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-difference empirical design. Trade liberalization affects domestic markups through both sales competition and the cost channel. To account for both, I combine markups constructed from Compustat data with Input-Output tables. I find that, as a result of normalization of trade with China, US firms reduced their markup on competing goods by -0.04% on average, while firms facing liberalization on their inputs instead increased their markups by $+1.4\%$. My findings suggest the anti-competitive effect of trade is as important as, and potentially larger than, the pro-competitive effects of trade.

*I am indebted to Robert Johnson for his guidance. All errors are my own.

1 Introduction

20 years after the China Shock there is evidence of its negative effects on manufacturing labor, but no consensus on its benefits. The classical view states trade is beneficial as long as the costs imposed on domestic producers is outweighed by the benefits for the broad base of consumers. In this sense, the widespread entry of inexpensive Chinese manufacturing imports should have reduced consumer prices, not only domestic manufacturing labor. To date, the size or even nature of this price reduction remains an open question. I argue the significant reduction in consumer prices is missing because US firms also adjust their markups in response to an increase of imports, not only on the exposed sector but also downstream.

The focus of this paper is to disentangle how firm adjusts their markup when facing increased import competition, in both direction and strength. As suggested by theory, I find two contradictory effects. First, changes in trade policy ease the entry of competitors at lower prices, making domestic products relatively more expensive. Incumbents firms react to this threat by decreasing their markups to avoid losing too many sales. This mechanism is known by the literature as the "pro-competitive" effect. The second, 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, decreasing costs of production. Under less than perfect competition, prices of the produced goods will decrease by less than the drop in production costs. In other words, the decrease in cost is not completely passed through to prices, increasing markups.

This paper provides evidence on how markups change as a response to increased import competition, in particular when firms are part of an Input-Output structure. I conduct my analysis in the context of the China Shock, both because its size can help uncover the competitive effects, and also due to its relevance for current discussion of US trade policy. I uncover the relation between import competition and markups using a difference-in-difference approach, similar to previous empirical evidence on other effects of China Shock. I combine firm-level markups constructed from Compustat data with the tariff gap of Chinese imports to the US before and after trade normalization, and use Input-Output tables constructed from BEA Make, Use, and Import tables.

In particular, I focus on the competitive effects at the firm level. This precision is important as the handful of studies that approach the subject have addressed different mechanisms. More clearly, and borrowing lexical from existing literature on markups, the competitive effects of imports in a given sector combine two distinct mechanisms. First, the within-firm competitive effects, that is how individual firm's change their markups in response to a rise in competition of imports. And second, the between-firm or reallocation competitive effects, which refers to how the reallocation of sales across firms changes aggregate markups, even with fixed markups for any given firm.

The full effect is a combination of both, a change in markups by individual firms and a reallocation of sales across firms with different markups. I focus on the within-firm effect to get a clear picture of the pro-competitive and anti-competitive mechanism, abstracting as much as possible from the reallocation of sales.

I find both a pro-competitive effect of imports, a decrease of markups by firms facing a surge in competing imports, and an anti-competitive effect of imports, that is an increase of markups in firms facing cost reductions due to an increase of imported inputs. I argue this second channel helps explain why evidence on the price reduction from the China Shock has been hard to pin down. Essentially, increased imports have an ambiguous net effect on a firm's markups. On the one hand, firms facing increased competition reduce their markups to avoid losing too much market share. On the other, firms buying inputs at reduced prices should increase their markups, as they do not fully pass-through the reduction in cost. The net effect is a combination of both, operating through suppler-buyer relations and the structure of costs. As a consequence, the effect on consumption prices are hidden in successive rounds of incomplete pass-through.

Some consequences of the China Shock have been studied to great depth. The more salient has been its association with the decline in manufacturing employment, as shown in Autor et al. [2013] Holmes and Stevens [2014] Pierce and Schott [2016] Acemoglu et al. [2016]. As for benefits, although Amiti et al. [2020] find Chinese imports reduced the prices paid at the border by

U.S. firms, the effect of the China Shock on consumer prices remains an open discussion. Two recent attempts of measuring the impact of the China Shock on consumer prices are Bai and Stumpner [2019], who find that a 5% reduction in domestic sourcing shares is associated with a 2pp decline in consumer prices, and Jaravel and Sager [2022], that instead find a 1% reduction is enough to get a 2pp decline in consumer prices. These results are different enough, and in particular have implications for price elasticities different enough, to keep open the empirical discussion of the effects of trade on consumer prices.

Associations between the China Shock and US markups have been hinted at before. Again, although mostly focused on the effect of the China Shock on inflation, Jaravel and Sager [2022] also conduct auxiliary empirical exercises touching on the pro-competitive effect of imports, combining within-firm and reallocation effects. Djolaud [2022] also discusses the pro-competitive effect of the China Shock on U.S. markups, but makes a distinct point about markup changes and the differences in product quality. The work most similar to this paper is Li and Miao [2018], who go as far as making the distinction between pro-competitive and anti-competitive effects in the context of the China Shock. However, my paper improves on their work, with a different empirical approach to the problem.

