The Competitive Effects of Imports*

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Abstract

This paper studies the effect of the China Shock on US markups using a difference-in-differences empirical design. I find that lowering tariffs on imports from China had a pro-competitive effect on US firms by interrupting the rising trajectory of markups. More specifically, firms facing the threat of import competition reduced the growth of their markups by 0.5 percentage points following US normalization of trade relations with China. The pro-competitive effect operated most clearly through intermediate goods, affecting both growth rates and to some extent levels. I also find a negative downstream effect of trade liberalization on markups, contradicting potential anti-competitive effects of increased import competition.

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1 Introduction

Twenty-five years after theU.S.opened to trade with China there is no consensus on its benefits. The entry of Chinese imports should have reduced consumer prices, both because the goods themselves were inexpensive, and because they pushed down the prices of domestic competitors. In this paper I focus on this second channel: whether opening to imports from China affected markups of competing U.S. firms. I find that the China Shock indeed exerted competitive pressure on U.S. firms, but in a context of previously growing markups. In other words, the gap between prices and costs widened throughout the 1990s, then narrowed briefly with the change in trade policy, and began expanding again afterwards. The China Shock did not revert the trend of growing U.S. markups; it only paused it.

This paper provides novel evidence of the pro-competitive effects of trade. I uncover the relationship between import competition and markups using a difference-in-differences approach, combining firm-level markups constructed from Compustat data with the gap in tariffs before the U.S. normalized trade relations with China. I also use U.S. Input-Output tables to track down effects downstream. I find that firms facing a 100 percentage points gap in ad-valorem tariffs lowered their markup growth by 4 percentage points. They also reduced their markups by 0.12 in the case of intermediate goods.

Theory would suggest two contradictory effect of increased import competition on markups. First, changes in trade policy ease the entry of competitors at lower prices, making domestic products relatively more expensive. Incumbent firms react to this threat by decreasing their markups to avoid losing too many sales. This mechanism is known in the literature as the "pro-competitive" effect of trade, which increases the welfare gains through enhanced competition. I find evidence of the pro-competitive effect of imports: firms facing a surge in competing imports do decrease their markups.

The second effect, which I refer to as the "anti-competitive" effect, refers to the downstream consequences of cheaper goods on markups. Input buyers face lower input prices, either from imports themselves or from domestic firms responding to those imports, thereby decreasing costs of production. Under less than perfect competition, prices of the produced goods decrease by less than the drop in production costs. In other words, the decrease in cost is not completely passed through to prices, which increases markups. However, I find no evidence of any anti-competitive effects. On the contrary, my estimations suggest a cascading pro-competitive effect, where trade lowers downstream markups, at least for smaller firms.

My analysis is closely related to previous work by Jaravel and Sager [2022], who focus on the effect of the China Shock on prices and conduct auxiliary empirical exercises on the pro-competitive effect. I improve on their work using a different empirical approach and narrowing down the problem to firm-level effects. My focus is on the competitive effects of imports at the firm level, abstracting from aggregate measures that rely on sales-weighted averages so that my results are not driven by changes in the reallocation of sales. Djolaud [2022] also discuss the pro-competitive effect of the China Shock on U.S. markups, but make a distinct point about product quality. As part of the same conversation, Amiti et al. [2020] find that the China Shock reduced the price ofU.S.imports, and Bai and Stumpner [2019] benchmark the potential price reduction to consumers at 0.19% per year, albeit assuming fixed markups. My paper also follows the empirical approach of the literature associating the China Shock with the decline in manufacturing employment, in particular Pierce and Schott [2016] but also Autor et al. [2013], Acemoglu et al. [2016], and Holmes and Stevens [2014].

A couple of recent studies also link trade to more structurally inspired considerations on competition. For example, Martynov and Zhang [2023] find different effects of output and input tariffs on the concentration of sales using data for Colombia. In a vein Impullitti and Kazmi [2023] discuss how pro-competitive effects can increase markups through reallocation of sales when discussing the entry of Spain into the EU. And in a more general sense, my work follows previous studies on trade and markups like Arkolakis et al. [2019], De Loecker et al. [2016], and Amiti and Konings [2007] as well as the growing literature on concentration in the US, for example De Loecker et al. [2020], Amiti and Heise [2021], Autor et al. [2020], and Gutiérrez and Philippon [2017].

Opening to trade with China interrupted markup growth in the U.S., and even reduced the level of markups for intermediate goods. However, it only paused the pre-existing growth path, so the domestic efficiency gains from increased competition were quickly absorbed. In the following section I describe how I construct the firm-level markups, as well as the tariff gaps. Section 3 presents the Results, and Section 4 concludes.

2 Data

2.1 Industry Exposure to Chinese Imports

2.1.1 Permanent Normal Trade Relations

The share of US imports from China in domestic supply increased from 0.6% in 1991 to 4.6% in 2007, with an inflection point in 2001 when China joined the WTO (Autor et al. [2013]). This rapid growth of Chinese imports is what the literature refers to as the China Shock. There were two main drivers for the fast entry of Chinese products in the US market. First, a series of reforms in the 1980s and 1990s increased manufacturing capabilities of China, making their goods more competitive and pushing their entry into markets around the world. Second, the US reduced tariffs to manufacturing imports from China in 2001, facilitating their entry to the domestic market.

Empirically analyzing the effect of the China Shock requires some nuance, as the increase in imports could also be explained by changes in domestic demand. This endogeneity problem has long been solved by previous literature using one of two empirical strategies. The first strategy employs the ratio of Chinese imports to total supply in the US market, using the penetration of Chinese imports in third countries as an instrument, as in Autor et al. [2013]. Exogeneity here relies on whether demand for imports in the US is sufficiently dissociated from demand for imports in third countries. Ultimately, this path tries to capture the increase in Chinese competitiveness, without confusing it with domestic trends. The other alternative is to focus on trade frictions, in particular the US tariff reduction, as in Pierce and Schott [2016]. Identification comes from the quasi-exogenous variation in the size of the liberalization across sectors. This alternative path captures how reducing the tariffs, or more precisely removing the uncertainty of the tariff reduction, eases the flow of imports. I will use the second approach based on the tariff change, but in practice, those sectors where tariffs drop by more were also those facing higher penetration of Chinese imports.

The institutional details that merit using the normalization of trade relations as a measure of trade liberalization can be summarized as follows. Up to 2001, the US imposed two sets of tariffs on China. The first, sometimes referred to as "column 2" tariffs, were originally set by the Smoot-Hawley Tariff Act of 1930. Years later, as China was seeking member status in the WTO, between 1980 and 2001 the US congress voted a second set of special temporary tariffs, referred to as the temporary "Normal Trade Relations" tariffs. This special status was granted for one year, subject to congress debate and with changing conditions. In October 2000 the US congress passed Permanent Normal Trade Relations (PNTR), fixing a version of the second set of tariffs. In this context, between 1980 and 2001 there was uncertainty about which tariffs would be imposed on imports from China to the US, the higher "column 2" tariffs or the lower "NTR" tariffs. After 2001 tariffs were set permanently at the lower level regime, removing any uncertainty. My measure of the China Shock will then be the gap in tariffs between the two regimes.

In practice, the difference in add-valorem tariffs between the non-NTR regime and the PNTR regime, or PNTR Gaps, are originally set at the 10-digit Harmonized System (HS) tariff line level. However, because the HS10 classification is used to categorize goods and not industries, the tariff lines need to be aggregated and corresponded to an industry classification. I make this aggregation anew, following a comparable procedure to Pierce and Schott [2016]. I start with the HS tariffs under each of the two tariff regimes, between 1989 and 2001, as compiled and constructed in Feenstra et al. [2002]. They amount to 133.807 HS10 tariff lines. Then I match each HS code to its end use, final goods or intermediate goods, which I elaborate by matching HS codes to BEC code and to national accounts classification I classify 98% of the HS lines in this way. Following, I assign NAICS6 categories to each HS line code, using the correspondence from Pierce and Schott [2012]. I match 68% of the HS8 lines to NAICS6 categories, noting their paper corresponds actual trade flows, so HS codes that present no trade in their period have no correspondence. A comparison of the gap I construct with the gaps in Pierce and Schott [2016] is available in Appendix 1.

