson, Margaret Kyle, and Heidi Williams, "The more we die, the more we sell? a simple test of the home-market effect," *The quarterly journal of economics*, 2019, *134* (2), 843–894.

Dixit, Avinash K and Robert S Pindyck, *Investment under uncertainty*, Princeton university press, 1994.

Eaton, Jonathan and Samuel Kortum, "Technology, geography, and trade," *Econometrica*, 2002, *70* (5), 1741–1779.

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

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

Faber, Benjamin and Thibault Fally, "Firm heterogeneity in consumption baskets: Evidence from home and store scanner data," *Working Paper*, 2017.

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

— **, Pinelopi K Goldberg, Patrick J Kennedy, and Amit K Khandelwal**, "The Return to Protectionism," *Working Paper*, 2019.

Feenstra, Robert C, "New product varieties and the measurement of international prices," *The American Economic Review*, 1994, pp. 157–177.

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

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

Flaaen, Aaron B, Ali Hortacsu, and Felix Tintelnot, "The Production Relocation and Price Effects of US Trade Policy: The Case of Washing Machines," Technical Report, National Bureau of Economic Research 2019.

Fort, Teresa C, Justin R Pierce, and Peter K Schott, "New perspectives on the decline of us manufacturing employment," *Journal of Economic Perspectives*, 2018, *32* (2), 47–72.

Gagnon, Etienne, David López-Salido, and Nicolas Vincent, "Individual price adjustment along the extensive margin," *NBER Macroeconomics Annual*, 2013, *27* (1), 235–281.

Goldberg, Pinelopi K. and Rebecca Hellerstein, "How Rigid are Producer Prices?," *Working Paper*, 2009.

Grullon, Gustavo, Yelena Larkin, and Roni Michaely, "Are US industries becoming more concentrated?," *Forthcoming, Review of Finance*, 2018.

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

Hansen, Lars Peter, "Large sample properties of generalized method of moments estimators," *Econometrica: Journal of the Econometric Society*, 1982, pp. 1029–1054.

He, Zheli, "Trade and Real Wages of the Rich and Poor," *Working Paper*, 2018.

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

Hottman, Colin and Ryan Monarch, "Estimating unequal gains across US consumers with supplier trade data," *FRB International Finance Discussion Paper*, 2018, (1220).

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

Jaeger, David A, Joakim Ruist, and Jan Stuhler, "Shift-share instruments and the impact of immigration," *Working Paper*, 2018.

Jaravel, Xavier, "The unequal gains from product innovations: Evidence from the us retail sector," *Quarterly Journal of Economics*, 2019.

Konny, Crystal G., Brendan K. Williams, and David M. Friedman, "Big Data in the U.S. Consumer Price Index: Experiences and Plans," in Katharine G. Abraham, Ron S. Jarmin, Brian Moyer, and Matthew D. Shapiro, eds., *Big Data for 21st Century Economic Statistics*, Chicago, IL: University of Chicago Press, 2019.

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

Krugman, Paul, "Scale economies, product differentiation, and the pattern of trade," *The American Economic Review*, 1980, *70* (5), 950–959.

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

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

Loecker, Jan De, Jan Eeckhout, and Gabriel Unger, "The rise of market power and the macroeconomic implications," *Working Paper*, 2017.

Melitz, Marc J, "The impact of trade on intra-industry reallocations and aggregate industry productivity," *econometrica*, 2003, *71* (6), 1695–1725.

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

Moulton, Brent R. and Karin E. Moses, "Addressing the Quality Change Issue in the Consumer Price Index," *Brookings Papers on Economic Activity*, 1997, *28* (1), 305–366.

Nakamura, Emi and Dawit Zerom, "Accounting for incomplete pass-through," *The Review of Economic Studies*, 2010, *77* (3), 1192–1230.

— and Jon Steinsson, "Five Facts about Prices: A Reevaluation of Menu Cost Models," *The Quarterly Journal of Economics*, 2008, *123* (4), 1415–1464.

— and Jón Steinsson, "Identification in macroeconomics," *Journal of Economic Perspectives*, 2018, *32* (3), 59–86.

— , — , Patrick Sun, and Daniel Villar, "The elusive costs of inflation: Price dispersion during the US great inflation," *The Quarterly Journal of Economics*, 2018, *133* (4), 1933–1980.

Ossa, Ralph, "Why trade matters after all," *Journal of International Economics*, 2015, *97* (2), 266–277.

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

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

— and — , "Trade liberalization and mortality: Evidence from US counties," *Working Paper*, 2016.

— and — , "Investment responses to trade liberalization: Evidence from US industries and establishments," *Journal of International Economics*, 2018, *115*, 203–222.

Porto, Guido, "Using survey data to assess the distributional effects of trade policy," *Journal of International Economics*, 2006.

Raval, Devesh, "Testing the Production Approach to Markup Estimation," *Working Paper*, 2019.

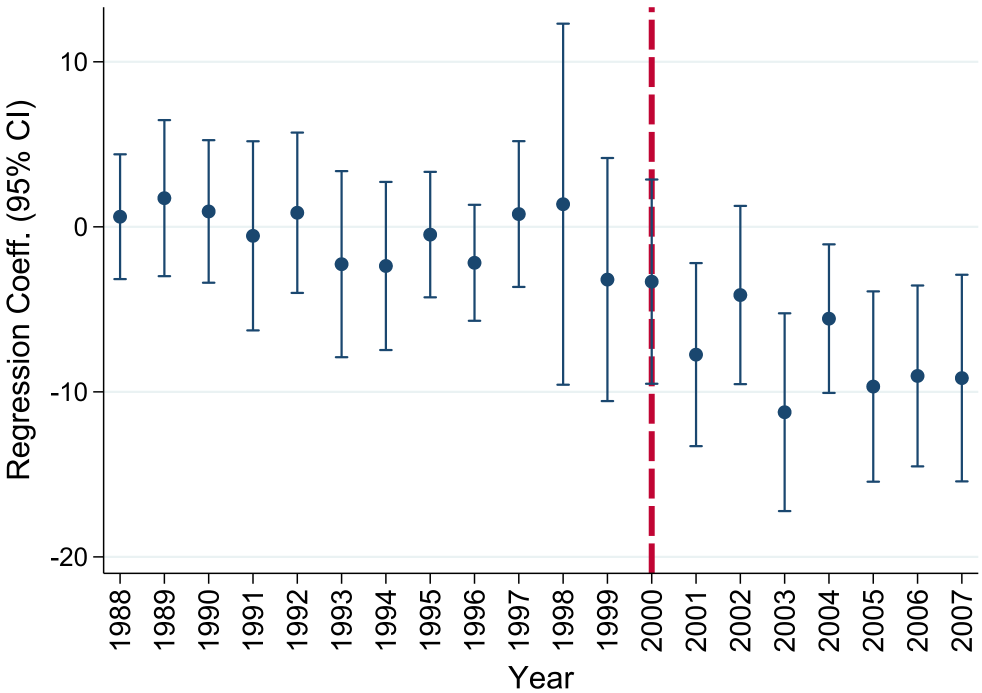
Simonovska, Ina and Michael E Waugh, "Trade models, trade elasticities, and the gains from trade," *National Bureau of Economic Research Working Paper*, 2014.

Stolper, Wolfgang F and Paul A Samuelson, "Protection and real wages," *The Review of Economic Studies*, 1941, *9* (1), 58–73.

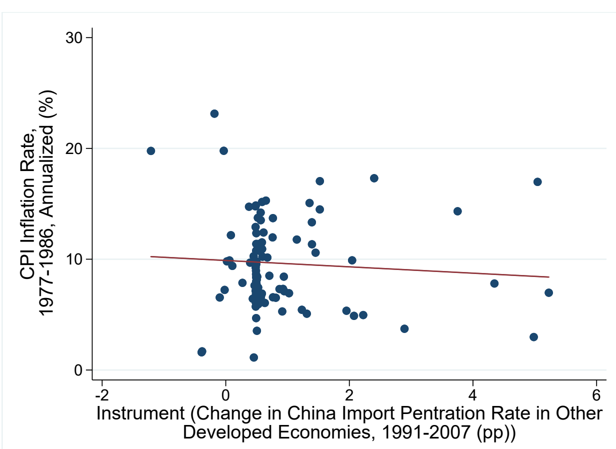
U.S. Bureau of Labor Statistics, *BLS Handbook of Methods*, Washington, DC: Bulletin of the United States Bureau of Labor Statistics, U.S. Dept. of Labor, 2018.

Figure 1: Testing for Pre-trends

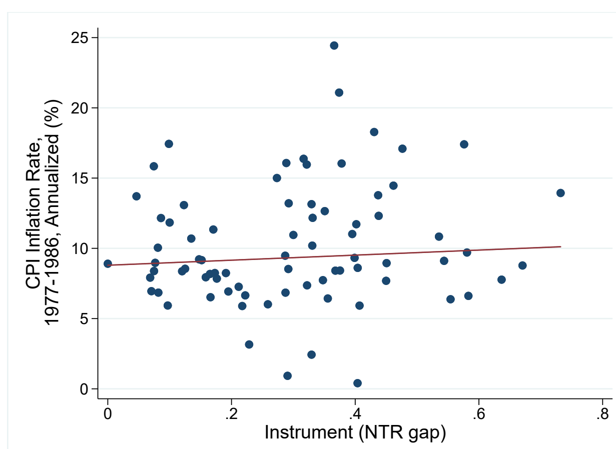
Panel A: Event Study for NTR Gap in Main Analysis Sample



Panel B: Placebo Reduced-Forms in Extended CPI Sample



(a) China IP in other developed economies

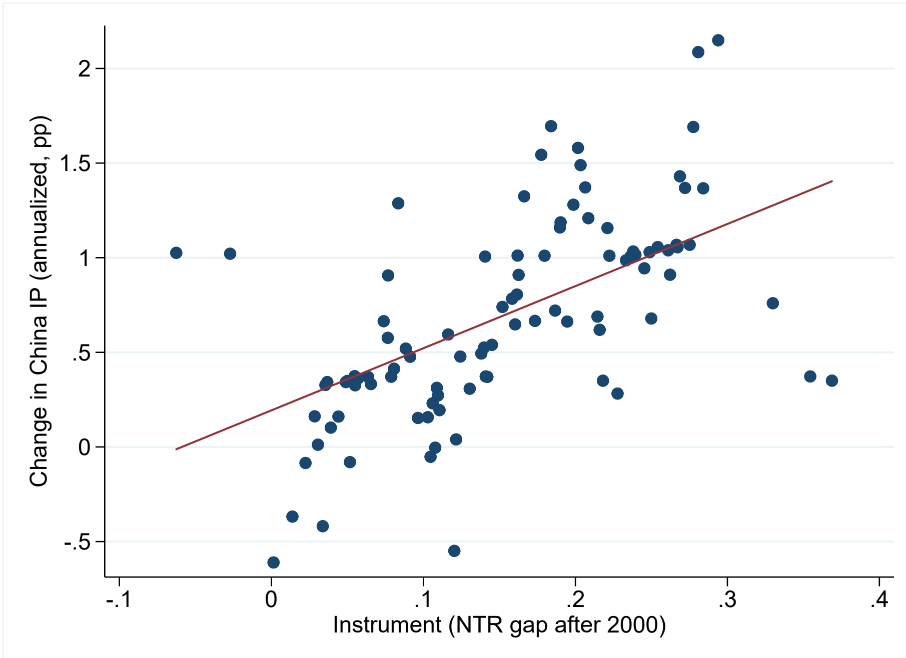


(b) NTR gap

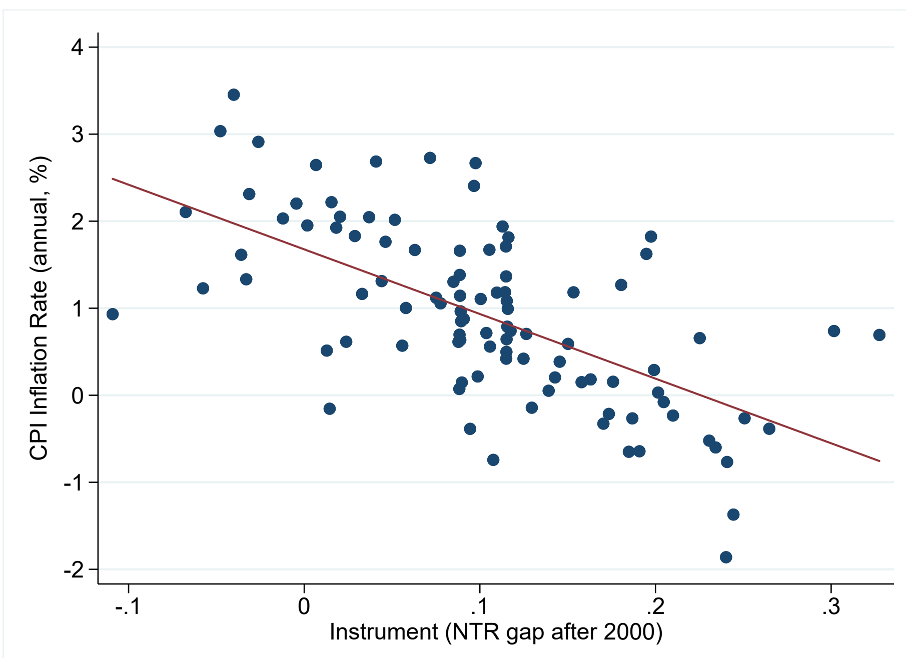
Notes: Panel A reports the estimates from the specification described in equation (2). Panel B reports the binned scatter plots for the reduced-form specifications in the extended CPI sample. Each dot represents 1% of the data and the OLS best-fit line is reported in red. The level of observation is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