Evidence on separate pro-competitive and anti-competitive effects is scarce, but also somewhat anticipated. Amiti and Konings [2007] already discussed the differential effects of trade liberalization in output tariff and input tariffs on productivity for Indonesia, suggesting markups as one of two key channels. De Loecker et al. [2016] use the markup estimation method from De Loecker and Warzynski [2012] to find the effects of tariff liberalization on firm's markups in India, and attempt to isolate the input and output channels. But these were not yet clearly focused on the anti-competitive effects.

On a broader sense, this discussion of trade and markups links to the growing literature on concentration in the US, among others in Amiti and Heise [2021] De Loecker et al. [2020] Autor et al. [2020] Gutiérrez and Philippon [2017]. A couple of recent studies have approach the subject from this direction, linking trade to market power and concentration. For example, in a recent job market paper, Martynov and Zhang [2023] find different effects of output and input tariffs on sales using data for Colombia, and link it to concentration of sales. In a similar line Impullitti and Kazmi [2023] discuss how pro-competitive effects can increase markups through reallocation of sales when discussing the entry of Spain in the EU. However, although the topics are closely related, this evidence puts more emphasis on the distribution of sales than markups or prices.

In that context, this paper combines the empirical approach of the China Shock literature with more structural-inspired consideration on competition, to establish a relevant mechanism affecting the gains from trade.

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 an increase in imports could also be explained by changes in domestic demand. This endogeneity problem has 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 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 overall those sectors where tariffs drop by more were also those facing higher penetration of Chinese imports.

The institutional details that merits using the normalization of trade relations as 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, in the process of achieving member status to 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. The fourth step is to assign categories from the Input-Output tables (which I call here IOcode) to the NAICS6 codes. I base this correspondence on relations from the 1997 Import Matrix by the BEA, which I manually match and clean. Out of the 110,607 HS codes with corresponding NAICS6 categories, I match 80% to an IOcode. Furthermore, I keep only the NTR gaps for 1999, set before the discussion on permanent trade relations. The 7,857 HS8 tariff lines for 1999, with corresponding NAICS6 code and

IOcode both in their 1997 versions, need to be averaged across industry categories. I choose to average across IOcode categories instead of NAICS6, as my measure of upstream exposure can only be defined at the IOcode level, and the correspondence is cleaner. A comparison of the gap I construct with the gaps in Pierce and Schott [2016] is available in Appendix 1.

The end results are 328 sectors from the Input-Output tables with their corresponding Gap.

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.

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

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)

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

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 use Input Gap_s^{DR} in my baseline specification for the anti-competitive effects, and introduce the alternative measures shortly after.

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 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

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

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:

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

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

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

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

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

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

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

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 $q_{it} = \ln(Q_{it} \exp(\epsilon_{it}))$. 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] and combine it 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, 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. Second, I force a balanced panel, dropping any firm that is not in the sample every year. 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 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. On the other hand, balancing the panel interacts with the extension of the period, so reducing the time interval would probably increase the number of surviving firms, as they have to survive for less years.

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 a balanced panel of 902 firms, distributed along 241 sectors, across 17 years.

2.4 Data Description

As summarized in Table 1.1, the mean Gap, that is the difference between tariff regimes affecting a firm's main activity, is $21,7\%$, ranging from no gap at all up to 81%. The mean Input Gap is lower, with a mean of $7,6\%$, ranging

[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

from no gap to 20%.

Table 1: Gap and Input Gap

	Mean	S.D.	Min	Max
Gap	0.217	0.187	0.00	0.81
Input Gap	0.076	0.048	0.00	0.20
Observations	241			

I present the distribution of each gap in Figure 1.1. 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.

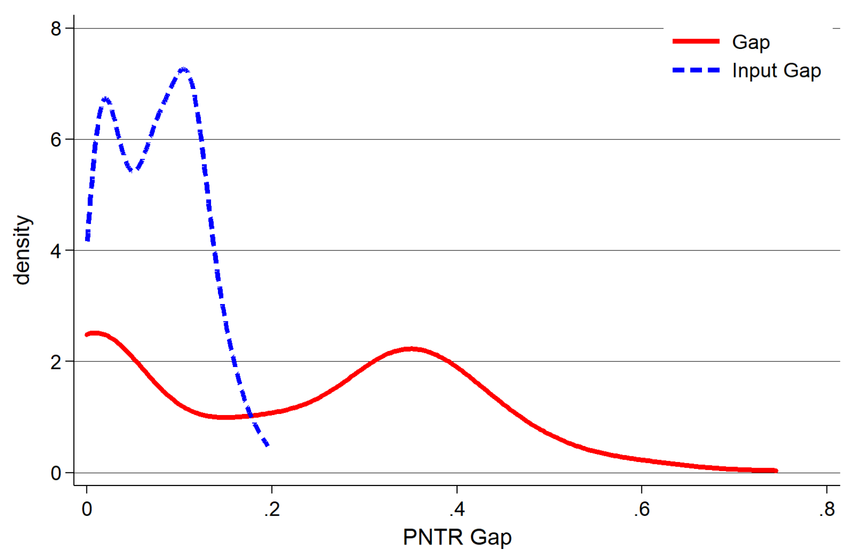

Figure 1: Density of Gap and Input Gap

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.