2.1.2 Industry Exposure

I will consider a firm to be directly exposed to the trade liberalization if its reported industry has a non-negative tariff gap across the two regimes. Insofar its reported industry corresponds to the goods or services it provides, this can be interpreted as the goods being sold by a firm being directly exposed to competing goods being sold by foreign firms. As discussed before, as measure of the China Shock I use the difference in add-valorem tariffs between the non-NTR regime and the PNTR regime. Using this difference allows me to leverage the sudden and unexpected reduction in tariff and tariff uncertainty to evaluate the effects of Chinese imports, as the tariff difference is unrelated to other contemporaneous circumstances. I will call the tariff gap for each sector s the Gap_s, representing the reduction in tariff uncertainty on the industry's own sales.

$$\text{Gap}_s \quad = \quad \text{Non-NTR Rate}_s - \text{NTR Rate}_s \tag{1}$$

Emphasizing the exogeneity of this identification strategy, one convenient feature of this definition is that 79% of the variation in Gap_s comes from the Non-NTR Rate_s, set by the Smoot-Hawley Tariff Act of 1930. This suggests the effect of the gap are not driven by manipulation close to the normalization of trade relations. In fact, because the Non-NTR Rate_s is usually higher than the NTR Rate_s , the gap will be higher the lower the normalized rate. I use the NTR gaps for 1999, the year before PNTR is passed.

A firm will be indirectly exposed to the trade liberalization if some inputs it uses to produce are directly exposed. Due to data availability, I assume all firms in a sector have the same input use. I take the input structure for each sector from Input-Output tables I construct for the US. In particular, I combine the detailed tables (495 sectors) for 1997 on Make, Use, and Import Matrices, published by the Bureau of Economic Activity (BEA). There are two difficulties with using the 1997 BEA data. First, imports are not separately taken into account in the Make and Use tables, making it difficult to track down the effective exposure of each sector to imports. This is important because the pricing conventions for each table are different, and distinguishing between domestic and imported products affects that pricing. Second, the Make and Use tables are not industry by industry tables, which complicates the analysis of upstream and downstream effects. The Make matrix represents how each industry (in rows) makes of each commodity (in columns), where industries could produce multiple commodities. With the reverse logic, the Use matrix represents how much of each commodity (in rows) is used by each industry (in columns), where industries could use multiple commodities. And the Import Matrix represents how each much of each commodity (in rows) is imported by each industry (in columns) or to final consumer, where again industries could use multiple commodities. Here the inputs in the Use table are total inputs, while the inputs in the Import Matrix are only the imported inputs. I combine the three tables to make a unified Input-Output matrix, tracking down domestic and foreign production separately, and matching industries to industries (as opposed to commodities to industries or vice-versa.

To capture each firm's exposure to imports on inputs, I also build an upstream measure of the tariff gap for each sector s. I will call this the Input Gap_s, defined as a weighted average of Gap_s from supplying industries

$$\text{Input Gap}_s = \sum_{s'} w_{s's} \text{Gap}_{s'} \tag{2}$$

where I construct $w_{s's}$, the weights of the supplying industry s' to supplied industry s, from the constructed Input-Output tables. In what follows I detail how I construct and use the weights.

Alternative approaches to constructing the weights Although the exercise of using the Input-Output matrices to construct upstream measures is present in previous literature, there is no consensus on which is the appropriate structure for it. More importantly, both in theory and practice this decisions is not innocuous. Therefore, I explore four alternative weight structures for eq.(2), based on transformations of the Direct Requirement Matrix A, which recover from the Input-Output tables.

I start by using the coefficients of A as weights $w_{s's}$, which represents the one-step upstream input use to produce a unit of output. I label this measure Input Gap_s^{DR} after the "Direct Requirement" matrix. This measure is similar to the definition used by Acemoglu et al. [2016], who construct their weights from the 1992 Use Table. In this measure the weights add up to less than one, $\sum_{s'} w_{s's} < 1$, as the columns of A add to the proportion of inputs to gross output for each sector.

$$DR = A \quad \text{and} \quad w_{s's} = \{DR\}_{s's} \tag{3}$$

As mentioned, the Direct Requirement measure only takes into account one step upstream inputs, but further upstream effects could be relevant in the transmission of the anti-competitive effect. To that effect, I construct a second measure of upstream exposure, Input Gap_s^{LR} after "Leontief Requirements", with a different set of weights based on matrix A. First I construct the Leontief Inverse $(I - A)^{-1}$, which summarizes weights for all direct and indirect effects, as shown in eq.(4)

$$(I - A)^{-1} \;=\; I + A + A^2 + \dots \tag{4}$$

Briefly looking at this summation, the first matrix I here represents the weights for effects on sales, then matrix A represents the weights of one-step upstream inputs used for production, A^2 the two-step upstream inputs, and so on. Therefore, to account for all upstream inputs used, I subtract matrix I from the Leontief Inverse so as to account for all direct and indirect requirements

$$LR = (I - A)^{-1} - I \quad \text{and} \quad w_{s's} = \{LR\}_{s's} \tag{5}$$

and use the coefficients in matrix LR as weights in eq.(2). Note again these weights do not add to one.

Although the two proposed measures for Input Gap_s represent different things, they both suffer from two related shortcomings when approximating the input use by firms. First, the diagonal elements of A account for within-sector trade, but from the average firm's perspective these could be just used internally. One step further, although I assign firms to one industry code, firms are actually multi-product, which could matter if some of the firm's use of inputs from similar sectors is actually happening in-house. And second, there is the attenuation occurring through the cost structure, which is different across sectors possibly affecting estimation. To account for these challenges, I construct two additional adjusted matrices of the previous, $DRAR$ and $LRAR$. The adjustment consists on identifying the elements of matrix A that share the same NAICS3 family and set them to zero, before re-scaling the coefficients so once again columns add to one. $DRAR$ matches the method used in Pierce and Schott [2016] for their upstream measure. I report results using Input $\text{Gap}_s^{\text{DRAR}}$ and Input $\text{Gap}_s^{\text{LRAR}}$ for the anti-competitive effects.

2.2 Measuring Markups

For my dependent variables, I construct firm-level yearly markups using the methodology developed by De Loecker and Warzynski [2012], with balance sheet data from Compustat, a comprehensive database published by Standard & Poor's. I access this data through the Wharton Research Data Services (WRDS) of the University of Pennsylvania. Compustat primarily draws its data from SEC filings, standardized and supplemented to allow for better comparisons. As a consequence, the firms covered are only publicly traded firms, which are comparatively larger, bigger, older, and more capital intensive than the universe of all firms[1].

To compute a firm's markup I use database "North America - Fundamentals Annual". The North America data base contains information on firms incorporated in the U.S. and

[1] De Loecker et al. [2020] provide context and references to this respect

Canada, where a company is added to the database when it files distinct 10K's or 10Q's with the SEC. Fundamentals Annual contains annual aggregate data on sales, costs and others, as used in financial statements (Balance Sheets, Income Statements, Cash Flows), as well as six-digit NAICS identification codes and equivalent SIC codes, from 1950 onward. This data is for firms incorporated in the U.S., consolidating all subsidiaries, but does not necessarily provide information on if and where those subsidiaries are.