Figure 2: Instrumental Variable Approach with the NTR Gap

Panel A: First Stage



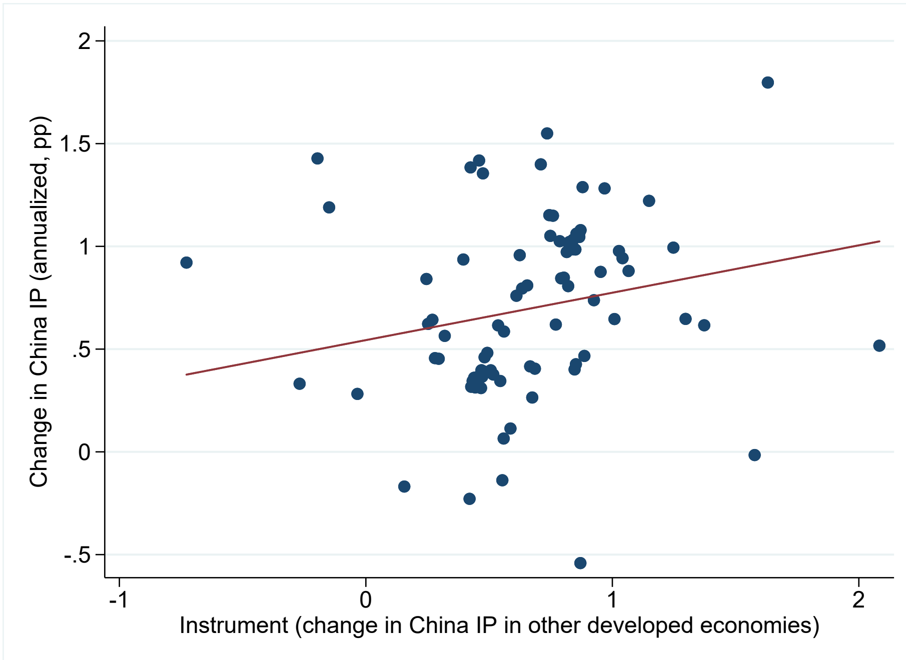
Panel B: Reduced-Form



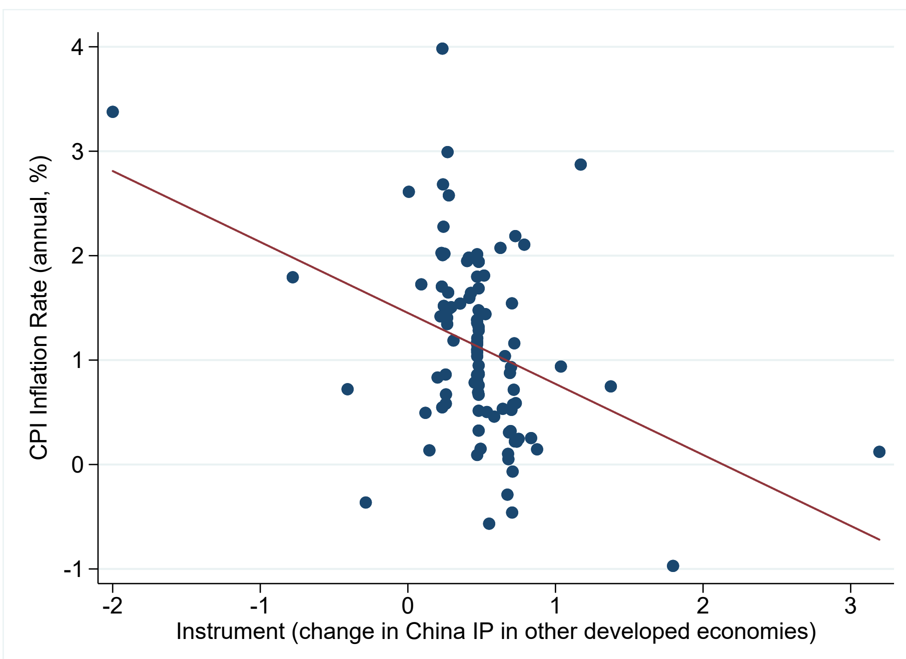
Notes: This figure reports the binned scatter plots for the first-stage (Panel A) and reduced-form (Panel B) relationships of the IV strategy using the NTR gap as an instrument. Each dot represents 1% of the data and the OLS best-fit line are reported in red. The level of observation is an ELI-by-period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

Figure 3: Instrumental Variable Approach with the Change in Import Penetration from China in Other Developed Economies

Panel A: First Stage



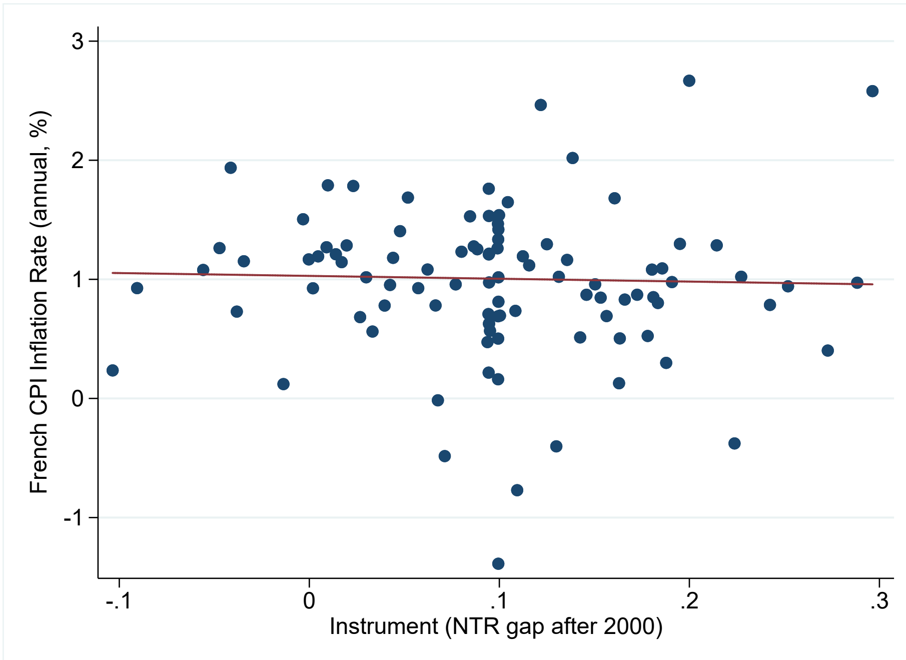
Panel B: Reduced-Form



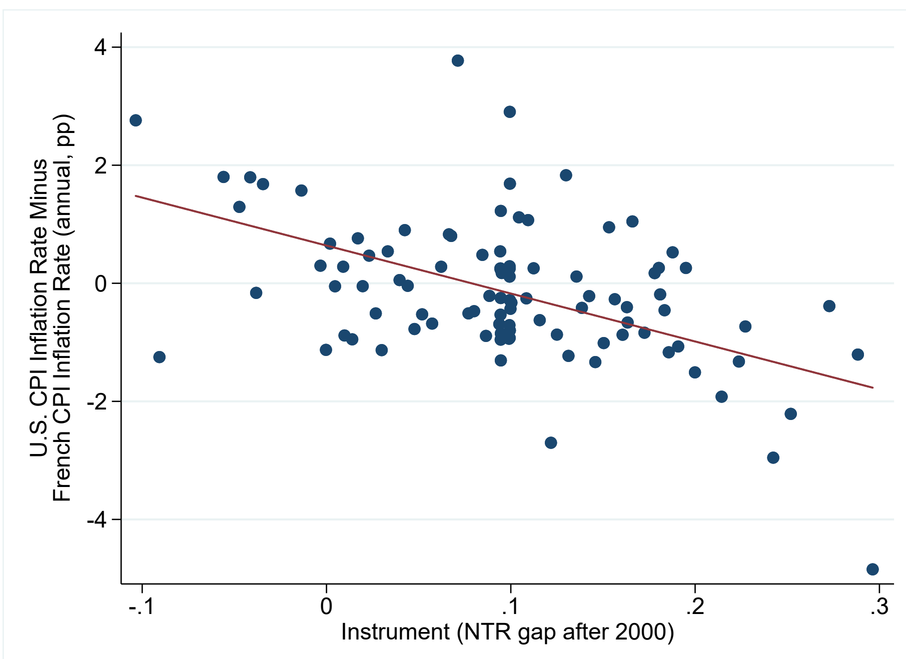
Notes: This figure reports the binned scatter plots for the first-stage (Panel A) and reduced-form (Panel B) relationships of the IV strategy using China IP in other developed economies as an instrument. Each dot represents 1% of the data and the OLS best-fine line are reported in red. The level of observation is an ELI-by-period cell. Consumption weights are used and the specifications are described in Section III.C.

Figure 4: Falsification Tests with the French CPI Data

Panel A: Placebo Reduced-Form



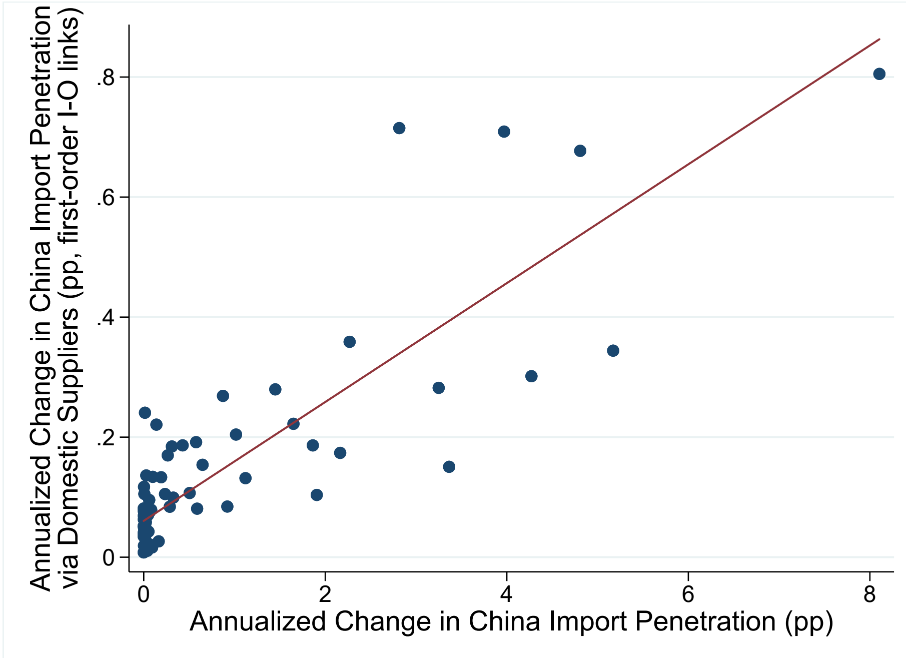
Panel B: Reduced-Form for Triple-Difference Specification



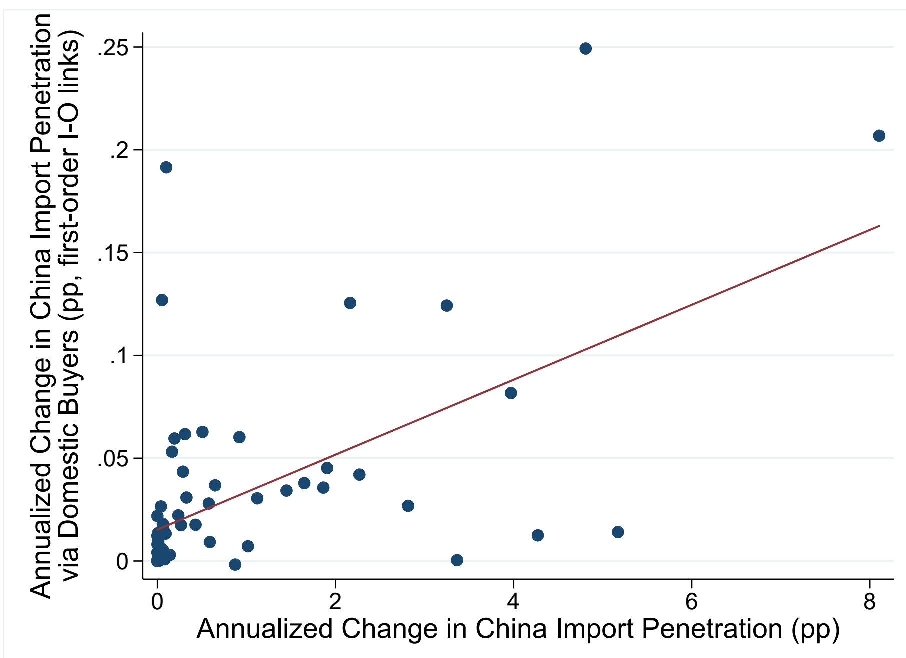
Notes: This figure reports the binned scatter plots for reduced-form relationships for the placebo test (Panel A) and triple difference (Panel B), using the NTR gap as an instrument. Each dot represents 1% of the data and the OLS best-fine line is reported in red. The level of observation is a COICOP-by-period cell. Consumption weights are used and the specifications are described in Section III.D.