Average markups between 1991-2007 are presented in Figure 1.2 . 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. I am however not keeping firm sales fixed at before PNTR levels, so the abstraction from reallocation mechanisms is not complete.

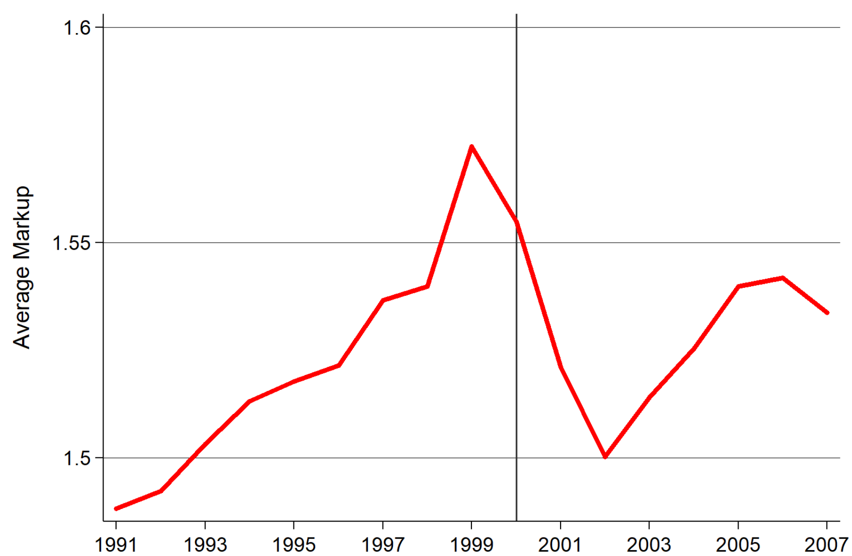

Figure 2: Average Markups - Balanced Panel

Regarding the particular period, 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.

Combining Gaps and Markups by sector, Table 1.2 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 and after the normalization of trade relations. All growth rates are in percentages, so the annualized rate of growth in Agriculture between 1991 and 2007 was -2.25% a year. Gap and Input Gap are the PNTR gaps, so the difference between add-valorem tariff regimes in agriculture was 4.79%. I also present the Gap's and Input Gap's corresponding standard deviations within each NAICS2 category, and the number of firms.

Table 2: Sample by NAICS2

	Markup	Growth	Pre	Post	Gap	S.D.	Input Gap	S.D.	Firms
Agriculture	1.22	-2.25	-2.48	-1.96	4.79	1.87	3.20	1.30	6
Mineral	1.32	0.38	0.92	-0.32	2.14	5.11	4.04	3.32	33
Utilities	1.40	-1.30	-0.21	-2.69	0.00	0.00	2.38	0.00	2
M. Durable	1.62	-0.17	-0.21	-0.13	31.51	16.66	9.15	3.92	204
M. Non-Durable	1.46	-0.03	0.22	-0.34	34.72	10.38	10.36	3.08	428
Retail	1.29	0.23	0.24	0.22	0.00	0.00	1.14	0.00	57
Transportation	1.40	0.82	1.50	-0.07	0.00	0.00	2.26	0.41	13
Information	2.41	1.12	0.20	2.29	0.00	0.00	2.20	0.50	29
Finance	1.58	0.45	-0.24	1.35	0.00	0.00	0.41	0.27	11
Real Estate	1.90	0.90	1.06	0.68	0.00	0.00	0.52	0.40	15
Professional	1.65	-0.28	0.13	-0.81	0.00	0.00	1.41	1.09	42
Administrative	1.40	-0.00	-0.09	0.11	0.00	0.00	1.47	1.10	22
Education	1.24	0.93	1.92	-0.35	0.00	0.00	1.27	0.48	4
Health Care	1.46	0.18	1.10	-1.01	0.00	0.00	3.60	0.79	17
Entertainment	1.70	-0.90	0.34	-2.50	0.00	0.00	1.07	0.32	4
Accomodation	1.30	-0.37	-0.13	-0.67	0.00	0.00	2.38	1.40	8
Other Services	1.27	0.35	-0.12	0.96	0.00	0.00	1.98	0.44	7

Noticeably, 632 out of 902 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 193 firms, followed by Chemical firms with 93.