With this data, I replicate the markup construction from De Loecker et al. [2020], from 1955 to 2016, using their estimation of the production function input elasticities. To briefly present the methodology for these markups, consider an economy with N firms, indexed by $i = 1, \ldots, N$. Firms are heterogeneous in terms of their productivity Ω_{it} and production technology $Q_{it}(.)$. In each period t, firm i minimizes the contemporaneous cost of production given the production function:

$$Q_{it} = Q_{it}\left(\Omega_{it}, \boldsymbol{V}_{it}, K_{it}\right) \tag{6}$$

where $\boldsymbol{V} = \left(V^1, \ldots, V^J\right)$ is the vector of variable inputs of production (including labor, intermediate inputs, materials,...), K_{it} is the capital stock and Ω_{it} is productivity. The key assumption is that within one period, variable inputs adjust without frictions, whereas capital is subject to adjustment costs and other frictions. This will make optimization conditional on optimal capital. Consider the Lagrangian objective function associated with the firm's cost minimization

$$\mathcal{L}\left(V_{it}, K_{it}, \lambda_{it}\right) = P_{it}^{V} V_{it} + r_{it} K_{it} + F_{it} - \lambda_{it}\left(\boldsymbol{Q}(.) - \bar{Q}_{it}\right) \tag{7}$$

where P^V is the price of the variable input, r is the user cost of capital, F_{it} is the fixed cost, $\boldsymbol{Q}(.)$ is the technology specified, $\bar{Q}$ is a scalar and λ is the Lagrange multiplier. Assume that variable input prices are given to the firm. The first-order condition with respect to the variable input V is given by

$$\frac{\delta \mathcal{L}}{\delta V_{it}} = P_{it}^{V} - \lambda_{it} \frac{\delta Q(.)}{\delta V_{it}} = 0 \tag{8}$$

Multiplying all terms by $\frac{V_{it}}{Q_{it}}$ and rearranging yields an expression for the output elasticity of input V, θ_{it}^{v}

$$\theta_{it}^{v} \equiv \frac{\delta Q(.)}{\delta V_{it}} \frac{V_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^{V} V_{it}}{Q_{it}} \tag{9}$$

The Lagrange multiplier λ is a direct measure of marginal cost. Now define the markup as the ratio of price to marginal cost $\mu = \frac{P}{\lambda}$, where P is the output price. Substituting marginal cost for the price to markup ratio, we obtain an expression for the markup

$$\mu_{it} = \theta_{it}^{v} \frac{P_{it} Q_{it}}{P_{it}^{V} V_{it}} \tag{10}$$

The expression of the markup is derived without specifying a conduct of the firm or a particular demand system. Also, note that with this approach to markup estimation there are in principle multiple first-order conditions (one for each variable input used in production) that yield an expression for the markup.

Regardless of which variable input of production is used, two key ingredients are needed to measure the markup: the revenue share of the variable input, $\frac{P_{it} Q_{it}}{P_{it}^{V} V_{it}}$, and the output elasticity of the variable input, θ_{it}^{v}. The revenue share of the variable input can be found in data, but the output elasticity has to be estimated. The basic specification for this estimation is Cobb-Douglas

$$Q_{it} = \Omega_{it} V_{it}^{\theta_t^{v}} K_{it}^{\theta_t^{K}} \tag{11}$$

and, applying logs

$$q_{it} = \theta_t^v v_{it} + \theta_t^K k_{it} + \omega_{it} + \epsilon_{it} \tag{12}$$

where $\omega_{it} = \ln \Omega_{it}$ is the productivity process, $v_{it} = \ln V_{it}$ are the variable inputs, $k_{it} = \ln K_{it}$ is the capital stock, and ϵ_{it} captures the measurement error of output, so $q_{it} = \ln\left(Q_{it} \exp\left(\epsilon_{it}\right)\right)$. Estimating this production function suffers from two problems: how to deal with the unobserved productivity shocks ω_{it}, and how to get units of output and inputs from revenue and expenditure data. Both problems can be solved using a control function approach, as proposed by Olley and Pakes [1996], and defining the structural error term appropriately.

Summing up the construction of markups, I take θ^v from De Loecker et al. [2020], estimated in five year moving windows, and combine them with balance sheet data compiled in Compustat for $\frac{P_{it}Q_{it}}{P_{it}^V V_{it}}$, in particular $P_{it}Q_{it}$ are the gross sales and $P_{it}^V V_{it}$ are the cost of gross sales.

2.3 Additional Empirical Details

To construct the sample, I start with the universe of Compustat firms between 1955 and 2016, a total of 19,041 firms. From them I make a selection to avoid a number of pitfalls. First, many firms report industry at less than NAICS6 level, so when matching at NAICS6 gaps I construct an average gap measure for that less specific industry. For example, if the firm is labelled at NAICS4, I assign it the average of all gaps across the NAICS6 codes contained in the NAICS4 category. Second, I focus on the period between 1991 and 2007, the years before and after the trade liberalization, with 2001 being the year of normalization of trade relations with China.

The next selection criteria has to do with whether multinational firms are present in my sample. Ideally, I would like to have US firms that sell only to the US domestic sector, making all markups domestic markups of domestic firms. So the first step is to drop those firms incorporated elsewhere. However, there are probably other foreign firms incorporated in the US in my sample, for example foreign firms with subsidiaries listed in the US and presenting balances accordingly. Depending on how much of the operation occurs outside US borders, this would attenuate the effects of the China Shock on markups. A particularly troublesome case would be having Chinese firms listed as US firms, as from their perspective the change to a regime with lower tariffs would have the opposite effect on markups. To prevent this, I manually remove Chinese firms in the Compustat base, as identified by the U.S.-China Economics and Security Review Commission [2]. Of course many US firms also export, attenuating the pro-competitive effect of the China Shock on their markups as their foreign destination markets might not face any change in tariff regimes, at least not at the same time. Likewise, inputs of US firms that produce abroad face tariffs wherever they produce, also dampening the anti-competitive effect of the China Shock.

The resulting sample covers an unbalanced panel of 4,637 firms, distributed along 888 sectors, across 17 years. That being said, for some specification, I will force a balanced panel, dropping any firm that is not in the sample across the full 17-year window. This choice implies I do not account for the effect of markups on entry-exit, and vice-versa, but I can abstract from the reallocation of sales and consequences of changing compositions, focusing on the effects of imports in within-firm markups. Another conceptual advantage of constructing the sample this way for some cases is it allows me to sidestep the discussion of how firms get in and out of my data set, which is not exactly entry or exit but instead listing and de-listing from the stock exchange.

[2] The U.S.-China Economic and Security Review Commission is a commission created by the US Congress at the time of normalization of trade relations, and is in charge of monitoring and submitting annual reports on the national security implications of bilateral trade between the US and China. The list they published identifying Chinese companies listed in the US is available at uscc.gov/research/chinese-companies-listed-major-us-stock-exchanges

2.4 Data Description

As summarized in Table 1, the mean Gap, that is the difference between tariff regimes affecting a firm's main activity, is 13, 3%, ranging from no gap at all up to 84%. The mean Input Gaps are lower for both the Direct Requirement Adjusted Rescaled (DRAR) and the Leontief Requirement Adjusted Rescaled versions, with a mean of 8, 6% ranging from 0.1% to 29.4% for the first, and a mean of 7, 9% ranging from 1.0% to 21.6% for the second.

Table 1: Gap and Input Gap

	Mean	S.D.	Min	Max
Gap	13.3	18.4	0.0	84.5
Input Gap DRAR	8.6	5.9	0.1	29.4
Input Gap LRAR	7.9	3.9	1.0	21.6
Observations	888			

I present the distribution of each gap in Figure 1. As mentioned above, for an average sector sales are more directly exposed to the normalization of trade relations than its cost structure, as not all factors used in production are intermediate goods, not all intermediates are exposed to trade, and out of those exposed to trade not all of them have non-zero gaps. On the other hand, all sales are potentially exposed to the China Shock if their gap is non-zero. I will use the variation of the Gap and Input Gap across sectors to detect differences in the evolution of markups. The gaps are defined for each sector, so all firms in a sector will have the same exposure to both.