Figure 5: The Role of Input-Output Linkages for Exposure to Trade with China

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



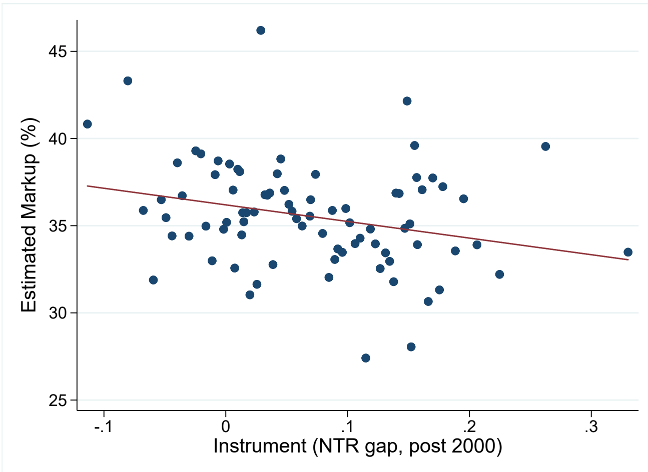
Panel B: Relationship between Direct and Indirect Import Competition



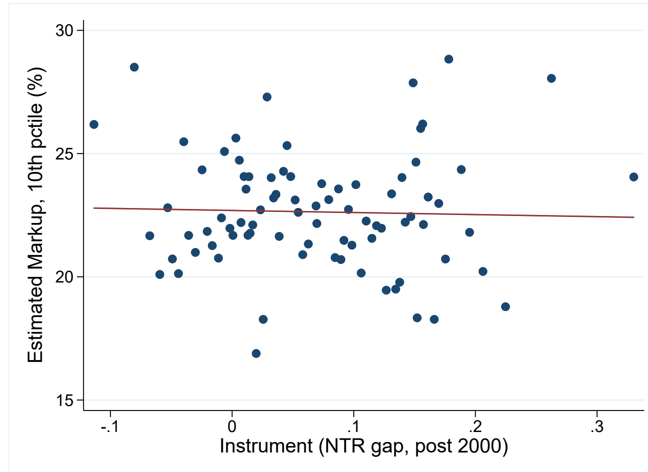
Notes: This figure shows the relationship between direct and indirect exposure to trade with China via domestic suppliers (Panel A) and buyers (Panel B). The specifications correspond to Columns (1) and (4) of Panel A of Table 6. The level of observation is a 6-digit IO industry-by-period. Each dot represents 1% of the data, using consumption weights, and the OLS best-fit line is shown in red. The steps to build the measures of indirect exposure to trade with China are described in Online Appendix A.D.

Figure 6: The Role of Markups

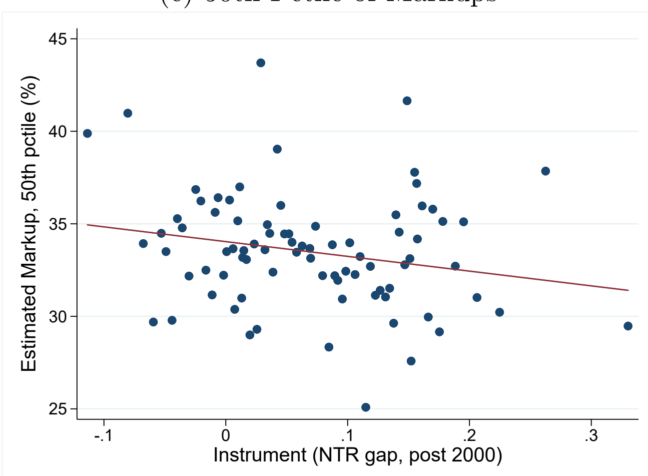
(a) Average Markup



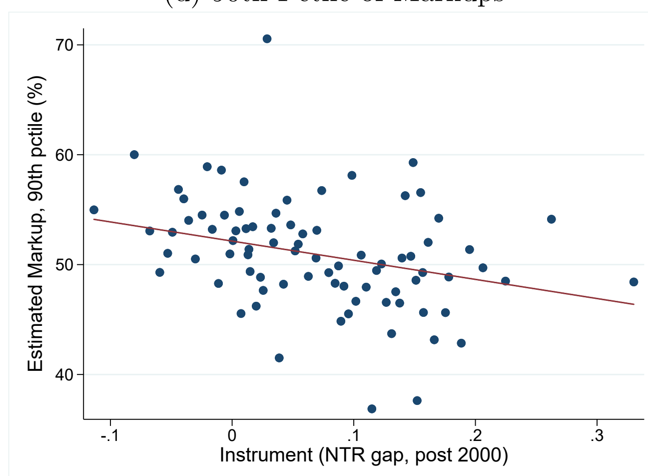
(b) 10th Pctile of Markups



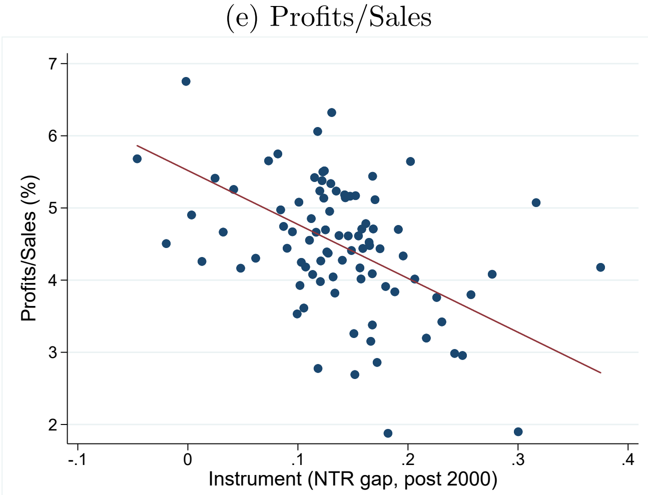
(c) 50th Pctile of Markups



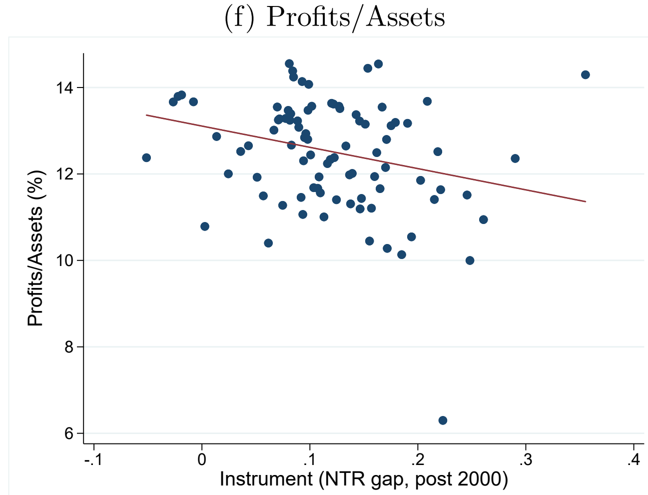
(d) 90th Pctile of Markups



(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. Source: Compustat North America Fundamentals Annual Data, (Wharton Research Data Services) and authors' calculations.

Table 1: Summary Statistics

	Mean	S.D.	p10	p50	p90	Observations N	Observations Aggreg. Level
Inflation, all (%)	1.15	6.75	-7.48	2.21	7.57		
Share of continued products (%)	80.75	16.96	61.10	86.45	96.11	3,774	ELI-by-year
Share of unavailable products	4.92	3.47	1.16	3.94	10.15		
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		
Goods	0.78	0.41	0.00	1.00	1.00		
Durables	0.18	0.38	0.00	0.00	1.00		
Apparel	0.11	0.32	0.00	0.00	1.00		
High Tech	0.08	0.26	0.00	0.00	0.00		
Contract Intensity	0.41	0.33	0.00	0.41	0.89	222	ELI
Sales Share to College Graduates	0.41	0.10	0.29	0.39	0.56		
Income Elasticity	0.98	0.50	0.33	1.00	1.65		
Sales Share to Inc.>\$60k	0.58	0.10	0.47	0.57	0.72		
Sales Share to Inc.>\$100k vs. <\$30k	0.64	0.14	0.47	0.64	0.82		

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^{***}			
	(0.89)	(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)
Δ China IP (pp)	-2.75^{***}	-1.78^{***}	-2.26^{***}	-2.10^{***}	-2.94^{**}
	(0.79)	(0.59)	(0.48)	(0.62)	(1.43)
First-stage F	30.23	24.01	37.50	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				✓	
6-digit IO Fixed Effects					✓
Instrument: NTR Gap	✓	✓	✓	✓	✓
N	444	444	400	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		7.59	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 specifications are described in Section III.C. In both panels, 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

	Δ China IP (in U.S., pp)	French CPI Inflation (pp)		
	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)
NTR Gap	3.22^{**}	-0.24		
	(1.27)	(1.82)		
Δ China IP (in U.S., pp)			-0.074	-0.27
			(0.38)	(0.91)
First-stage F			20.71	15.73
COICOP F.E.	✓	✓	✓	
Period-specific Goods F.E.	✓	✓	✓	
2001-2007 only				✓
Goods, Durables & Apparel F.E.				✓
N	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^{**}		
	(1.27)	(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: 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)	-2.60^{***}	-2.10^{***}	-2.07^{**}	-1.69^{**}
	(1.08)	(0.81)	(1.06)	(0.84)
First-stage F	21.44	24.04	21.44	24.04
NAICS F.E.	✓		✓	
Period-specific Computers F.E.	✓		✓	
2000-2007 only		✓		✓
Computers 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 6: The Role of Input-Output Linkages

Panel A: 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

Panel B: IV with Controls for 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

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 7: The Role of Domestic Production Costs

Panel A: 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 $\times$Interaction	-0.074	0.43
	(1.274)	(0.71)
Interacted indicators:		
Related Trade > p90	✓	
Capital Intensity > Median		✓
First-stage F	9.403	8.05
Period-specific Goods F.E.	✓	✓
Durables & Apparel Time-Varying F.E.	✓	✓
N	306	306

Panel B: 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: The specifications are described in Section IV.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. The instrument is the NTR gap. Standard errors are clustered by ELIs.*** denotes statistical significance at the 1% level, ** at the 5% level.

Table 8: The Role of Markups

Panel A: Baseline Estimates

	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			407.303
NAICS F.E.	✓	✓	✓
Period-specific Goods F.E.	✓	✓	✓
N	796	796	796

Panel B: Analysis by Quantile and with 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 specifications and sample are described in Section IV.D. The level of observation is a 6-digit NAICS-by-period cell. In Panel A, the instrument is the NTR gap. 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 9: Heterogeneity by Market Structure

Panel A: Main Sample (CPI)

	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$\times$High Concentration	-1.29^{**}				
	(0.53)				
Δ China IP$\times$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

Panel B: 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$\times$High Concentration	-1.70^{**}				
	(0.96)				
Δ China IP$\times$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: The specifications and samples are described in Section IV.D. "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 in Panel A, and a 6-digit NAICS-by-period cell in Panel B. In both panels, standard errors are clustered by industries.*** denotes statistical significance at the 1% level, ** at the 5% level, * at the 10% level.

Table 10: 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 the sample of ELIs that can be matched to the NBER-CES Manufacturing database. Panel B presents estimates of consumer surplus per displaced jobs in this sample, following the methodology discussed in Section V.A, in the year 2000. For Columns (1) to (3), the increase in consumer surplus per displaced job is computed as $\frac{\beta_{price}}{\beta_{emp}} \cdot \frac{\sum_j Cons_j}{\sum_j Emp_j}$. Columns (4) to (6) use the formula $\frac{\beta_{price}}{\beta_{emp}} \cdot \frac{\sum_j \Delta ChinaIP_j \cdot Cons_j}{\sum_j \Delta ChinaIP_j \cdot Emp_j}$, which gives larger weights to product categories with a larger increase in trade with China. All values are given in dollars for the year 2000.

Table 11: 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 $\frac{EV^{HI}-EV^{LI}}{EV^{All}} = \frac{\sum_j \left(s_j^{HI}-s_j^{LI}\right)\beta_j \Delta China IP_j}{\sum_j s_j^{All}\beta_j \Delta China IP_j}$, described in Section V.B.

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

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July 2019

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.[74] 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 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.

Aggregation. Aggregation to the ELI proceeds as follows. Let $p_{i,t}$ be a price quote within a given

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

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,

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

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,[75]

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

This price index can be derived from a more general CES price aggregator when the elasticity of substitution is 1. The general CES price index is,

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

where σ is the elasticity of substitution and the CES price aggregator is,

$$P_t = \left(\sum_{i=1}^{N} p_{i,t}^{1-\sigma}\right) .$$

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

[75] 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.

old. In this case, the BLS implements a quality 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.

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.[76]

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

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

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 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. For the purposes of the current paper, however, a unit elasticity of substitution obviates us from identifying the elasticity's value in each ELI. Furthermore, the unit elasticity is a conservative parameter choice: if the true elasticity of substitution is above one (between products within the same ELI), then the unit elasticity of substitution understates the effect of the China shock on inflation within an ELI. Suppose that the China shock increases price dispersion within an ELI. In this case, a higher elasticity of substitution ($\sigma > 1$) implies that consumers are more sensitive to price changes and substitute their purchases to lower priced items. In turn, the product category's price index will be lower when the elasticity of substitution is higher. Empirically, we find that product categories that experience higher Chinese import penetration following China joining the WTO are indeed characterized by higher price dispersion. Therefore, by choosing a higher elasticity of substitution we would estimate a larger deflationary effect from increased Chinese trade (which would be more difficult to reconcile by the class of trade models we study in Section IV.A).