Table 3: Sample Manuf. by NAICS3

	Markup	Growth	Pre	Post	Gap	S.D.	Input Gap	S.D.	Firms
Fo+Be+To	1.56	0.12	0.15	0.09	18.07	13.88	7.14	4.30	48
Textile	1.24	-0.06	0.01	-0.15	44.14	7.91	16.27	1.63	7
Apparel	1.38	0.20	0.28	0.09	44.99	14.79	13.59	2.26	13
Paper	1.22	-0.38	-0.10	-0.73	30.84	5.33	8.48	2.73	15
Printing	1.30	-0.49	-0.32	-0.71	13.40	6.74	7.63	0.36	5
Petr+Coal	1.16	-0.87	-0.46	-1.39	23.25	19.79	3.96	3.25	7
Chemical	1.90	-0.18	-0.33	0.00	37.24	14.76	8.97	2.75	93
Plastics	1.24	-0.76	-0.99	-0.47	31.97	14.02	12.81	1.70	16
Wood	1.05	-0.43	-0.71	-0.06	33.42	13.12	9.14	2.81	7
Mineral	1.18	-0.42	-0.67	-0.10	17.01	10.86	4.64	1.63	10
Prim. Metal	1.03	0.19	0.42	-0.12	25.20	17.63	9.84	2.97	4
Fab. Metal	1.16	-0.15	0.12	-0.50	31.89	17.27	8.30	2.21	25
Machinery	1.37	-0.02	0.05	-0.11	31.82	7.58	11.44	1.97	64
Electronics	1.60	-0.02	0.33	-0.48	36.55	5.40	10.38	3.37	193
Appliances	1.24	-0.14	0.06	-0.39	36.57	4.62	11.09	2.19	29
M. Vehicles	1.14	-0.43	-0.54	-0.28	22.94	7.78	13.03	2.40	24
O. Transport	1.13	-0.34	-0.32	-0.36	28.54	10.95	11.49	2.93	20
Furniture	1.26	-0.38	-0.28	-0.50	35.47	16.91	9.55	2.02	11
Misc. Manuf.	1.89	0.72	1.31	-0.03	46.20	9.52	9.10	1.35	41

For the following analysis, I will use both the alternative Input Gap measures describe above in section 1.2.1, as well as versions that split treatment between manufacturing and non-manufacturing firms. Here I briefly present moments of both. First in Table 1.4 the alternative measures of the Input Gap

Table 4: Descriptive Statistics - Alternative Input Gap

	Mean	S.D.	Min	Max
Input Gap DR	0.076	0.047	0.00	0.20
Input Gap LR	0.145	0.144	0.00	1.70
Input Gap DRAR	0.100	0.059	0.00	0.27
Input Gap LRAR	0.088	0.039	0.02	0.21
Observations	235			

and in Table 1.5 the manufacturing (M) and non-manufacturing (NM) split for all gaps

Table 5: Descriptive Statistics - Manufacturing/non-Manufacturing gaps

	Mean	S.D.	Min	Max
Markup	1.415	0.554	0.82	5.80
Markup M.	1.363	0.409	0.97	4.99
Markup NM.	1.552	0.809	0.82	5.80
Gap M.	0.295	0.152	0.00	0.74
Gap NM.	0.009	0.031	0.00	0.18
Input Gap DR M.	0.096	0.037	0.01	0.20
Input Gap DR NM.	0.022	0.023	0.00	0.16
Input Gap LR M.	0.182	0.151	0.03	1.70
Input Gap LR NM.	0.049	0.045	0.00	0.33
Input Gap DRAR M.	0.117	0.059	0.00	0.27
Input Gap DRAR NM.	0.055	0.030	0.01	0.14
Input Gap LRAR M.	0.099	0.039	0.02	0.21
Input Gap LRAR NM.	0.059	0.021	0.02	0.12
Observations	235			

3 Empirical Evidence

3.1 Pro-competitive Effect

3.1.1 Empirical Exercise

Given its importance in the literature, I first look for empirical evidence on the pro-competitive effect where, as suggested in Figure 1.2, markups should decrease with the normalization of trade. Because there is no conclusive evidence yet on the pro-competitive effect of the China Shock, I adopt an exploratory approach. To disentangle how much if any of the drop in the average markups in my sample can be attributed to trade liberalization, I use three different empirical strategies. First I estimate a battery of panel difference-in-difference specifications, with alternate structures for time fixed effects, both in levels and in first differences. I complement this first strategy with the corresponding event studies, allowing the coefficients associated to the Gap to vary year by year. And third, I estimate a stacked difference regression model, which suppresses some short term dynamics. I present the equations associated to each strategy to then report their results together.

I start by estimating four alternate panel regression difference-in-difference models, as determined by the following equations

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

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

$$\mu_{ist} = \phi_{is} + \phi_t + \gamma_{is}t + \beta\left(\text{Post}_t \times \text{Gap}_s\right) + \epsilon_{ist} \tag{15}$$

$$\mu_{ist} = \phi_{is} + \phi_{st} + \gamma_{is}t + \beta\left(\text{Post}_t \times \text{Gap}_s\right) + \epsilon_{ist} \tag{16}$$

where μ_{ist} is the markup of firm i in sector s on year t. Gap_s is the difference between tariffs under permanent normalized trade relations (PNTR) and temporary normalized trade relations, as described in section 1.2.1.2. The dummy $\text{Post}_t = 1$ for years 2001 onward, representing the timing of the normalization of trade with China. ϕ_{is} are firm-specific fixed effects, present in all specifications. ϕ_t are year fixed effects, ϕ_{st} are NAICS2-specific year fixed effect capturing differential sector dynamics along the business cycle, and γ_{is} are firm-specific time trends representing within-firm markup trends. The overall aim of these four equations is the same, but they differ on the structure of time fixed-effects to account for possible confounding problem, as cyclical behavior or persistence in markups.