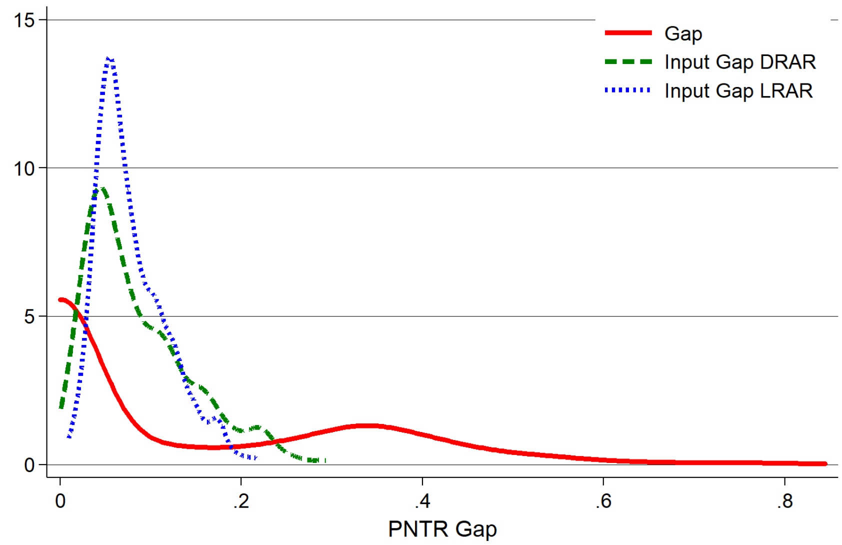

Figure 1: Density of Gap and Input Gap

Average markups between 1991-2007 are presented in Figure 2. The higher blue line corresponds to the simple average of markups, and the lower red line corresponds to the sales-weighted average of markups. Prima facie, it seems there is an upward trend up to the year 2000 (right before the normalization), a drop in 2001-2002, retaking the growth path afterwards. The timing coincides with the normalization of trade in 2001, but also with the recession between March and November 2001. I focus my analysis on the evolution of average markups, as opposed to weighted averages or "aggregate" markups, or other moments of their distribution.

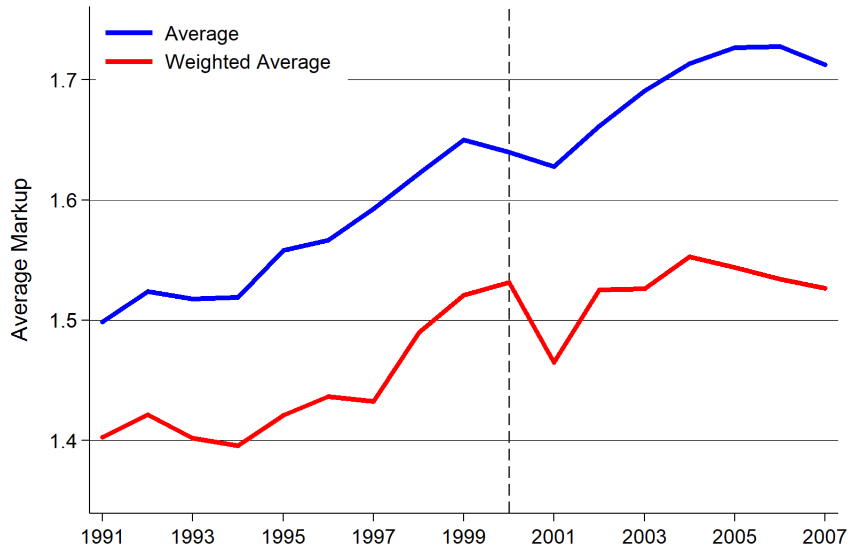

Figure 2: Average Markups - Balanced Panel

Figure 3 presents the evolution of average markups in green when forcing the balanced panel, in other words only taking in to account firms that report markups for the full 17-year window. I keep the same scale for simplicity. Comparing to the blue lin figure 2, its analog in the unbalanced sample, the average markups in the balanced panel are lower and increase by less. This highlights the role of composition, and the difference in both levels and growth rates. That being said, this graph also displays the same pattern of growth, drop with the China Shock, and growth again.

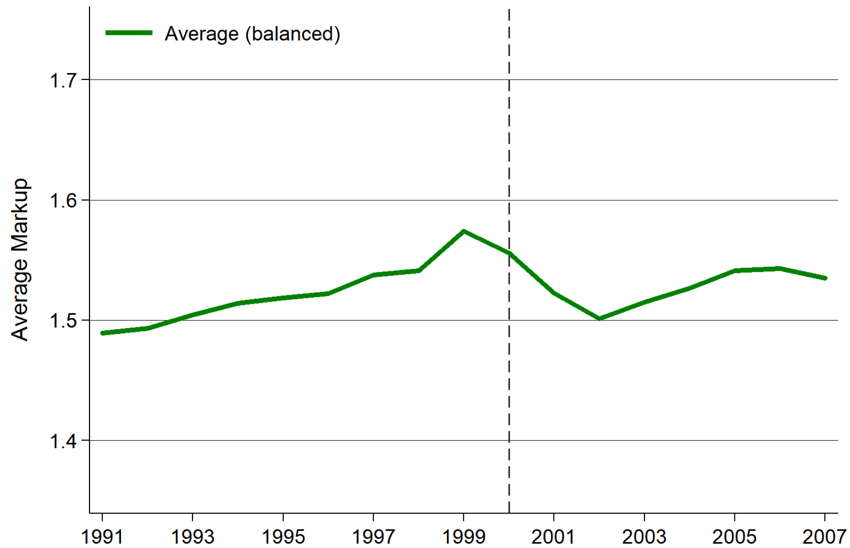

Figure 3: Average Markups - Balanced Panel

Regarding the period used, note the business cycle is presumed to affect markups. In particular within this sample, between March and November 2001 the US economy suffered a recession according to the NBER. However, it remains an open discussion whether markups are pro-cyclical or counter-cyclical, and could also depend on the nature of the shocks, as discussed in Nekarda and Ramey [2019]. But whichever the case, the timing of the normalization of trade relations with China is close enough so as to be considered, as it is generally accepted that some sectors are more affected by the business cycle than others. This means markups will face heterogeneous effects across sectors from at least three directions: the reduction in the Input Gap, the reduction in the Gap, and the sector-specific response to the business cycle.

Table 2: Sample by NAICS2

	Markup	Growth	Pre	Post	Gap	S.D.	Input Gap	S.D.	Firms
Agriculture	1.45	-1.03	-0.99	-1.17	6.44	6.71	6.12	2.26	21
Mineral	1.51	-0.47	0.09	-0.61	0.84	2.69	5.17	1.99	190
Utilities	1.47	-0.50	0.29	-1.69	0.00	0.00	4.81	2.17	17
Construction	1.28	0.47	0.47	-0.14	0.00	0.00	.	.	40
M. Durable	1.65	-0.14	-0.09	-0.06	28.76	18.87	8.84	6.77	710
M. Non-Durable	1.48	-0.00	0.26	-0.22	34.22	13.16	9.50	4.52	1632
42	1.28	-0.32	-0.31	-1.10	0.00	0.00	4.82	0.00	131
Retail	1.31	0.04	0.11	0.11	0.00	0.00	2.99	0.00	308
Transportation	1.29	-0.32	-0.58	0.22	0.00	0.00	3.98	1.52	80
Information	2.45	0.18	0.09	0.95	0.00	0.00	4.76	2.02	486
Finance	1.71	-0.63	-0.72	1.89	0.00	0.00	1.41	0.62	118
Real Estate	2.21	1.56	1.70	1.71	0.00	0.00	2.25	1.02	99
Professional	1.57	-0.39	-0.36	-0.96	0.00	0.00	3.71	1.85	297
Administrative	1.50	0.03	-0.04	-0.08	0.00	0.00	3.83	2.26	154
Education	1.74	0.65	0.76	0.21	0.00	0.00	3.70	0.78	25
Health Care	1.46	-0.29	-0.20	-0.87	0.00	0.00	7.08	1.51	125
Entertainment	1.52	-1.68	-2.01	-1.20	0.00	0.00	3.69	0.86	47
Accomodation	1.22	-0.64	-0.78	-0.15	0.00	0.00	5.02	1.69	120
Other Services	1.46	-0.17	-0.04	-0.62	0.00	0.00	8.67	6.06	35

Combining Gaps and Markups by sector, Table 2 presents a summary of the key moments grouped in NAICS2 sector. The first column "Markup" presents the average markup between 1991 and 2007 across all firms in each sector. The following column "Growth" presents the annualized growth rate of markups, with "Pre" and "Post" representing the annualized growth rate of markups before (1991-2000) and after (2001-2007) the normalization of trade relations. All growth rates are in percentages, so the annualized rate of growth in Agriculture between 1991 and 2007 was -1.03% a year. Gap and Input Gap are the PNTR gaps, so the difference between add-valorem tariff regimes in agriculture was 6.44%. I also present the Gap's and Input Gap's corresponding standard deviations within each NAICS2 category, and the number of firms.