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 (2018), 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. An industry j may be directly expose to trade with China via import competition in its own product category. But it may also be exposed indirectly, for example if it buys intermediate inputs from China (or from domestic producers who face increased competition with China) or if it sells some of its output to domestic producers who are increasingly likely to buy from China instead. This appendix describes the computation of indirect exposure to China, via either supplier effects (i.e., via the cost of intermediate inputs) or buyer effects (i.e., import competition from China over the supply of intermediate inputs).[77]

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.[78]

A stylized example with two industries illustrates the way we measure supplier effects. The matrix formulas given below apply regardless of the number of industries.

[77] Our analysis is similar to 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.

[78] U is commodity (row) by industries (columns), while U^I is industry by industry. M^C is (row) by commodities (columns). Each column of M^C sums to one because it reflects the share of production of each commodity produced by each industry.

Commodity/Industry	A	B
A	30	5
B	10	40
Total Cost of Intermediate Inputs	40	45
Value Added (Labor, Capital, Surplus)	60	155
Total Output	100	200

(a) **Use Table for Supplier Analysis, Dollars**

Commodity/Industry	A	B
A	0.3	0.025
B	0.1	0.2
Total Intermediates	0.4	0.225
Value Added (Labor, Capital, Surplus)	0.6	0.775
Total Output	1	1

(b) **Use Table for Supplier Analysis, Shares**

In this stylized example, we define the "supplier first-order linkages" as follows:

$$\boldsymbol{D^C} = \begin{pmatrix} 0.3 & 0.025 \\ 0.1 & 0.2 \end{pmatrix}$$

Conceptually, this matrix gives the direct input requirement (in dollars, expressed as a fraction of demand normalized to \$1). To produce $\boldsymbol{y} = \begin{pmatrix} A^y \\ B^y \end{pmatrix}$, the economy requires $\boldsymbol{D^C} \cdot \boldsymbol{y}$ units of inputs $\boldsymbol{x} = \begin{pmatrix} 0.3 \cdot A^y + 0.025 \cdot B^y \\ 0.1 \cdot A^y + 0.2 \cdot B^y \end{pmatrix}$. For the "second round" of inputs, the economy requires $\boldsymbol{D^C \cdot (D^C \cdot y) = (D^C)^2 \cdot y}$, etc. We first focus on direct effects only.

Assume that the vector of import penetration across industries is given by:

$$\boldsymbol{IP} = \begin{pmatrix} A & B \\ 10\% & 20\% \end{pmatrix}$$

By also assuming that the IP ratios apply to both sales of intermediates inputs and final use products, we can readily apply them to the use of intermediates. We can then compute the "first-order" importance of IP in the production cost of each industry:

$$\boldsymbol{C^{IP,FirstOrder}} = \boldsymbol{IP \cdot D^C} = \begin{pmatrix} A & B \\ 5\% & 4.25\% \end{pmatrix}$$

Next, we want to characterize the importance of IP in production cost for each industry, accounting for higher-order input-output effects. Conceptually, we adjust the IP measure (denoted $\boldsymbol{IP}$ above) so that it reflects the importance of import penetration in the "IO-adjusted cost structure", not simply its importance in the direct supplier industries. Production of intermediates requires production of other intermediates, which in turn also relies on intermediates, etc. We assess the total importance of imports by using the following matrix, which captures the infinite chain of spending ("production requirements") that is set off when requiring an additional unit of each input:

$$\boldsymbol{T}^C = \boldsymbol{I} + \boldsymbol{D^C} + \left(\boldsymbol{D^C}\right)^{\boldsymbol{2}} + \left(\boldsymbol{D^C}\right)^3 + ... = \left(\boldsymbol{I} - \boldsymbol{D^C}\right)^{\boldsymbol{-1}}$$

We then normalize matrix $\boldsymbol{T^C}$ so that each column sums to one, denoted $\boldsymbol{T^{C,Norm}}$. Conceptually, the normalized matrix shows the share of each industry in "total induced (upstream) input cost". We then compute average import penetration, using the entries of $\boldsymbol{T}^{C,Norm}$ as weights:

$$\boldsymbol{IP^{,IO,C}} = \boldsymbol{IP} \cdot \boldsymbol{T^{C,Norm}}$$

Finally, our "IO-adjusted" importance of IP in production cost in each industry is given by:

$$\boldsymbol{C^{IP,IO}} = \boldsymbol{IP^{IO,C}} \cdot \boldsymbol{D^C}$$

We then compute how these measures vary over time. We keep the $\boldsymbol{D^C}$ matrix fixed since we only have detailed data on IO linkages in 2007, but the import penetration vectors vary over time.

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", processed as discussed above.

Industry/Commodity	A	B
A	30	10
B	5	40
(1) Total Sales to Intermediate Inputs	35	50
(2) Total Sales to Domestic Final Consumers (personal consumption, investment, govt., some of which from imports)	500	175
(3) Exports	20	75
(4) Imports	-455	-100
Total Output	100	200
Domestic Absorption = (1)+(2)	535	225
Sales of Domestic Producers Excluding Exports = (1)+(2)+(4)	80	125
Total Sales of Domestic Producers = (1)+(2)+(3)+(4) = Total Output	100	200

(c) **Use Table for Buyer Analysis, Dollars**

Commodity	A	B
(1) Share of Domestic Producers in Domestic Sales = Sales of Domestic Producers Excluding Exports/Domestic Absorption	0.1495	0.5555
Share of Sales of Domestic Producers to Domestic Intermediates = Total Sales to Intermediate Inputs * (1) / Total Sales of Domestic Producers	0.052	0.1388
Share of Domestic Sales of Domestic Producers to Domestic Intermediates = Total Sales to Intermediate Inputs/Domestic Absorption	0.065	0.222

(d) **Use Table for Buyer Analysis, Shares**

In our baseline analysis, we use the share of domestic intermediates in the total sales of domestic producers. The definition is given in Figure (d) above. We define the buyer first-order effects as follows:

$$\boldsymbol{D^B} = \begin{pmatrix} 0.04485 & 0.027775 \\ 0.007475 & 0.1111 \end{pmatrix}$$

When selling $\boldsymbol{y} = \begin{pmatrix} A^y \\ B^y \end{pmatrix}$ units of output, domestic producers sell $\boldsymbol{D^B \cdot y}$ units as inputs to other domestic producers, denoted $\boldsymbol{x} = \begin{pmatrix} 0.04485 \cdot A^y + 0.027775 \cdot B^y \\ 0.007475 \cdot A^y + 0.1111 \cdot B^y \end{pmatrix}$. In the "second round" they sell $\boldsymbol{D^B \cdot (D^B \cdot y) = (D^B)^2 \cdot y}$, etc.

Assume that the vector of import penetration across industries is:

$$\boldsymbol{IP} = \begin{pmatrix} A & B \\ 10\% & 20\% \end{pmatrix}$$

We can then compute the "first-order" importance of IP for "indirect import competition" in each industry, which is defined as follows:

$$\boldsymbol{B^{IP,FirstOrder}} = \boldsymbol{IP}\cdot \boldsymbol{D^{B}} = \begin{pmatrix} A & B \\ 0.598\% & 2.49\% \end{pmatrix}$$

These quantities indicate the degree of import competition faced by each industry in downstream markets. In this example, it is very low for industry A because intermediates are not very important for demand in that industry; but it is larger for industry B.

Following a reasoning similar to before, we account for higher-order input output linkages as follows:

$$\boldsymbol{T^{B}} = \boldsymbol{I} + \boldsymbol{D^{B}} + \left(\boldsymbol{D^{B}}\right)^{\boldsymbol{2}} + \left(\boldsymbol{D^{B}}\right)^{3} + ... = \left(\boldsymbol{I} - \boldsymbol{D^{B}}\right)^{\boldsymbol{-1}}$$

We then normalize matrix $\boldsymbol{T^{B}}$ so that each column sums to one, denoted $\boldsymbol{T^{B,Norm}}$. Conceptually, the normalized matrix shows the share of each industry in "total induced (downstream) sales". We then compute average import penetration, using the entry of $\boldsymbol{T^{B,Norm}}$ as weights:

$$\boldsymbol{IP^{,IO,B}} = \boldsymbol{IP} \cdot \boldsymbol{T^{B,Norm}}$$

Finally, our "IO-adjusted" importance of indirect import competition for each industry is:

$$\boldsymbol{B^{IP,IO}} = \boldsymbol{IP^{IO,B}} \cdot \boldsymbol{D^{B}}$$

As for the supplier effects, we keep the $\boldsymbol{D^{B}}$ matrix fixed but let the import penetration vectors vary over time.

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.[79] 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.

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

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

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

where

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

is item i's share of total sales in the sample from the NAICS category. Notice that the Laspeyres index can be re-expressed as a CES price index (see Section A.A) with an assumed elasticity of substitution of zero, which is derived from a Leontief aggregate production technology.

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.

A.F Estimated Markups and Profitability Ratios

In this appendix, we describe how we use Compustat to estimate markups and compute profitability ratios.

Estimated Markup. To estimate markup in Compustat, we follow De Loecker et al. (2017). They derive expressions for markups based on observables by exploiting cost minimization of a variable input of production. A key assumption underlying this approach is that the producer is a "price taker" for variable inputs. The main advantages of this approach are twofold: (a) theoretically, it does not require a specific model of how firms compete or specific assumptions about the demand system; (b) empirically, firms' financial statements are sufficient to implement this approach, there is no need for separate information on prices and quantities.

In this framework, the gross markup is defined as the difference between the consumer price P_{it}^{Q} and the shadow value of one more unit of production to the firm, λ_{it}, which is itself defined by the firm's cost-minimization problem. For firm i at time t, output comes from a production function using variable inputs (labor, intermediates, materials, etc.), capital and a fixed cost. Intuitively, the gross markup is the wedge between the willingness to pay of consumers for one more unit of output (P_{it}^{Q}) and the "reservation price" of the supplier to produce one more unit (λ_{it}).

The reservation price, λ_{it}, can be solved for in terms of observables by solving the cost-minimization problem of the producer,

$$\Lambda = \min_{V_{it},K_{it}} P_{it}^{V} V_{it} + r_{it} K_{it} + F_{it} - \lambda_{it} \left(Q(V_{it}, K_{it}) - \overline{Q_{it}} \right),$$

where the first-order condition with respect to variable costs yields an expression for λ_{it},

$$\lambda_{it} = \frac{P_{it}^{V} V_{it}}{Q_{it}} \theta_{it}^{v}, \tag{A1}$$

where the output elasticity of production with respect to variable inputs is,

$$\theta_{it}^{v} \equiv \frac{\partial Q(V_{it}, K_{it})}{\partial V_{it}} \frac{V_{it}}{Q_{it}}.$$

De Loecker et al. (2017) estimate the output elasticity of production with respect to variable inputs, θ_{it}^{v}, using various production functions. Defining the gross markups as $\mu_{it} \equiv \frac{P_{it}^{Q}}{\lambda_{it}}$ and substituting into equation (A1) yields

$$\mu_{it} = \theta_{it}^{v} \underbrace{\frac{P_{it}^{Q} Q_{it}}{P_{it}^{V} V_{it}}}_{\equiv \frac{SALES_{it}}{COGS_{it}}} . \tag{A2}$$

For intuition, it is instructive to consider the following heuristic derivation of the markup. Conceptually, the markup can be viewed as the wedge between the reservation price the consumer would be willing to pay to have the producer use one more unit of variable inputs ($P_{it}^{Q} \times \frac{\partial Q(.)}{\partial V_{it}}$), and the reservation price of the producer for doing so (P_{it}^{V}). The wedge is therefore given by $\mu_{it} = \frac{P_{it}^{Q}}{P_{it}^{V}} \frac{\partial Q(.)}{\partial V_{it}} = \frac{P_{it}^{Q} Q_{it}}{P_{it}^{V} V_{it}} \cdot \theta_{it}^{v}$, as in (A2). A positive wedge between reservation prices constitutes an inefficiency.

We follow the data construction steps of De Loecker et al. (2017) in the Compustat North America – Fundamentals Annual data set (obtained through WRDS). The steps we take are identical to De Loecker et al. (2017), except that we assign a firm to a unique 6-digit NAICS industry (instead of the focus on more aggregated 2-digit industries in their paper). We eliminate firms with reported cost-of-goods to sales, and SG&A to sales ratio's in the top and bottom 1 percent, where the percentiles are computed for each year separately.

Following equation (A2), two key variables are used two compute markups: total sales (variable "SALE" in Compustat) and the total cost of goods sold (variable "COGS" in Compustat). Furthermore, for our baseline specification we use a time-invariant and sector-invariant elasticity $\theta_{it}^{v} = 0.85$, because De Loecker et al. (2017) show that their results are driven by changes in the ratio of sales to cost of goods sold, and remain very similar whether or not the elasticity is allowed to vary over time and across sectors (see their Appendix B1). Panel A of Online Appendix Figure A8 reports trends in markups over time: the average markup is increasing, but this increase is not uniform across the markup distribution and is driven by the top of the distribution.