I also estimate a set of regression models taking first differences with respect to time in eq.(1.13-1.16), which allows me to estimate the same coefficient β in a different way

$$\Delta\mu_{ist} = \quad \Delta\phi_t \quad + \beta\left(\text{Post}_t \times \text{Gap}_s\right) + \Delta\epsilon_{ist} \tag{17}$$

$$\Delta\mu_{ist} = \quad \Delta\phi_{st} \quad + \beta\left(\text{Post}_t \times \text{Gap}_s\right) + \Delta\epsilon_{ist} \tag{18}$$

$$\Delta\mu_{ist} = \quad \Delta\phi_t + \gamma_{is} \quad + \beta\left(\text{Post}_t \times \text{Gap}_s\right) + \Delta\epsilon_{ist} \tag{19}$$

$$\Delta\mu_{ist} = \quad \Delta\phi_{st} + \gamma_{is} \quad + \beta\left(\text{Post}_t \times \text{Gap}_s\right) + \Delta\epsilon_{ist} \tag{20}$$

where now $\Delta\mu_{ist} = (\mu_{ist} - \mu_{ist-1})$, $\Delta\phi_t = (\phi_t - \phi_{t-1})$ are year fixed effects, $\Delta\phi_{st}$ are NAICS2-specific year fixed effect. γ_{is} are now firm-specific fixed effects, equivalent to the firm-specific time trends in levels. The coefficient β in first differences is conceptually the same as the one in levels. Also the residuals are now the first difference of the previous residuals as $\Delta\epsilon_{ist} = (\epsilon_{ist} - \epsilon_{ist-1})$.

The difference in difference approach focuses on average effects before and after treatment, so it is usually complemented with corresponding event studies. This allows me to first visualize whether the parallel trend assumption makes sense in this case, but second is suggestive of possible dynamic effects. These dynamic effects are somewhat to be expected in this case as imports phase in. So I estimate the event studies corresponding to equations (1.13-1.16), in order

$$\mu_{ist} = \delta_{is} + \delta_t + \psi_t \left(\text{Year}_t \times \text{Gap}_s\right) + u_{ist} \tag{21}$$

$$\mu_{ist} = \delta_{is} + \delta_{st} + \psi_t \left(\text{Year}_t \times \text{Gap}_s\right) + u_{ist} \tag{22}$$

$$\mu_{ist} = \delta_{is} + \delta_t + \eta_{is} t + \psi_t \left(\text{Year}_t \times \text{Gap}_s\right) + u_{ist} \tag{23}$$

$$\mu_{ist} = \delta_{is} + \delta_{st} + \eta_{is} t + \psi_t \left(\text{Year}_t \times \text{Gap}_s\right) + u_{ist} \tag{24}$$

where ψ_t will be a separate coefficient for each year, δ_{is} are firm-specific fixed effects, and δ_t are year fixed effect. δ_{st} are NAICS2-specific year fixed effect, aimed at capturing differential sector dynamics along the business cycle. η_{is} are firm-specific time trends, representing within-firm markup trends. Again, the four equations are similar, but differ on the structure of time fixed-effects. The event studies in first differences are defined as

$$\Delta\mu_{ist} = \Delta\delta_t + \psi_t \left(\text{Year}_t \times \text{Gap}_s\right) + \Delta u_{ist} \tag{25}$$

$$\Delta\mu_{ist} = \Delta\delta_{st} + \psi_t \left(\text{Year}_t \times \text{Gap}_s\right) + \Delta u_{ist} \tag{26}$$

$$\Delta\mu_{ist} = \Delta\delta_t + \eta_{is} + \psi_t \left(\text{Year}_t \times \text{Gap}_s\right) + \Delta u_{ist} \tag{27}$$

$$\Delta\mu_{ist} = \Delta\delta_{st} + \eta_{is} + \psi_t \left(\text{Year}_t \times \text{Gap}_s\right) + \Delta u_{ist} \tag{28}$$

I estimate stacked difference models, used by the China Shock literature. This approach abstracts from short-term movements, focusing instead in more stable trends. The model in stacked differences of markups divides time in two sub-periods $\tau = (1991 - 2000)$ and $\tau = (2000 - 2007)$. The dependent variable $\tilde{\mu}_{is\tau}$ will be the stacked difference of markups, defined as

$$\tilde{\mu}_{is(1991-2000)} = \frac{\mu_{2000} - \mu_{1991}}{2000 - 1991} \tag{29}$$

which is equivalent to taking the average of the differences for each year of the sub-period. The equations in stacked differences analog to the models in first differences eq.(1.17-1.20)

$$\tilde{\mu}_{is\tau} = \tilde{\phi}_{\tau} + \tilde{\beta}\left(\text{Post}_t \times \text{Gap}_s\right) + \tilde{\epsilon}_{is\tau} \tag{30}$$

$$\tilde{\mu}_{is\tau} = \tilde{\phi}_{s\tau} + \tilde{\beta}\left(\text{Post}_t \times \text{Gap}_s\right) + \tilde{\epsilon}_{is\tau} \tag{31}$$

$$\tilde{\mu}_{is\tau} = \tilde{\phi}_{\tau} + \tilde{\gamma}_{is} + \tilde{\beta}\left(\text{Post}_t \times \text{Gap}_s\right) + \tilde{\epsilon}_{is\tau} \tag{32}$$

$$\tilde{\mu}_{is\tau} = \tilde{\phi}_{s\tau} + \tilde{\gamma}_{is} + \tilde{\beta}\left(\text{Post}_t \times \text{Gap}_s\right) + \tilde{\epsilon}_{is\tau} \tag{33}$$

Summing up, I combine four different empirical strategies: difference-in-difference in levels, difference-in-difference in first differences, event studies, and stacked differences; with four ways of structuring time fixed effects: year fixed effects, year fixed effects by NAICS2 group, year fixed effects with firm time trends, and year fixed effects by NAICS2 group with firm time trends.