Table 3: Sample Manuf. by NAICS3

	Markup	Growth	Pre	Post	Gap	S.D.	Input Gap	S.D.	Firms
Fo+Be+To	1.49	0.04	-0.12	0.17	15.24	1137.73	6.50	275.26	132
Textile	1.19	-0.20	-0.18	-0.21	45.04	965.38	17.61	628.25	35
Apparel	1.38	0.20	0.26	0.50	34.17	2220.55	18.34	745.01	60
Paper	1.26	-1.08	-0.94	-1.15	27.82	1107.11	9.53	556.68	51
Printing	1.43	-0.18	0.02	-0.47	13.72	863.30	15.06	228.57	25
Petr+Coal	1.14	-0.41	-0.94	0.59	15.50	1620.74	4.19	534.49	29
Chemical	2.02	0.05	0.25	0.00	31.71	1851.47	4.99	308.26	320
Plastics	1.26	-0.61	-0.79	-0.46	39.21	1902.34	18.39	317.67	73
Wood	1.21	-0.57	-0.62	-0.41	22.38	1063.11	13.92	576.14	30
Mineral	1.27	-0.46	-0.03	-0.38	23.52	1539.91	8.64	274.68	39
Prim. Metal	1.01	-0.52	-0.52	-0.53	19.08	1320.30	7.74	376.77	57
Fab. Metal	1.20	-0.30	-0.08	-0.62	29.70	1992.25	11.78	338.57	95
Machinery	1.33	-0.18	-0.07	-0.18	29.42	1277.91	12.25	370.88	226
Electronics	1.64	0.08	0.45	-0.25	36.16	622.25	6.16	246.49	734
Appliances	1.27	-0.37	-0.10	-0.32	35.38	674.22	12.86	347.66	95
M. Vehicles	1.11	-0.36	-0.50	-0.10	23.56	1029.74	15.34	175.00	89
O. Transport	1.15	-0.02	-0.04	-0.02	26.74	1141.79	15.22	345.49	51
Furniture	1.29	-0.21	-0.16	-0.38	39.43	1120.58	15.19	238.13	31
Misc. Manuf.	1.80	0.87	1.25	0.22	47.70	1697.14	11.26	322.73	195

Noticeably, 2,342 out of 4,637 firms are in manufacturing, so I present in Table 3 a similar breakdown focusing on manufacturing sectors, grouped at NAICS3 level. Electronics firms are the most represented, with 734 firms, followed by Chemical firms with 320. Finally, Table 4 presents the initial Input Gaps using the Direct Requirement and Leontief Requirement matrices, with their adjusted and rescaled versions, as describe above.

Table 4: Descriptive Statistics - Alternative Input Gap

	Mean	S.D.	Min	Max
Input Gap DR	0.058	0.049	0.00	0.20
Input Gap LR	0.111	0.117	0.00	1.72
Input Gap DRAR	0.086	0.059	0.00	0.29
Input Gap LRAR	0.079	0.039	0.01	0.22
Observations	869			

3 Competitive Effect

In this section I study how the pro-competitive effect operated in domestic markups when the U.S. liberalized trade with China in 2001. The inflow of imports (or its threat) induces domestic firms to reduce their markups to avoid losing market share. To do so, I combine markups constructed using the De Loecker and Warzynski [2012] method with the PNTR gaps used by Pierce and Schott [2016].

Aggregate markups could decrease because individual firm markups go down for a given composition of sales, because the composition of sales shifts towards firms with lower markups, or both. I focus on the first effect, the change in markups for the individual firm, rather than the sales-weighted average of markups. That allows me to abstract from the reallocation effect, where aggregate markups change due to changes in the composition of sales. I will however weight the effect by firms' pre-tariff sales to account for size-related heterogeneity.

One obstacle to finding this effect is that markups in the U.S. have been growing since 1980, and continued doing so at least until 2016 (De Loecker et al. [2020]). To account for this, my main specifications focus on changes in the growth rate of markups. If markups are growing, the pro-competitive effect might not lower the level of markups but may instead slow its growth. I find evidence of pro-competitive effects both in growth rates and in levels.

3.1 Markup Growth

I estimate the effect that the normalization of trade relations with China had on the growth of domestic markups using the following difference-in-differences framework:

$$\Delta \ln \mu_{ist} = \phi_{is} + \phi_t + \beta \left(\text{Post}_t \times \text{Gap}_s\right) + \epsilon_{ist} \tag{13}$$

where μ_{ist} is the markup of firm i in sector s in year t. Gap_s is the difference between tariffs under permanent normal trade relations (PNTR) and temporary normal trade relations, as described in the Data section. The dummy $\text{Post}_t = 1$ for years 2001 and onward, indicating the period after the the normalization of trade with China. Furthermore, ϕ_{is} are the firm fixed effects, and ϕ_t are year fixed effects, both included in all specifications.

Results from estimating eq (13) are presented in column 1 of Table 5 below. The negative coefficient associated with the Gap shows that the growth of markups was lower for firms exposed to the normalization of trade. In other words, the China Shock slowed down or even reversed the growth of markups on impact.

Table 5: Markup Growth and Gaps

	$\Delta \ln \mu$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gap	-4.13***	-3.43***	-3.48***	-3.10**	-2.97**	-3.78***	-3.92***	-3.98***
	(1.21)	(1.15)	(0.77)	(1.26)	(1.26)	(1.16)	(1.22)	(1.22)
Input Gap_{DR}^{AR}				-3.33			0.99	
				(3.17)			(2.80)	
Input Gap_{LR}^{AR}					-6.22			2.10
					(4.86)			(4.05)
Δ log Capital		-0.98	-1.57	-0.97	-0.97	-2.93**	-2.93**	-2.93**
		(0.63)	(1.65)	(0.63)	(0.63)	(1.29)	(1.29)	(1.29)
Δ log Employees		-0.41	-1.69	-0.37	-0.37	-3.09***	-3.09***	-3.09***
		(0.69)	(1.70)	(0.69)	(0.69)	(1.11)	(1.11)	(1.11)
Δ log Overhead		0.93	3.91**	0.94	0.94	6.28***	6.29***	6.29***
		(1.21)	(1.94)	(1.21)	(1.21)	(2.03)	(2.03)	(2.03)
Constant	0.25***	0.05	0.24**	0.13	0.19	0.09	0.07	0.04
	(0.08)	(0.14)	(0.11)	(0.14)	(0.16)	(0.11)	(0.11)	(0.13)
Full Window			✓					
Sales-weighted						✓	✓	✓
Observations	66,597	60,485	14,891	60,217	60,217	49,271	49,124	49,124
Mean Dep.Var.	-0.01	-0.21	-0.04	-0.21	-0.21	-0.12	-0.12	-0.12

Standard errors in parentheses, clustered by NAICS4. All specifications with Firm and Year FE.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This result could be driven by other changes in the behavior of the firm that are not linked to competitive pressure from Chinese goods. One scenario is linked to changes in the firm's cost structure that are not incorporated in the construction of markups. With that in mind, I re-estimate eq (13) controlling for changes in the growth rate of capital, number of employees, and overhead.

The composition of the sample could also be driving this result, i.e., the coefficient associated with the Gap could be negative not because firms adjust markups downward, but because firms with higher markups do not survive opening up to trade. Trying to isolate that change in composition, I estimate the model with the previous controls but restricting the sample to firms that report their financial statements throughout the full window, meaning every year from 1991 to 2007. Results are presented in column 3, and remain unchanged despite using only a quarter of the original sample. Because this specification is forcing a balanced panel of firms, the result in column 3 is closest to an average effect on the growth rate of firm markups.