Profitability Ratios. For robustness analysis, we compute two profitability ratios, profits over sales and profits over assets. To calculate profits, we use the markup measure in equation (A2) and account for all costs, including fixed costs:

$$\Pi_i = S_{it} - P_t^{V} V_t - r_t K_{it} - P_t^{X} X_t.$$

With Π_i denoting profits, the profit rate as a share of sales is $\pi_{it} = \frac{\Pi_i}{SALE_{it}}$. This measure scales the profits by firm size as measured by its revenue. From an investment viewpoint, we may want to measure the return on assets. Therefore we also compute an analogous measure, now dividing by total capital instead of total sales: $\pi_{it} = \frac{\Pi_i}{K_{it}}$.

Panel B of Online Appendix Figure A8 reports the trends in profitability over time. The trends paint a picture similar to the markup trends: profitability has been increasing over time, and particularly so for the most profitable firms.

B Theory Appendix

B.A Connecting the IV Specification to First-Order Price Effects

In this appendix, we derive equation (5) in the main text. We proceed in two steps. First, we show that the elasticity of substitution σ governs the relationship between a percentage change in relative prices and a percentage change in relative expenditure shares. Second, we re-write this relationship to match the definition of the variables used in our empirical analysis.

Suppose there are two countries, the U.S. and China, denoted by "us" and "ch" respectively. Let P_i^j and X_i^j denote the price and quantity of industry i's output produced in country $j \in us, ch$. For notational compactness we will omit the industry subscript in the remainder of this section. Denote the expenditure share on Chinese goods by $S^{ch} = P^{ch}X^{ch}/(P^{us}X^{us} + P^{ch}X^{ch})$ so that the share of U.S. goods is $1 - S^{ch}$. Lastly, define the elasticity of substitution between U.S. and Chinese produced goods by

$$\sigma \equiv -\frac{d\log(X^{ch}/X^{us})}{d\log(P^{ch}/P^{us})}$$

Accordingly, the elasticity of relative expenditures, $(P^{ch}X^{ch})/(P^{us}X^{us})$, with respect to relative prices, P^{ch}/P^{us}, is

$$\frac{d\log(P^{ch}X^{ch}/P^{us}X^{us})}{d\log(P^{ch}/P^{us})} = \frac{1}{X^{ch}/X^{us}} \cdot \left((X^{ch}/X^{us}) + (P^{ch}/P^{us})\frac{d(X^{ch}/X^{us})}{d(P^{ch}/P^{us})}\right).$$

Rearranging and applying the definition of σ gives,

$$d\log(P^{ch}/P^{us}) = -\frac{1}{\sigma - 1} d\log\left(\frac{P^{ch}X^{ch}}{P^{us}X^{us}}\right)$$

Then, given the definitions of U.S. and Chinese goods expenditure shares, we know that,

$$\begin{aligned} d\log\left(\frac{P^{ch}X^{ch}}{P^{us}X^{us}}\right) &= \frac{P^{us}X^{us}}{P^{ch}X^{ch}} d\left(\frac{P^{ch}X^{ch}}{P^{us}X^{us}}\right) \\ &= \frac{1 - S^{ch}}{S^{ch}} d\left(\frac{S^{ch}}{1 - S^{ch}}\right) \\ &= \frac{1 - S^{ch}}{S^{ch}} \left(\frac{1}{1 - S^{ch}} + \frac{S^{ch}}{(1 - S^{ch})^2}\right) dS^{ch} \\ &= \left(\frac{1}{1 - S^{ch}}\right) \cdot \frac{dS^{ch}}{S^{ch}}. \end{aligned}$$

By assuming that the domestic price remains unchanged, we can write,

$$d\log\left(\frac{P^{ch}}{P^{us}}\right) = d\log(P^{ch}) \equiv \pi^{ch},$$
$$\pi \equiv d\log(P) = S^{ch}\pi^{ch}$$

Hence, plugging in the previous expressions, we obtain equation (5) as desired,

$$\pi = -\frac{1}{(\sigma-1)(1-S^{ch})}dS^{ch}.$$

In the data, we work with a first-order approximation to this equation (i.e. with the observed change in import penetration from China, $\Delta ChinaIP$) rather than with the infinitesimal change dS^{ch} that makes the equation hold exactly.

B.B 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). 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 Online Appendix Table A9), 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 is 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

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

Next we will 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:

$$
\Delta\log(W_j) = \frac{1}{1-\sigma}\Delta\log(\lambda_{jj}) \tag{B3}
$$

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 (B3) 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:

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

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:

$$\Delta \log\left(p_s^j\right) = \alpha - \frac{1}{1-\sigma_s} \Delta \log(\lambda_{jj}^s) + \epsilon_j. \tag{B4}$$

Equation (B4) corresponds to our IV specification using the log change in the domestic expenditure share as the endogenous variable, as we do in Online Appendix Table A9. Note that our baseline IV specifications are of the form:

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

where j indexes the home country (the U.S. in our case). This specification can be derived from equation (B4) by making two approximations: (i) China is the only trade partner of the US, i.e. $\lambda_{jj}^s + \lambda_{jChina}^s = 1 \; \forall s$; (ii) the initial import share from China is small. Under these assumptions, we have

$$\begin{aligned} \Delta \log(P_j^s) &= \alpha - \frac{1}{1-\sigma_s} \Delta \log(1-\lambda_{jChina}^s) + \epsilon_j, \\ &\approx \alpha + \frac{1}{1-\sigma_s} \Delta \lambda_{jChina}^s + \epsilon_j. \end{aligned} \tag{B5}$$

Since our empirical specification uses spending weights, we should recover a spending-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.

B.C Connecting the IV Specification to Models with Endogenous Markups

In this appendix, we derive the equations presented in Section IV.D, which connect our IV specification to models with endogenous markups and motivate several tests of the markup channel.

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.

We consider the economic environment in Amiti et al. (2018b) to characterize markups. We first specialize their setting to contain only two producers in each industry, then extend the derivations to many producers. 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.[80]

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. (2018b) show that firm i's profit-maximizing price is the solution to a fixed-point equation:

$$\log(p_{is}) = \log(mc_{is}) + \log(\mu_i(p_{is}, p_{-is}, \zeta_s)), \tag{B6}$$

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 (B6) can be totally differentiated to study our proposed perturbation of the equilibrium:

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

which can be simplified to,

$$d\log(p_{is}) = \frac{1}{1+\Gamma_{is}} d\log(mc_{is}) + \frac{\Gamma_{-is}}{1+\Gamma_{is}} d\log(p_{-is}) + \varepsilon_s. \tag{B7}$$

Equation (B7) is the accounting decomposition from Amiti et al. (2018b). 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. (2018b) 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. (2018b) 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).[81]

[80] Amiti et al. (2018b) 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. (2018).

[81] Amiti et al. (2018b) show that this assumption holds for the nested-CES demand structure as weall as a first-order

Perturbation and first-order approximation. Assuming $\Gamma_{is} = \Gamma_{-is} \equiv \Gamma_s$, 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:

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

where the first and second lines follow from (B7) with $\varepsilon_s = 0$, the third is implied by CES demand, and the fourth follows from Roy's identity. This completes the proof of equations (9), (10) and (11) in the main text.

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. $dln(c^{US}) = 0$ and $dln(c^{Chn}) \neq 0$. Therefore we have $dln\left(p_s^{US}\right) = \frac{\Gamma_s}{1+\Gamma_s} dln\left(p_s^{China}\right)$. Given this, the first two lines in the system of equations above imply:

$$\begin{aligned}
d\log\left(p_s^{China}\right) &= \frac{1+\Gamma_s}{1+2\Gamma_s} d\log\left(c_s^{China}\right), \\
d\log\left(p_s^{US}\right) &= \frac{\Gamma_s}{1+2\Gamma_s} d\log\left(c_s^{China}\right).
\end{aligned}$$

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

$$dS_s^{China} = -\frac{(\sigma_s - 1)S_s^{China}(1-S_s^{China})}{1+2\Gamma_s} d\log\left(c_s^{China}\right), \tag{B8}$$

$$d\log(p_s) = \frac{S_s^{China} + \Gamma_s}{1+2\Gamma_s} d\log\left(c_s^{China}\right). \tag{B9}$$

Equation (B8) gives an expression for the change in the import penetration rate from China (in percentage points), while equation (B9) gives the change in the industry price index (in log points). Combining equations (B8) and (B9) give the relationship between the industry price index and the change in the import penetration rate from China:

$$d\log(p_s) = -\frac{1 + \Gamma_s / S_s^{China}}{(\sigma_s - 1)(1 - S_s^{China})} \cdot dS_s^{China}. \tag{B10}$$

In the data, we work with a first-order approximation to (B10), 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 $dln(p_s)$ that make (B10) hold exactly. This completes the proof of equation (12) in the main text.

approximation for a broad class of models with symmetric preferences.

Heterogeneity by market structure. We extend the model to a setting with multiple firms to derive predictions of the markup channel that we can test empirically across product categories with different levels of (domestic) market concentration. Suppose there are N producers in each sector, of which $N-1$ are U.S. producers and one based in China. Producers can equivalently be viewed as differentiated product varieties. For simplicity assume that the $N-1$ U.S. producers are symmetric. Given symmetry, the price change for any one of the $N-1$ symmetric U.S. producers can be expressed in terms of their own marginal cost, the price change of the $N-2$ other U.S. producers in the industry and the Chinese importer,

$$d\log(p_s^{US}) = \frac{1}{1+\Gamma_s} d\log\left(c_s^{US}\right) + \frac{\Gamma_s}{1+\Gamma_s}\left[(N-2)d\log\left(p_s^{US}\right) + d\log\left(p_s^{China}\right)\right]$$

and the price change for the Chinese producer in industry s can be written as a function of its own marginal cost and the prices of the $N-1$ U.S. competitors,

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

Suppose the Chinese marginal cost changes, but the U.S. producers' marginal costs do not change. Thus, setting $d\log(c_s^{US}) = 0$ allows us to rewrite U.S. producer price changes in industry s as,

$$d\log(p_s^{US}) \quad = \quad \frac{\frac{\Gamma_s}{1+\Gamma_s}}{1-\frac{\Gamma_s}{1+\Gamma_s}(N-2)} d\log\left(p_s^{China}\right)$$

and substituting this into the expression for the change in the Chinese producer's price yields,

$$d\log(p_s^{China}) \quad = \quad \frac{\frac{1}{1+\Gamma_s}}{1-\frac{\Gamma_s}{1+\Gamma_s}(N-1)\frac{\frac{\Gamma_s}{1+\Gamma_s}}{1-\frac{\Gamma_s}{1+\Gamma_s}(N-2)}} d\log\left(c_s^{China}\right).$$

Finally, when we substitute this expression back into the price change for U.S. producers, we obtain the price change as a function of the Chinese marginal cost shock,

$$d\log(p_s^{US}) = \frac{\frac{\Gamma_s}{1+\Gamma_s}}{1-\frac{\Gamma_s}{1+\Gamma_s}(N-2)} \cdot \frac{\frac{1}{1+\Gamma_s}}{1-\frac{\Gamma_s}{1+\Gamma_s}(N-1)\frac{\frac{\Gamma_s}{1+\Gamma_s}}{1-\frac{\Gamma_s}{1+\Gamma_s}(N-2)}} d\log\left(c_s^{China}\right).$$

For notational compactness, we will define the parameters (α, κ) in terms of the two price change expressions as follows,

$$\begin{aligned} d\log(p_s^{China}) &= \kappa \cdot d\log\left(c_s^{China}\right), \\ d\log(p_s^{US}) &= \alpha\kappa \cdot d\log\left(c_s^{China}\right). \end{aligned}$$

Accordingly, the change in expenditure share of Chinese produced goods is,

$$\begin{aligned} d\log\left(S_s^{China}\right) &= (1-\sigma)\left(\sum_{k=1}^{N}\frac{(1-S_s^{China})}{N-1}\right)\left[d\log(p_s^{China})-\sum_{k=1}^{N}d\log(p_s^{US})\right] \\ dS_s^{China} &= (1-\sigma)(1-S_s^{China})S_s^{China}\left[1-(N-1)\alpha\right]\kappa\cdot d\log\left(c_s^{China}\right). \end{aligned}$$

Furthermore, the total price change in industry s is,

$$\begin{aligned} d\log(p_s) &= \sum_{k=1}^{N}\frac{(1-S_s^{China})}{N-1}d\log(p_s^{US})+S_s^{China}d\log(p_s^{China}) \\ &= d\log(p_s^{US})+S_s^{China}\left(d\log(p_s^{China})-d\log(p_s^{US})\right) \\ &= \left[\alpha+S_s^{China}(1-\alpha)\right]\kappa\cdot d\log\left(c_s^{China}\right) \end{aligned}$$

Thus we can derive the relationship between the change in import penetration from China and the industry price index as,

$$\begin{aligned} \frac{d\log(p_s)}{dS_s^{China}} &= -\frac{\left[\alpha+S_s^{China}(1-\alpha)\right]\kappa\cdot d\log\left(c_s^{China}\right)}{(\sigma_s-1)(1-S_s^{China})S_s^{China}\left[1-(N-1)\alpha\right]\kappa\cdot d\log\left(c_s^{China}\right)} \\ &= -\frac{1+\frac{\alpha}{1-\alpha}\frac{1}{S_s^{China}}}{(\sigma_s-1)(1-S_s^{China})}. \end{aligned}$$

Given the definition of α, we can write the expression using the fact that:

$$\frac{\alpha}{1-\alpha} = \frac{\Gamma_s}{1-\Gamma_s(N-2)}.$$

Thus, the full expression for the N-firm model equivalent of our IV specification is,

$$d\log(p_s) = -\frac{1+\frac{\Gamma_s/S_s^{China}}{1-\Gamma_s(N-2)}}{(\sigma_s-1)(1-S_s^{China})}\cdot dS_s^{China}. \tag{B11}$$

Notice that this expression reduces to the case in equation (B10) when $N=2$.