3.1.2 Results - Pro-Competitive

Results for the pro-competitive effects are presented Table 6. Panel A starts by presenting results for the difference-in-difference models with markups in levels, using different time fixed effects as defined in eq.(1.13-1.16). Results are inconclusive but somewhat revealing. Changing the structure of time fixed-effects seems makes a difference, suggestive of the secular growth of markups in the case of firm-level time trends, and of heterogeneous responses across large sector groups in the case of the separate year fixed effects by NAICS2 groups.

Advancing on this sector heterogeneity, and taking into account the characteristics of the trade liberalization episode, I split treatment between manufacturing and non-manufacturing sectors with a dummy variable

$$\begin{aligned}
\mu_{ist} = \quad & \phi_{is} + \phi_t & + \beta_{\text{Manuf}} \left(\text{Post}_t \times \text{Gap}_s \times 1_{s \in m} \right) \quad (34) \\
& & + \beta_{\text{NoManuf}} \left(\text{Post}_t \times \text{Gap}_s \times 1_{s \notin m} \right) + \epsilon_{ist} \\
\mu_{ist} = \quad & \phi_{is} + \phi_{st} & + \beta_{\text{Manuf}} \left(\text{Post}_t \times \text{Gap}_s \times 1_{s \in m} \right) \quad (35) \\
& & + \beta_{\text{NoManuf}} \left(\text{Post}_t \times \text{Gap}_s \times 1_{s \notin m} \right) + \epsilon_{ist} \\
\mu_{ist} = \quad & \phi_{is} + \phi_t + \gamma_{is} t & + \beta_{\text{Manuf}} \left(\text{Post}_t \times \text{Gap}_s \times 1_{s \in m} \right) \quad (36) \\
& & + \beta_{\text{NoManuf}} \left(\text{Post}_t \times \text{Gap}_s \times 1_{s \notin m} \right) + \epsilon_{ist} \\
\mu_{ist} = \quad & \phi_{is} + \phi_{st} + \gamma_{is} t & + \beta_{\text{Manuf}} \left(\text{Post}_t \times \text{Gap}_s \times 1_{s \in m} \right) \quad (37) \\
& & + \beta_{\text{NoManuf}} \left(\text{Post}_t \times \text{Gap}_s \times 1_{s \notin m} \right) + \epsilon_{ist}
\end{aligned}$$

where $1_{s \in m} = 1$ if the NAICS2 sector group the firm belongs to is in manufacturing, and zero otherwise. Likewise $1_{s \notin m} = 1$ if it does not belong to manufacturing, and zero otherwise. Results are also in Panel A, split between "Gap - Manuf." and "Gap - Non Manuf.". For all specifications, the coefficients of manufacturing and non-manufacturing are opposites. This might relate to the fact manufacturing sectors are exposed tothe Gap mostly on their sales, while non-manufacturing sectors are affected mostly through their inputs. Also, the standard errors are larger for non-manufacturing. This is to be expected given Table 1.2, as manufacturing firms take up two-thirds of the sample, but also because most of the variation in Gap is also found in manufacturing.

Table 6: Pro-Competitive Effect

	(1) Year FE Firm FE	(2) Year-Sector FE Firm FE	(3) Year FE Firm FE Firm Trends	(4) Year-Sector FE Firm FE Firm Trends
Panel A: Markup Level (N=15,334)				
Gap - All Sectors	-0.08	0.13	-0.03	-0.03
	(0.11)	(0.15)	(0.10)	(0.14)
Gap - Manuf.	-0.08	0.13	-0.03	-0.05
	(0.11)	(0.15)	(0.10)	(0.14)
Gap - Non Manuf.	0.63	-0.03	0.94	1.89*
	(0.55)	(0.67)	(0.68)	(1.07)
Panel B: First Difference (N=15,334)				
Gap - All Sectors	-0.02	0.03	-0.03**	0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Gap - Manuf.	-0.02	0.03	-0.03*	0.00
	(0.02)	(0.02)	(0.02)	(0.02)
Gap - Non Manuf.	0.31*	0.07	0.44*	0.21
	(0.16)	(0.15)	(0.23)	(0.24)
Panel C: Stacked Difference (N=1,804)				
Gap - All Sectors	-0.02	0.00	-0.02	0.01
	(0.02)	(0.01)	(0.03)	(0.03)
Gap - Manuf.	-0.02	0.01	-0.02	0.01
	(0.02)	(0.01)	(0.03)	(0.03)
Gap - Non Manuf.	-0.27	-0.21	0.14	0.04
	(0.17)	(0.16)	(0.42)	(0.28)

*** p<0.01, ** p<0.05, * p<0.1 Standard errors are clustered by sector. Each coefficient labeled "Gap - All Sectors" is the result of a different estimation. Coefficient pairs labeled "Gap - Manuf." and "Gap - Non Manuf." are the result of a different estimation for each column.