Figure 4 presents the event study corresponding to column 3 of Table 5. Here the average growth rate of markups after the normalization of trade in 2001 is significantly lower, and returns to its normal level at least until 2005-2006. That is, the normalization of trade interrupted the growth of markups immediately, and may have further dampened markup growth in subsequent years.

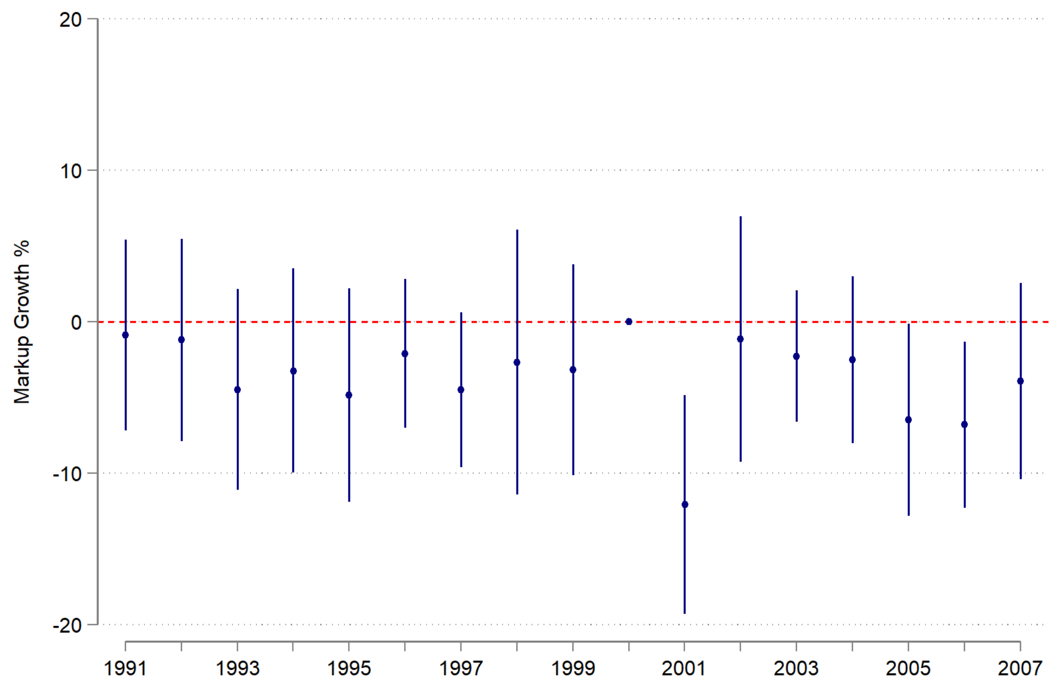

Figure 4: Gap - Event Study

Another force that could be influencing the trajectories of markups is a decline in upstream markups. Opening to trade could also be lowering costs, creating an anti-competitive effect on markups. Further, if the pro-competitive effect could interrupt the growth of markups, the anti-competitive effect should reinforce that growth. To check for the upstream effect of the gap, I estimate coefficients for the two upstream gaps, one associated with the Direct Requirements and another with the Leontief requirements, both adjusted and rescaled as discussed. Results are presented in columns 4 and 5, showing no evidence of either measure of the anti-competitive effect operating on the growth rate of markups.

Finally, columns 6-8 repeat the specification of columns 2, 4, and 5 of Table 5, but weighting the regressions by firm sales. More specifically, the regressions are weighted by firm sales before the normalization of trade, placing more weight on larger firms. For all three specifications, the pro-competitive effect remains at -4 percentage points, with no evidence of an anti-competitive effect.

In the same line, Figure 5 presents an event study analogous to Figure 1, now weighting by firm sales before the change in trade policy. Again, the growth rate of markups tempered significantly on the first year for firms exposed to increased competition from foreign goods. Closing the gap in tariffs with China lowered the growth rate of markups in competing domestic firms.

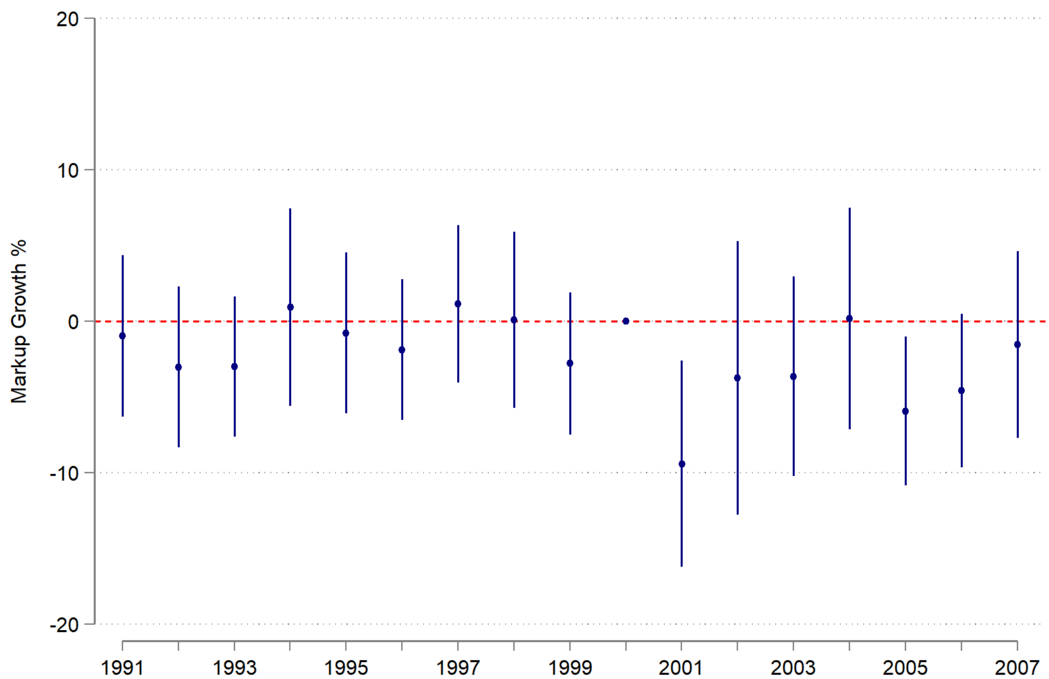

Figure 5: Gap (sales-weighted) - Event Study

To expand on the previous analysis, I split the effect of trade policy between the gap in tariffs affecting intermediate goods and the gap affecting final goods. This allows me to distinguish the effect that closing the gap had on intermediates separately from the effect on final goods, both for competing sales labeled Gap Final and Gap Inter, and in inputs labeled Input Gap Final and Input Gap Inter. With these new gaps, I estimate analogous specifications to the previous table, to facilitate comparisons. Results are presented in Table 6.

Table 6: Markup Growth, Final and Intermediate Gaps

	$\Delta \ln \mu$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gap Final	-1.25	-1.14	-1.05	-0.65	-0.56	-1.00	-0.97	-0.99
	(1.22)	(1.16)	(0.70)	(1.18)	(1.19)	(0.91)	(0.94)	(0.94)
Gap Inter	-2.61*	-1.84	-2.56***	-1.47	-1.44	-2.96***	-2.83***	-2.79**
	(1.56)	(1.45)	(0.75)	(1.48)	(1.47)	(1.08)	(1.09)	(1.08)
Input Gap Final$_{DR}^{AR}$				2.99			3.73	
				(6.24)			(6.38)	
Input Gap Inter$_{DR}^{AR}$				-7.82**			-2.10	
				(3.63)			(3.36)	
Input Gap Final$_{LR}^{AR}$					3.60			8.94
					(11.15)			(10.08)
Input Gap Inter$_{LR}^{AR}$					-12.14**			-4.47
					(5.88)			(5.40)
Controls		✓	✓	✓	✓	✓	✓	✓
Full Window			✓					
Sales-weighted						✓	✓	✓
Observations	66,597	60,485	14,891	60,217	60,217	49,271	49,124	49,124
Mean Dep.Var.	-0.01	-0.21	-0.04	-0.21	-0.21	-0.12	-0.12	-0.12

Standard errors in parentheses, clustered by NAICS4. All specifications with Firm and Year FE.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Columns 1 and 2 of Table 6 broadly match the corresponding coefficients in Table 5, but splitting the treatment weakens identification of the separate estimates. However, constraining the sample provides more clarity. Column 3 estimates the effect of the separate gaps with controls but using only the firms that remained in the sample for the full period between 1991 and 2007. For these firms, the moderation in markup growth is clearer on intermediate goods, with a 2.56 percentage point reduction in markups for firms facing an ad valorem tariff reduction of 100 percentage points after the normalization.