To compute how Γ_s may vary across industries, we use the expression derived by Amiti et al. (2018b) under Betrand competition. With a Cobb-Douglas aggregator across sectors, in our setting with equally-sized firms we have:

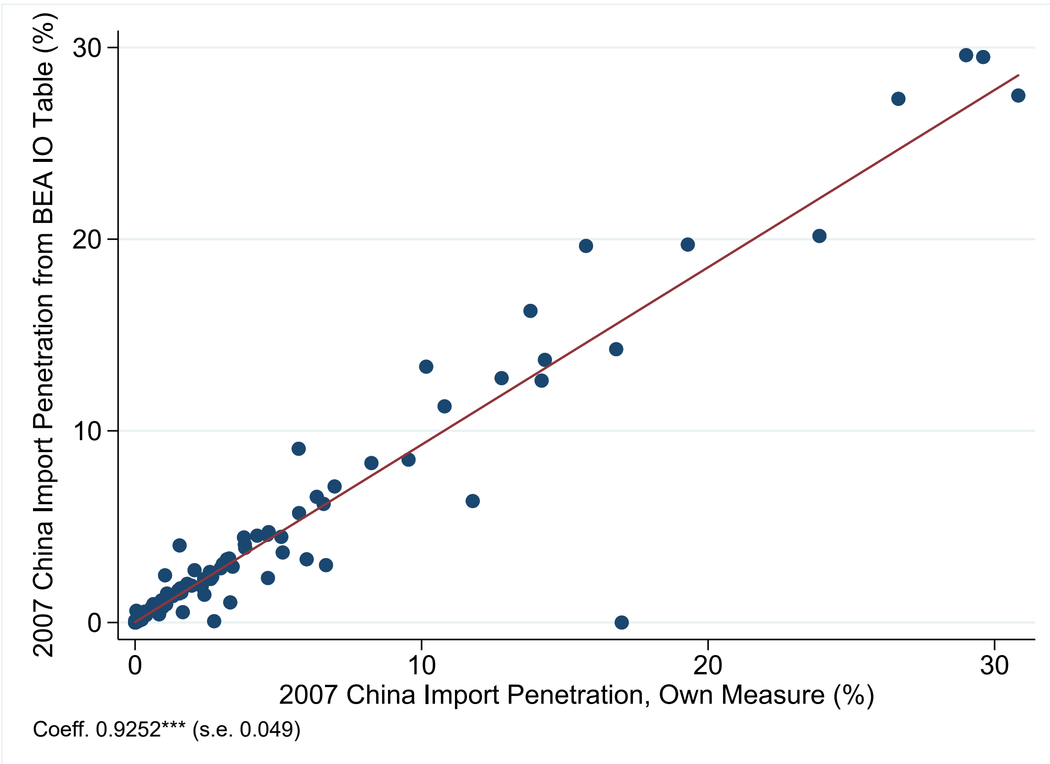
$$\Gamma_s = \frac{(\sigma_s-1)\cdot H_s}{1+(\sigma_s-1)(1-H_s)}, \tag{B12}$$

where σ_s is the elasticity of substitution within the industry and $H_s = h_s/10,000$, with h_s denoting the Herfindahl index. Intuitively, H_s is the market share of the typical firm in industry s, which is equal to $1/N_s$ with equally-sized firms. A higher typical market share reflects larger markup power, therefore Γ_s is larger when the market is more concentrated, i.e. when H_s is higher. As the economy approaches perfect competition ($N_s \to \infty$), $H_s \to 0$ and $\Gamma_s \to 0$.

These expressions show that the markup channel predicts a larger price response when the domestic market is more concentrated and when the initial import penetration rate from China is small. We calibrate the predicted heterogeneity across product categories from equations (B11) and (B12). We use data on domestic Herfindahl indices from the U.S. Census (for H_s) and on the initial import penetration rate from China (for S_s^{China}). We find that the relationships are non-linear: the price response is particularly strong when the initial import penetration rate is small and when the domestic market is more concentrated. These results motivate the tests implemented in Section IV.D.

C Online Appendix Tables and Figures

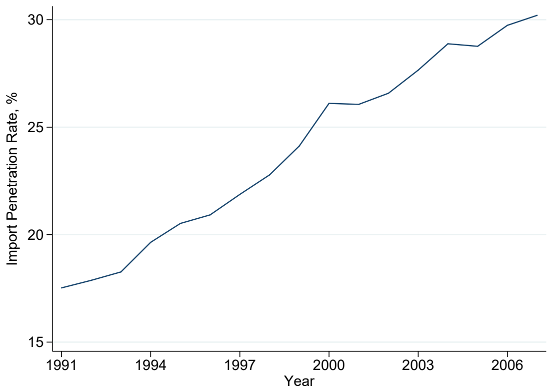
Figure A1: Validation of Import Penetration Measure against BEA Measure for 2007



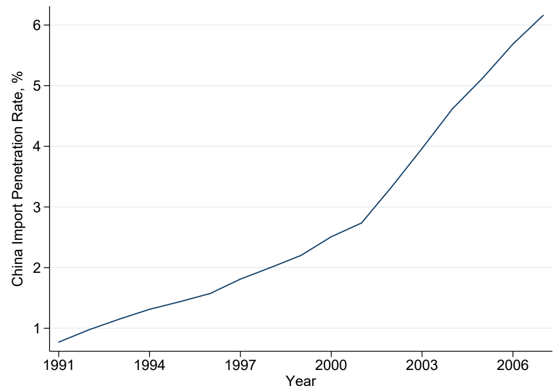
Notes: This figure reports a validation test to assess the accuracy of the import penetration measure used in the analysis. The x-axis corresponds to the measure of import penetration from China described in Section II.A, except that we aggregate the data to the level of the 6-digit IO industries defined in the BEA's 2007 input-output table. 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; the data is then linked and aggregated to the level of IO industries. The y-axis gives the measure of import penetration provided by the BEA's input-output table for 2007, at the level of approximately 400 industries. The BEA gives the full import penetration rates across industries, which we convert to import penetration rates for China by using the share of China in trade for each industry. We conduct this comparison in 2007 because in earlier years the input-output table is significantly more aggregated. The figure reports a binned scatter plot, where each dot represents 1% of the underlying data. The close relationship between the two measures, with a slope close to one, alleviates potential measurement concerns.

Figure A2: Chinese Import Penetration over Time and Across Industries

Panel A: For Manufacturing



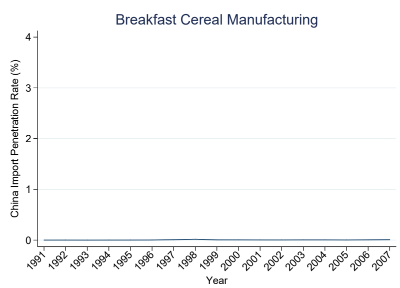
(a) All Trade



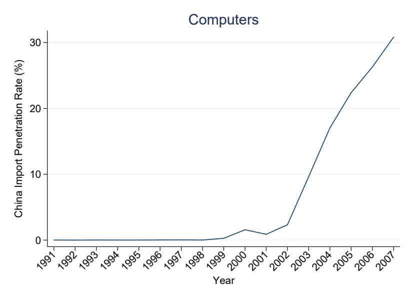
(b) Trade with China

Panel B: For Selected Manufacturing Industries

(a) Men's footwear



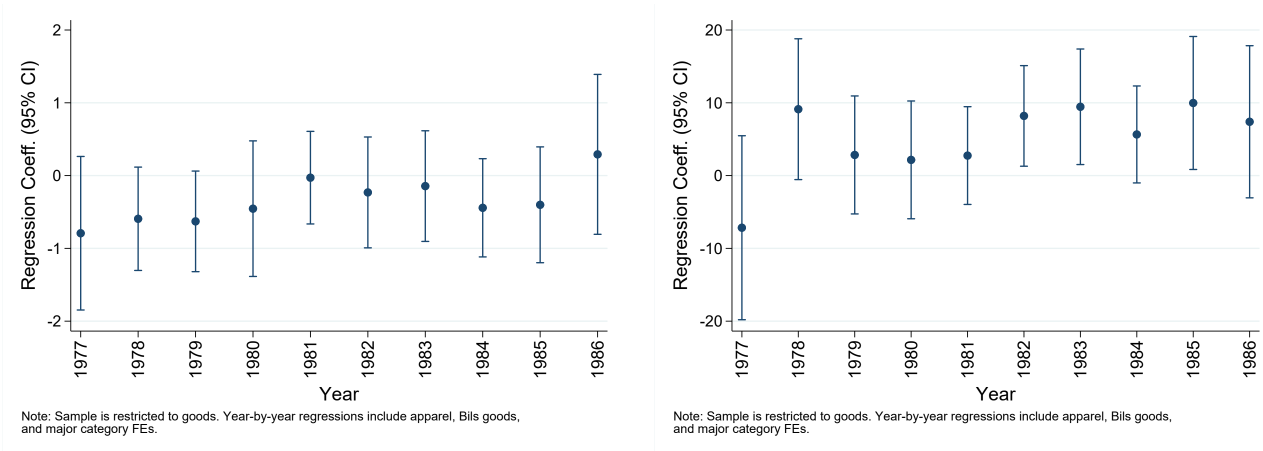
(b) Breakfast cereal



(c) Computers

Notes: This figure reports trends in import penetration rate over time, for manufacturing (Panel A) and for selected manufacturing industries (Panel B). The data source in the NBER-CES Manufacturing Industry database. The import penetration rate from country c in industry j is defined as $IP_j^c = Imports_j^c/(DomesticProduction_j + Imports_j - Exports_j)$. Panel B illustrates the type of variation across industries that can be leveraged to study the impact of trade on consumer prices. In particular, Panel B illustrates that it is possible to use only "within-industry" variation over time (i.e., with industry fixed effects in a specification using the change in the import penetration rate as the independent variables). Indeed, industries are exposed to China very differently over time: there is a steady increase for footwear, no exposure for breakfast cereals, and a fast increase for computers only after 2000.

Figure A3: Testing for Pre-trends in the Extended CPI Sample

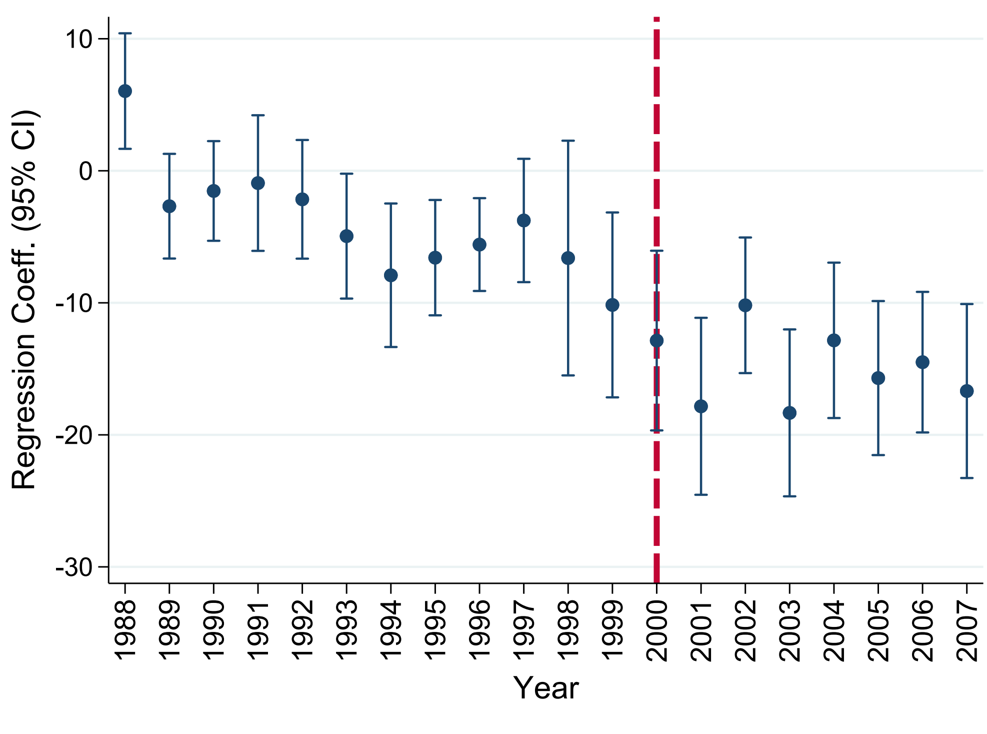


(a) China IP in other developed economies

(b) NTR gap

Notes: The specification is the same as described in Section III.B, but using the extended CPI sample described in Online Appendix A.C. F-tests indicates that we cannot reject that the estimated coefficients are jointly insignificant.