With regards to the structure of time, I present in Panel B of Table 1.6 results for the models in first differences, as in eq.(1.17-1.20). Here taking first differences also affects the results, in particular reducing standard errors. This is suggestive of serial correlation in the error term, which would make first difference estimation more reliable. I add a similar split as above between manufacturing and non-manufacturing sectors, again resulting in opposite-signed coefficients and standard errors an order of magnitude larger for non-manufacturing.

From the results in Panels A and B, it seems there could be a pro-competitive result, that involves firm-specific time trends and a split between manufacturing and non-manufacturing sectors. Also, results have smaller errors using first differences, which suggests there could be auto-correlation in firm markups.

In panel C I present results for the stacked differences strategy. As mentioned before, the aim here is to abstract from short-term dynamics which could making inference more difficult. I repeat the structure of alternative time fixed effects and manufacturing/non-manufacturing split. Again, the coefficients are not precise, and the time fixed-effect structure seems to makes a difference. In particular here, there is an increase in R-squared for specification with firm fixed effects, which was not the case when estimating the analog model in levels. There also seems to be sector heterogeneity involved, as results with year fixed effects by NAICS2 grouping are again systematically different than those with common year fixed effects.

Finally, I switch to the event studies empirical strategy. As described above, I estimate analog specifications to the ones just presented, now with coefficients varying year by year for the Gap. And again, this strategy helps visualize both whether the parallel trends assumption holds, required for identification, and any change in the effect of the Gap after treatment. Figure 1.3 presents the results, divided in four graphs. The top two correspond to the event studies with markups in levels, as in eq.(1.21-1.22) on the left with year fixed effects and separate year fixed effect for each NAICS 2 sector, and as in eq.(1.23-1.24) on the right with the same fixed effects but adding firm-specific time trends. The bottom two display results for similar specifications but now with markups in first differences, as in eq.(1.25-1.26) on the left, and in eq.(1.27-1.28) on the right.

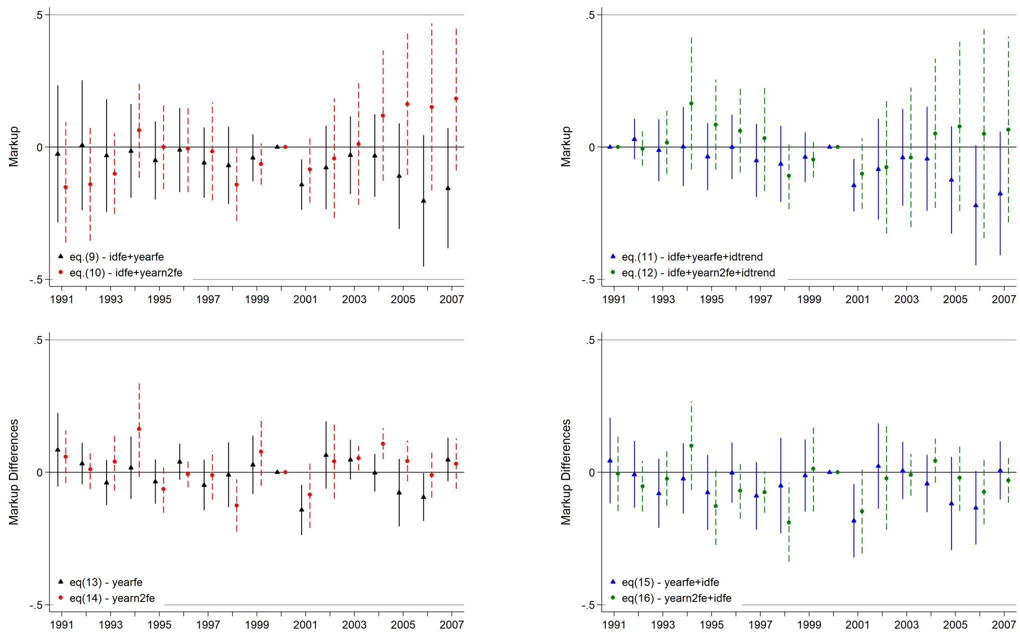

Figure 3: Pro-Competitive - Event Studies

Here confidence intervals are smaller when estimating the event studies in first differences instead of levels. In terms of the pro-competitive effect, most coefficients associated with the Gap are negative for 2001, the year of normalization, and trending down after 2002. This would be consistent with an initial step reduction, followed by the effects of phasing in imports.

I make a similar split as above between manufacturing and non-manufacturing sectors, and estimate their event studies in levels and first differences. For clarity I also present the results split in two figures, as the size difference of the standard errors hinders visualization. In Figure 1.4 I plot the coefficients associated to manufacturing, both for models in levels and first differences, with two specification per graph as before. Figure 1.5 is built the same way but with the coefficients for non-manufacturing.