Going back to the full sample, I add the two definitions of Input gaps in columns 4 and 5 of Table 6, differentiating again between intermediate and final goods. Comparing to column 2, which also uses the full sample and controls, these specifications suggest a reduction in the growth of markups from increased upstream liberalization. This goes in the opposite direction of the anti-competitive effect proposed before. Notably, restricting these two specification to the full sample wash away this upstream negative effect on markups, and confirms the pro-competitive result of intermediates from column 3 (results not shown).

Given the only difference between specifications 2 and 3 comes from constraining the sample, it seems that changes in composition may distort the estimates. In either case, splitting into final and intermediate gaps seem to highlight the role of intermediates, and confirm that composition plays an important role in the average. So once again, in columns 5-8 I turn to using the full unbalanced panel while weighting the regression by sales. The pro-competitive effect is again clearer on intermediate goods, and no upstream effect shows significant coefficients.

All in all, there is evidence of a pro-competitive effect of the China shock, which corresponds to a 4 percentage point reduction in markup growth for domestic firms competing with Chinese imports. This is true on average, whether weighting by sales or using a balanced or unbalanced panel, with or without controls, and whether accounting for upstream effects or not. The effect is strongest in 2001, with additional evidence of slower markup growth in 2005 and 2006. Intermediate goods appear to play a larger role in this pro-competitive effect, and there is no immediate evidence of an anti-competitive effect; if anything, the evidence points in the opposite direction. That being said, composition does matter when distinguishing separate effects on intermediate and final goods.

3.2 Markup Level

In this section I also try to differentiate the growth of markups from the effect that the China Shock had on the level of markups. The empirical approach remains a difference-in-differences framework as before, now using the level of markups (in ln) rather than their growth rate. Results are less conclusive, but do reinforce some interesting aspects of the previous section. The specifications are the same, but using firm markups instead of markup growth:

$$\ln \mu_{ist} = \phi_{is} + \phi_t + \beta \left(\text{Post}_t \times \text{Gap}_s\right) + \epsilon_{ist} \tag{14}$$

where μ_{ist} is now the markup of firm i in sector s in year t. Otherwise, the exercise remains analogous to the one in the previous section. Results from estimating eq(14) are presented in column 1 of Table 7 below.

Table 7: Markup and Gaps

	$\ln \mu$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gap	0.01	0.01	-0.03	0.05	0.05	-0.03	-0.01	-0.01
	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Input Gap_{DR}^{AR}				-0.32***			-0.15	
				(0.09)			(0.12)	
Input Gap_{LR}^{AR}					-0.53***			-0.28
					(0.14)			(0.18)
ln Capital		-0.02***	-0.02**	-0.02***	-0.02***	-0.01	-0.01	-0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ln Employees		-0.03***	-0.07***	-0.03***	-0.03***	-0.08***	-0.08***	-0.08***
		(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ln Overhead		0.07***	0.12***	0.07***	0.07***	0.11***	0.11***	0.11***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.36***	-0.16	-0.67***	-0.15	-0.15	-0.80***	-0.79***	-0.79***
	(0.00)	(0.10)	(0.20)	(0.10)	(0.10)	(0.17)	(0.17)	(0.17)
Full Window			✓					
Sales-weighted						✓	✓	✓
Observations	74,153	67,994	15,017	67,673	67,673	52,252	52,097	52,097
Mean Dep.Var.	0.36	0.36	0.35	0.36	0.36	0.27	0.27	0.27

Standard errors in parentheses, clustered by NAICS4. All columns with Firm and Year FE.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

At first glance, the first row suggests that the level of markups for firms affected was not significantly different after the normalization. This does not appear to be driven by composition either. And once again, markups are negatively affected by upstream competition from imports, in opposition to the idea of an anti-competitive effect. This effect fades when weighting by size, suggesting that smaller firms are most affected when their suppliers face increased competition. In addition, controls appear to be more relevant in explaining the level of markups. Firms with higher markups have larger overheads and fewer employees across all specifications. They also seem to have lower capital on average, although this connection disappears when weighting by sales.

Table 8: Markup, Final and Intermediate Gaps

	$\ln \mu$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gap Final	0.11*	0.10*	0.04	0.12**	0.12**	0.04	0.05	0.06
	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
Gap Inter	-0.14***	-0.12***	-0.12**	-0.11***	-0.11***	-0.07*	-0.06	-0.07
	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Input Gap Final$_{DR}^{AR}$				-0.16			0.02	
				(0.19)			(0.21)	
Input Gap Inter$_{DR}^{AR}$				-0.21**			-0.20	
				(0.10)			(0.16)	
Input Gap Final$_{LR}^{AR}$					-0.36			-0.17
					(0.34)			(0.38)
Input Gap Inter$_{LR}^{AR}$					-0.30*			-0.22
					(0.16)			(0.26)
Controls		✓	✓	✓	✓	✓	✓	✓
Full Window			✓					
Sales-weighted						✓	✓	✓
Observations	74,153	67,994	15,017	67,673	67,673	52,252	52,097	52,097
Mean Dep.Var.	0.36	0.36	0.35	0.36	0.36	0.27	0.27	0.27

Standard errors in parentheses, clustered by NAICS4. All specifications with Firm and Year FE.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Splitting the gap between final and intermediate goods suggests that, if there is a pro-competitive effect to be found in levels, it mainly operates on intermediate goods. Even more, markups for intermediate goods seem to decrease, while markups for final goods seem to increase, although less clearly. And once again, if there is an upstream effect to be considered, it is not increasing markups but rather reducing them. Most notably, all effects seem to disappear when weighting by size, suggesting much of the previous analysis is driven by smaller firms. But even if the effect is only on firms with less sales before the policy change, the negative effect on markups is either widespread or strong enough to move the average. The event study in Figure 6 below, corresponding to column 2 of Table 8, seems to confirm that as well.