Figure A4: Testing for Pre-trends Without Controls

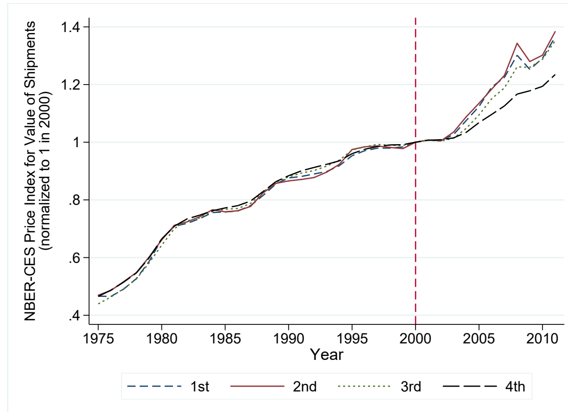


Notes: The specification is the same as described in Section III.B, but without fixed effects for apparel or durables. The figure exhibits pre-trends, in contrast with Figure 1 in the main text. These results indicate that including fixed effects for apparel and durables is important to ensure that a causal interpretation of the estimates is plausible.

Figure A5: Long-Run Event Studies in NBER-CES Manufacturing Database

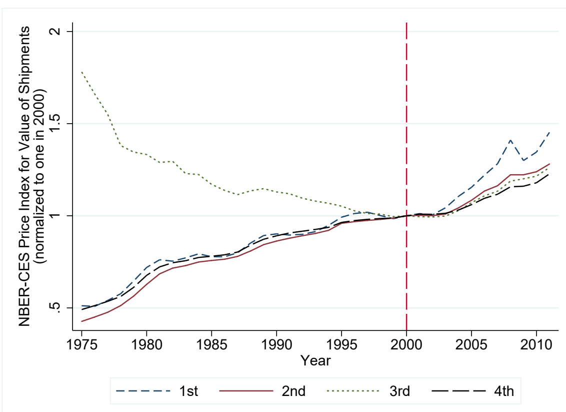
Panel A: Excluding NAICS 334, Computers and Electronics

(a) NTR gap, by quartiles

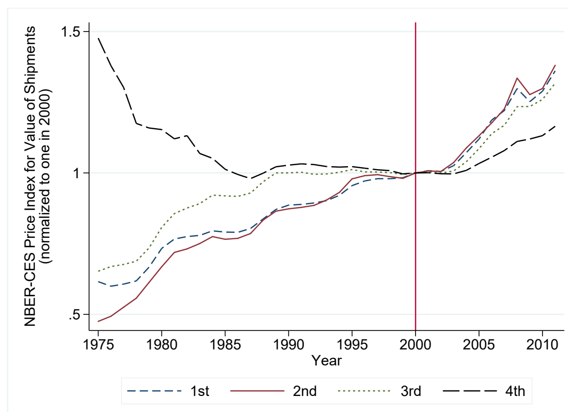


(b) China IP in other developed economies, by quartiles

Panel B: Including NAICS 334, Computers and Electronics



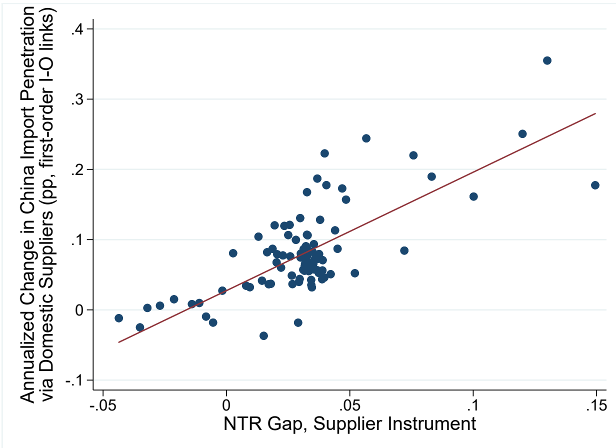
(a) NTR gap, by quartiles



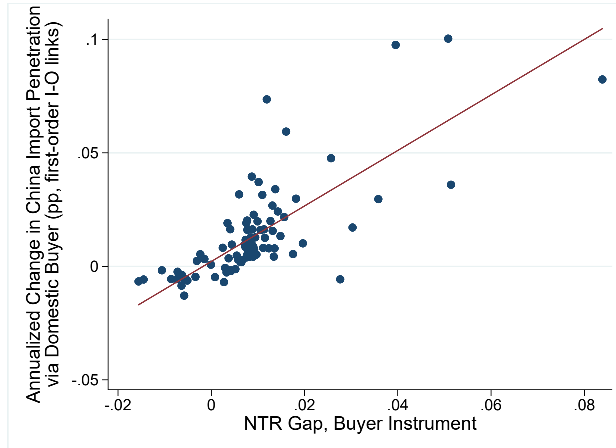
(b) China IP in other developed economies, by quartiles

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. 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 support the causal interpretation of the estimates presented in Section III. 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).

Figure A6: First-Stage Relationships for Supplier and Buyer Effects



(i) Exposure via Suppliers

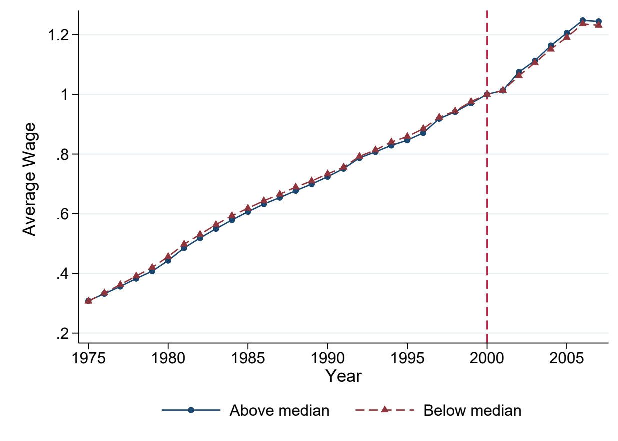


(ii) Exposure via Buyers

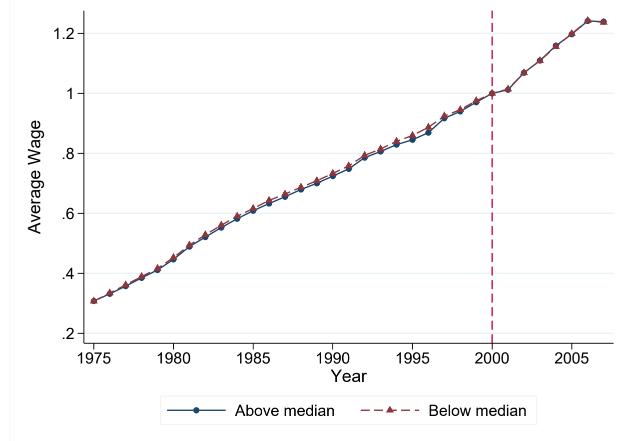
Notes: This figure reports the first-stage relationships for indirect effects via suppliers (sub-figure (a)) and buyers (sub-figure (b)) using the NTR gap instrument. The specifications correspond to Column (1) of Online Appendix Table A15. The level of observation is a 6-digit IO industry-by-period. Each dot represents 1% of the data, using consumption weights, and the OLS best-fit line is shown in red. The steps to build the measures of indirect exposure to trade with China are described in Online Appendix A.D.

Figure A7: The Roles of Wages and Total Factor Productivity

Panel A: Event Studies for Wages

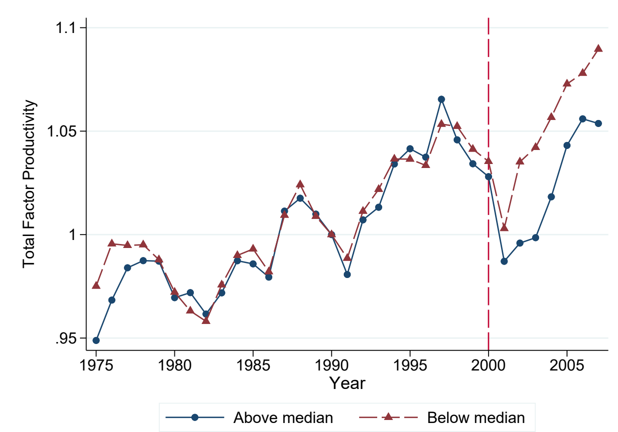


(i) NTR gap

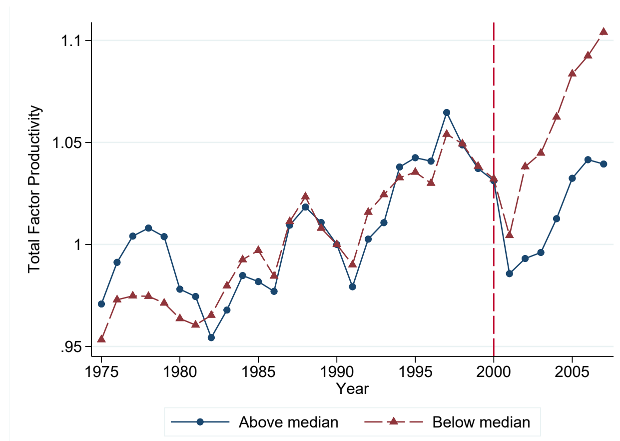


(ii) Change in China IP in Other Developed Economies

Panel B: Event Studies for Total Factor Productivity



(i) NTR gap

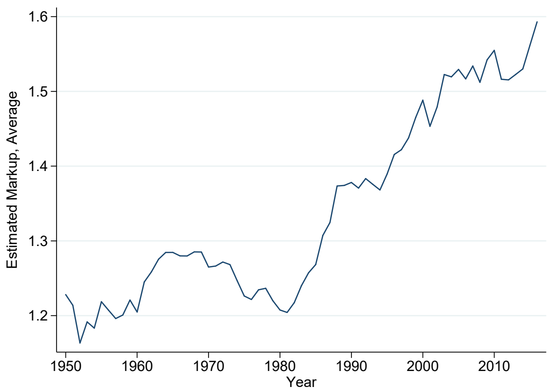


(ii) Change in China IP in Other Developed Economies

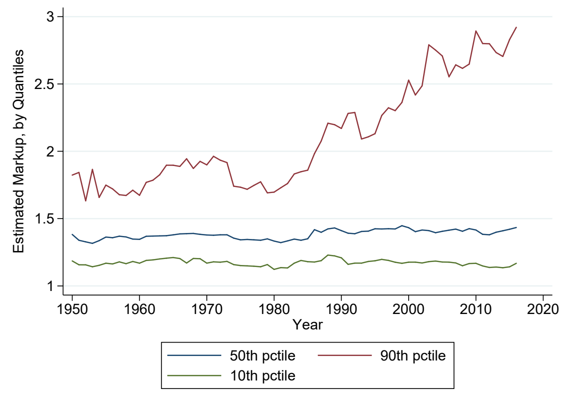
Notes: Panel A of this figure reports the path of average wages across industries that are more or less exposed to our instruments for trade with China, using a median split. Panel B reports a similar event study for Total Factor Productivity. Wages and TFP are measured in the NBER CES Manufacturing database. The change in import penetration rate from China in other developed economies is measured over the period 2000-2007. Wages and TFP are normalized to one in 1990.

Figure A8: Summary Statistics for Estimated Markups and Profitability Measures

Panel A: Estimated Markups

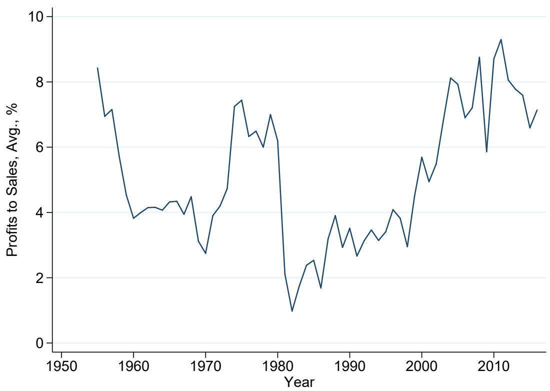


(a) Average

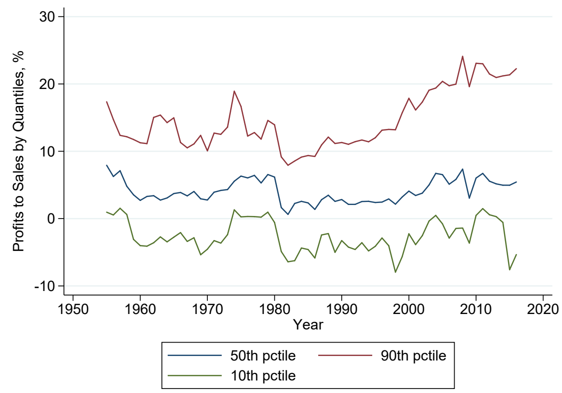


(b) Quantiles

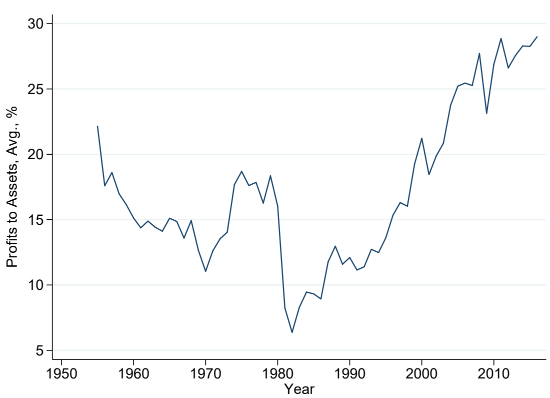
Panel B: Profitability Measures



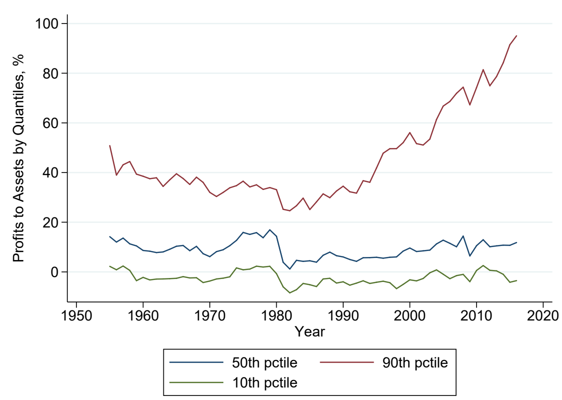
(a) Profits/Sales, Average



(b) Profits/Sales, Quantiles



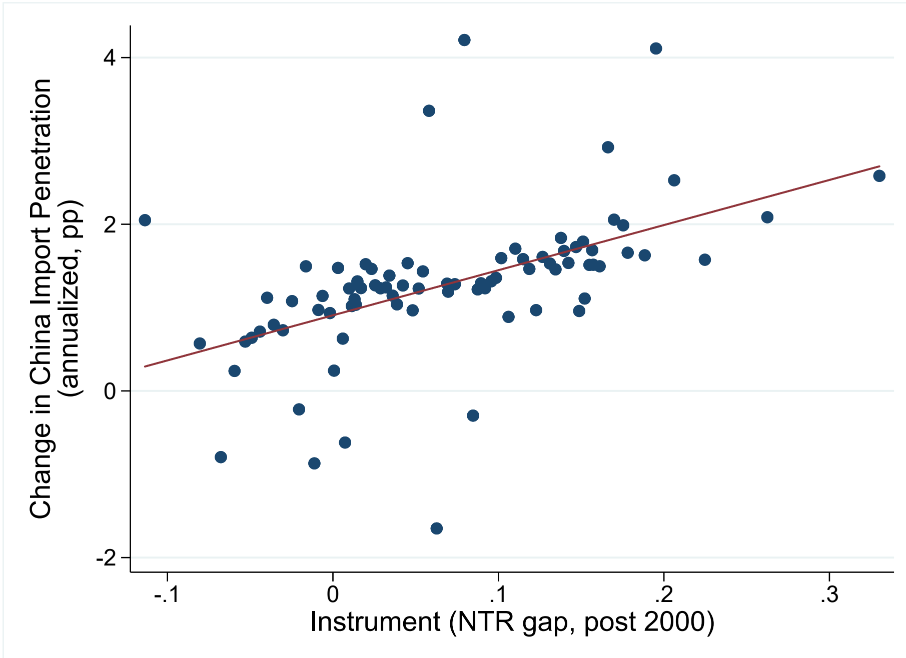
(c) Profits/Assets, Average



(d) Profits/Assets, Quantiles

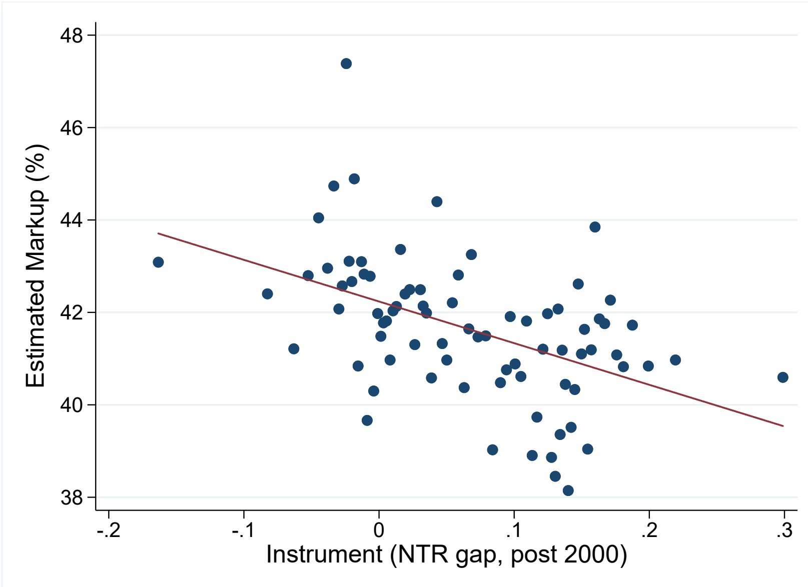
Notes: This figure reports trends in estimated markups. We follow the methodology of De Loecker et al. (2017) (described in Appendix A.F) and obtain similar results. Statistics are computed using sales as weights. Source: Compustat North America Fundamentals Annual Data, (Wharton Research Data Services) and authors' calculations.

Figure A9: First-Stage in Compsutat Sample



Notes: This figure shows the binned scatter plots for the relationships between the NTR gap instrument and the change in import penetration from China in the Compustat Sample. Each dot represents 1% of the data, using consumption weights, and the OLS best-fit lines are reported in red. The specification and the Compustat sample are described in Section IV.D. The level of observation is a NAICS industry-by-period. Source: Compustat North America Fundamentals Annual Data, (Wharton Research Data Services) and authors' calculations.

Figure A10: The Response of Markups, Controlling for Firm Fixed Effects



Notes: This figure shows the binned scatter plots for the relationships between the NTR gap instrument and the estimated markups in the Compustat Sample with firm fixed effects. Each dot represents 1% of the data, using consumption weights, and the OLS best-fit lines are reported in red. The level of observation is a Compustat firm-by-period. The point estimate and standard error are reported in Online Appendix Table A17. Source: Compustat North America Fundamentals Annual Data, (Wharton Research Data Services) and authors' calculations.

Table A1: Summary Statistics for Input-Output Sample

Panel A: First-Order Exposure

	Mean	S.D.	p10	p50	p90	N
ΔChina IP in U.S., direct (pp, annualized)	0.5407	1.248	0	0.0064	1.99	170
ΔChina IP in U.S., first-order downstream/buyer (pp, annualized)	0.0251	0.0529	0	0.0053283	0.0609737	170
ΔChina IP in U.S., first-order upstream/supplier (pp, annualized)	0.11409	0.1624	0.0097	0.0634	0.291862	170
ΔChina IP in Europe, direct (pp, annualized)	0.36405	0.8880	0	0.01232	1.32402	170
ΔChina IP in Europe, first-order downstream/buyer (pp, annualized)	0.02161	0.04371	0	0.00708	0.05378	170
ΔChina IP in Europe, first-order upstream/supplier (pp, annualized)	0.11008	0.16980	0.00770	0.05267	0.29486	170
NTR Gap (pp)	0.17894	0.1905	0	0.12788	0.419	170
NTR Gap, first-order downstream/ buyer (pp, annualized)	0.0253	0.02768	0.000083	0.01851	0.05575	170
NTR Gap, first-order upstream/supplier (pp, annualized)	0.075163	0.05664	0.0154	0.06135	0.15507	170
Share of own prod. in total intermediates	0.0666	0.090	0.00025	0.02526	0.20141	369

Panel B: Higher-Order Exposure

	Mean	S.D.	p10	p50	p90	N
ΔChina IP in U.S., first-order downstream/buyer (pp, annualized)	0.02494	0.04498	0	0.00874	0.063045	170
ΔChina IP in U.S., first-order upstream/supplier (pp, annualized)	0.08752	0.09966	0.0161	0.05918	0.19671	170
ΔChina IP in Europe, first-order downstream/buyer (pp, annualized)	0.02147	0.0381	0.00008	0.00854	0.04880	170
ΔChina IP in Europe, first-order upstream/supplier (pp, annualized)	0.0959	0.1157	0.01378	0.05565	0.2294	170
NTR Gap, first-order downstream/ buyer (pp, annualized)	0.0250	0.0251	0.000362	0.0183	0.05435	170
NTR Gap, first-order upstream/supplier (pp, annualized)	0.0595	0.03634	0.0183	0.0517	0.11364	170

Notes: This table presents summary statistics for the input-output sample, which are described in Section II.A. Panel A reports first-order exposure measures, while panel B reports higher-order exposure measures, which are computed as explained in Online Appendix A.D. The sample extends between 1991 and 2007 and is divided into two periods, 1991-1999 and 2000-2007. The level of observation is a 6-digit IO code by period. All variables are defined for final consumption IO industries only, except "share of own production in total intermediates", which is defined for all IO codes.

Table A2: Summary Statistics for PPI Sample

						Observations	
	Mean	S.D.	p10	p50	p90	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: This table 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 A3: 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 A4: 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 A5: 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 A6: 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 $\times$ Capital Intensity	4.786**	
	(2.308)	
Δ China IP Other		1.353***
		(0.331)
Δ China IP Other $\times$ 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 A7: 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 A8: 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 elastictity. 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 A9: 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)
Cragg-Donald 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 A10: 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)	-1.50^{**}	-1.92^{*}	-0.83^{*}	-0.98^{*}
	(0.71)	(1.15)	(0.46)	(0.48)
First-stage F	748.98	604.61	748.98	604.61
NAICS F.E.	✓		✓	
Period-specific Computers F.E.	✓		✓	
2000-2007 only		✓		✓
Computers F.E.		✓		✓
N	550	275	550	275

Notes: The specifications are the same as for Table 5 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 A11: 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 5, 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 A12: 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 A13: 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 A14: 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 for Table 6 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 A15: 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. The first-stage relationships for Column (1) are depicted in Online Appendix Figure A6. 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 A16: 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 A17: The Response of Markups, Controlling for Firm Fixed Effects

	U.S. CPI Inflation
	OLS
	(1)
NTR Gap	-9.01^{***}
	(2.63)
Firm F.E.	Yes
N NAICS	796

Notes: This table reports the results from the specificatoin described in Section IV.D, except that the level of observation is a Compustat firm (rather than a NAICS code) and firm fixed effects are used. The recent literature documents that trends of rising markups and falling labor share are driven by reallocation of spending, i.e. market shares for firms with initially high markups tend to increase over time (e.g., Baqaee and Farhi (2017), De Loecker et al. (2017), Autor et al. (2017)). In contrast, trade-induced competition predicts that markups should fall *within* firms (equation (9)). To test this prediction, we amend our research design. We repeat our IV specification (3) but keep the data at the firm level; we run firm-level regressions, with the firm-level estimated markup as the outcome and firm fixed effects as controls. As previously, the independent variable is the industry-level change in import penetration from China. Due to firm fixed effects, this specification isolates changes in markups *within* firms. In contrast, in the specifications from Table 8, the observed change in markup is at the industry level, after aggregation with sales weights, and it could result from either within-firm markup changes or reallocation effects *between* firms (i.e., after the China shocks consumers could reallocate spending toward firms with lower markups). The point estimate of 9.01 (s.e. 2.63) is statistcally indistinguishable from our baseline reduced-form estimate of 9.52 (s.e. 4.34), reported in Panel A of Table 8 (Column (2)). This result indicates that controlling for firm fixed effects leaves the baseline estimate unchanged, implying that changes in markup are not driven by reallocation of sales across firms; rather, markups fall within firms. This finding is consistent with the predictions of the markup channel. Online Appendix Figure A10 depicts the relationship graphically. Standard errors are clustered at the level of NAICS code, because the NTR gap instrument is observed at this level of aggregation.*** denotes statistical significance at the 1% level, ** at the 5% level. Source: Compustat North America Fundamentals Annual Data, (Wharton Research Data Services) and authors' calculations.

Table A18: 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 A19: 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 A20: Distributional Effects via the Expenditure Channel, Interacted Specifications

<table>
<tr><td></td><td colspan="2">U.S. CPI Inflation (pp)</td></tr>
<tr><td></td><td>(1)</td><td>(2)</td></tr>
<tr><td>Δ China IP (pp)</td><td>-3.59^{***}</td><td>-3.01^{***}</td></tr>
<tr><td></td><td>(1.22)</td><td>(0.87)</td></tr>
<tr><td>Δ China IP×Interaction</td><td>3.40^{**}</td><td>2.28^{***}</td></tr>
<tr><td></td><td>(1.72)</td><td>(1.02)</td></tr>
<tr><td>Interacted variable (standardized by S.D.)</td><td>Expenditure Elast.</td><td>Share Inc. >60k</td></tr>
<tr><td>ELI F.E. & interacted-variable-by-period F.E.</td><td colspan="2">✓</td></tr>
<tr><td>N</td><td>332</td><td>332</td></tr>
</table>

Notes: This table reports the results from our baseline IV specification (3), including linear interaction terms characterizing the consumers across product categories. Column (1) use the expenditure elasticity, standardized by its standard deviation, as the interaction term. The results indicate that as the income elasticity increases by one standard deviation, the price fall is mitigated by 3.40 percentage points. Column (2) documents similar results with another interaction term, the share of sales to consumers with annual earnings above $60,000. The price effect is mitigated by 2.28 percentage points as the share of sales to this group of consumers increases by one standard deviation. These patterns indicate that, for a given trade shock, the price response is stronger in product categories that sell to lower-income consumers.