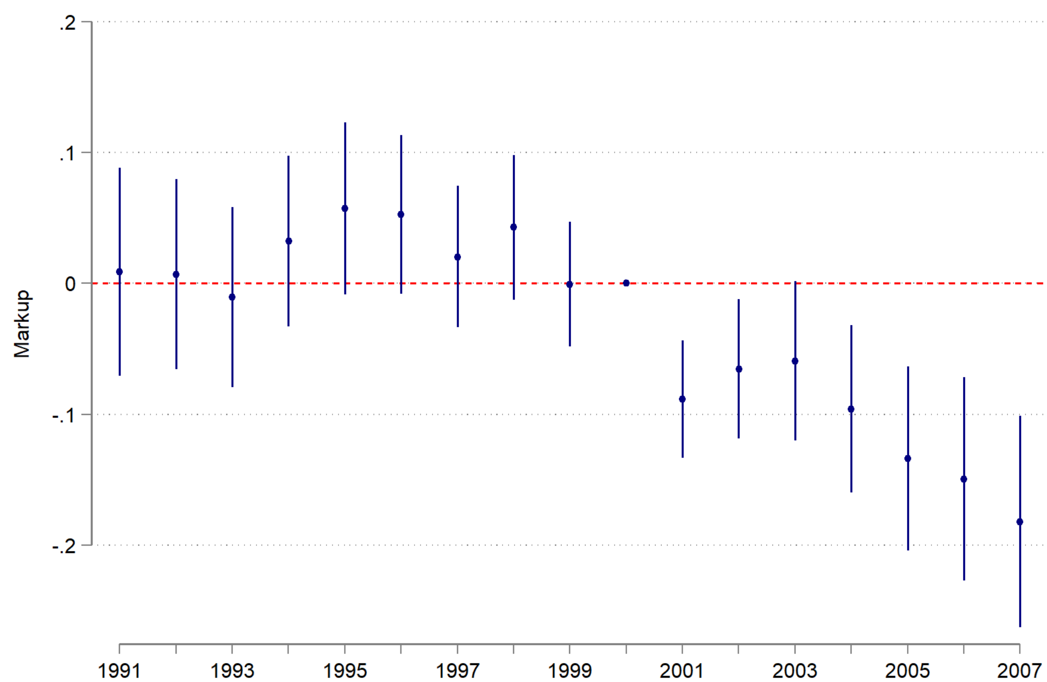

Figure 6: Gap Intermediate - Event Study

Summarizing, the pro-competitive effect is more elusive in levels, but it still seems to operate primarily through intermediate goods. However, unlike the analysis in growth rates, weighting by size attenuates all effects, suggesting these coefficients are mostly influenced by firms with lower sales in the year 2000. Evidence of upstream-downstream spillovers from the liberalization of trade continue to appear in the direction of reducing markups and through intermediate goods.

4 Conclusion

In this paper I use a difference-in-differences approach to uncover the pro-competitive effects of imports on domestic markups. I find that firms facing a 100 percentage point gap in ad valorem tariffs decreased the growth rate of their markups by 4 percentage points. The average gap was 13.3 percentage points, so the average drop in markup growth was 0.5 percentage points. When splitting the tariff gaps between intermediate and final goods, the effect is more clearly identified for intermediate goods, accounting for about three-fifths of the total. The pro-competitive effect in levels is also more clearly identified on intermediate goods.

The negative effect of upstream liberalization is somewhat puzzling. This effect seems to be driven by smaller firms given the negative coefficient is only significant in the simple averages. However, the underlying mechanism is not immediately clear. One hypothesis is that the reallocation of sales induces exit of smaller firms with higher markups, creating a pro-competitive-purification effect. It is important to note that entry and exit from Compustat data is about listing and de-listing in the stock exchange, which is not immediately the same as opening or closing for business (e.g. mergers and acquisitions). A different hypothesis is that this effect stems from the destruction of supplier-buyer relations, and the cost that forming new links imposes on the surviving firms.

There are alternate avenues to explore my line of inquiry. In the trade side, I focus on the PNTR Gaps, but other approaches can and have been used to identify the China Shock. The US normalization of trade with China and the NTR gap as a consequence has the benefit of being quasi-exogenous, but the limitation of being tied to tariff uncertainty instead of a change in tariffs. There are a number of other strategies that use the flow of imports more directly (e.g., import penetration, sourcing shares) accompanied of appropriate instruments. Similarly, although markups are an interesting object, they are difficult to interpret and measure. Using the response of equity prices to trade shocks could add information, but they may also reflect other confounding phenomena, like changes in monetary policy or in expectations.

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5 Gap Comparison

To check my procedure in construct the gaps is sound, I compare them with use with those used in Pierce and Schott [2016], publicly available for download by the authors. For a number of reasons, the resulting gaps do not match exactly. First, they focus on manufacturing gaps only, whereas I have gaps for other sectors, which increases the prevalence of null gaps. Also, their definition of sector is that of industrial family, a category they construct which I do not use as it serves a different purpose. In my case, I use the Input-Output tables and their corresponding codes. Comparing the results, I have 326 gaps with a mean of 0.30 and a standard deviation of 0.17, while their results is 424 gaps, with a mean of 0.30 and a standard deviation of 0.008. To compare to their densities, I drop the non-manufacturing codes from my gaps, leaving 302 gaps with a mean of 0.32 and standard deviation of 0.16. The densities are presented in Figure $A.1$ below.

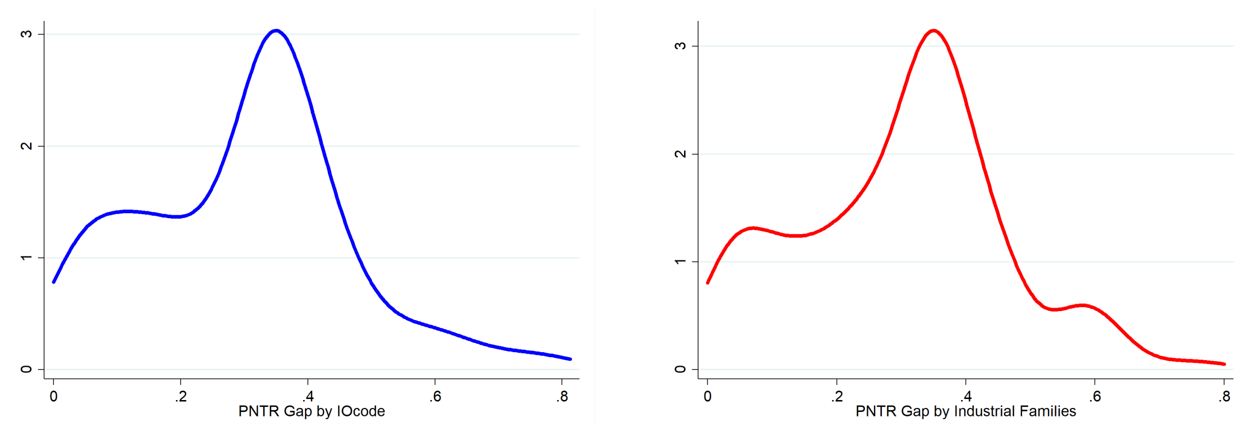

Figure 7: Gaps

Note in Figure $A.1$ the image on the left is defined for IOcodes, while the original PNTR Gap is defined by Industrial Family. As an additional check, I can translate my gaps into Industrial Families using the NAICS6 codes. I correspond my NAICS6 gaps to industrial families as in the original paper, and get a linear correlation of 0.87. Both the density and scatter plot of the two gaps are presented in Figure A.2.

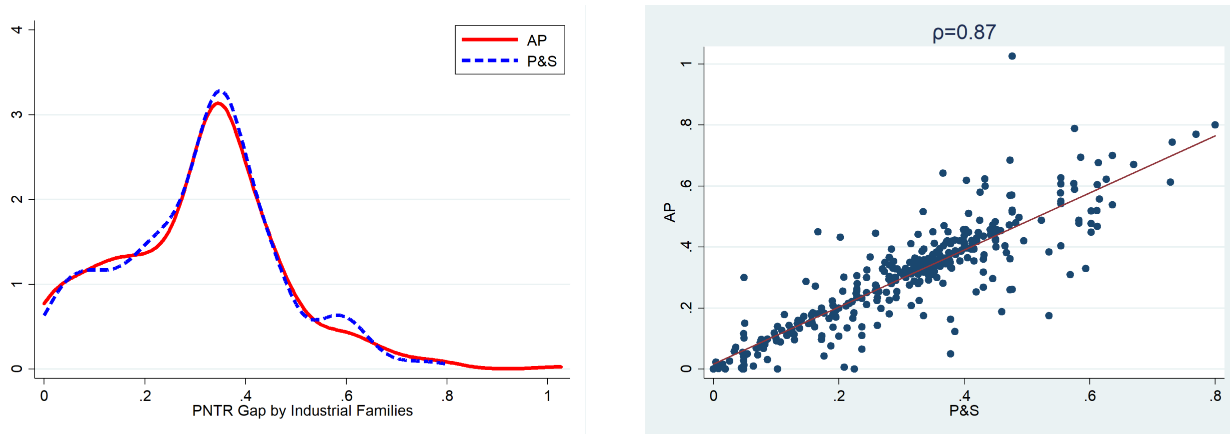

Figure 8: Gaps