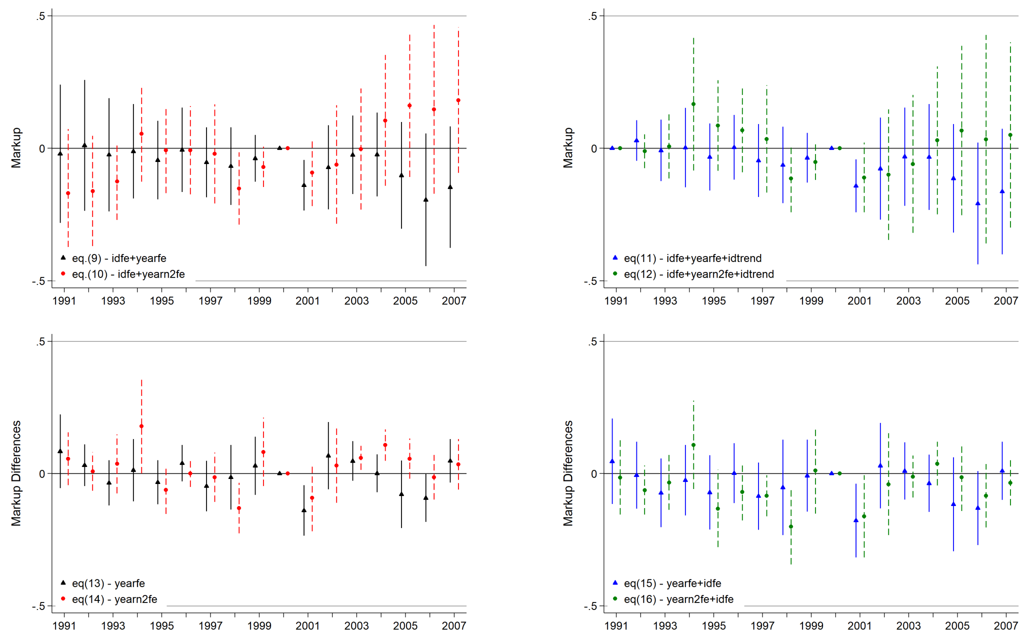

Figure 4: Pro-competitive in Manufacturing - Event Studies

The event studies for only manufacturing in Figure 1.4 look very similar to the total effect, just slightly more precise. On the other hand, the event studies for non-manufacturing in Figure 1.5 have larger standard errors, with coefficients trending upward on average after 2001.

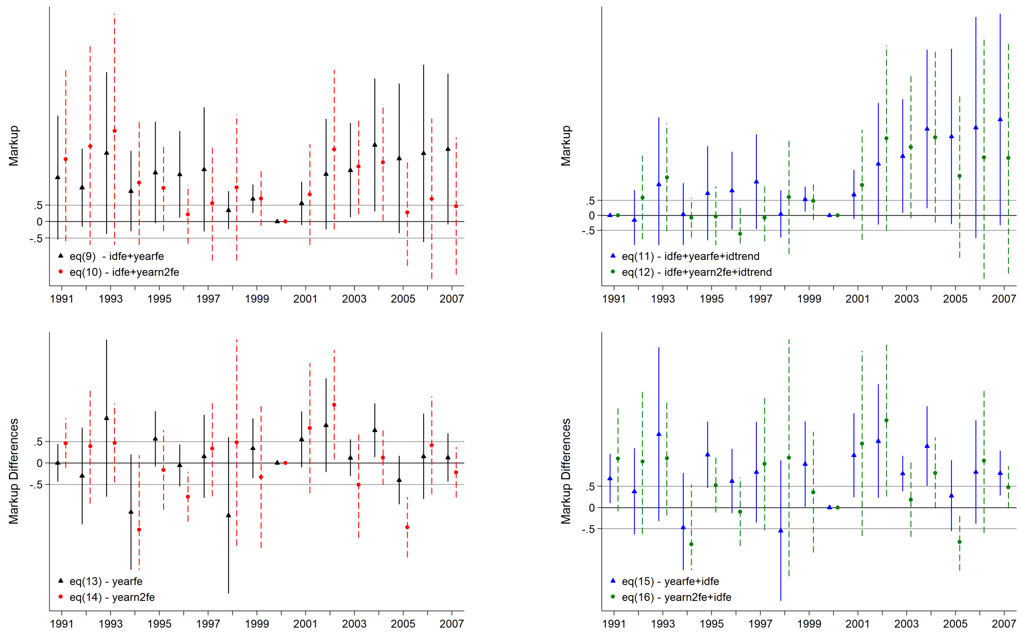

Figure 5: Pro-competitive in non-Manufacturing - Event Studies

The event study analysis shows results for the pro-competitive effect have large standard errors, especially for non-manufacturing sectors, but estimates trending negative. From the trajectory of coefficients one can also conjecture there is initial jump down of markups when the tariff uncertainty is resolved, and move down gradually consistent with the phasing in of imports from China. It also shows manufacturing and non-manufacturing sectors behave different.

Up to here, evidence on the pro-competitive effect is not clear cut. However, casting a wide net in search for it provides additional clues on how to proceed in the following analysis. In particular, firm-level time trends seem very relevant. Also, taking first difference reduces standard errors, possibly because of serial correlation. Results are also very different when splitting between manufacturing and non-manufacturing.

3.2 Pro-competitive and Anti-competitive Effects

3.2.1 Empirical Exercise

Going back to the main focus of this paper, I return to the anti-competitive effect. One way to proceed would be to mimic the analysis for the pro-competitive effect, changing the Gap treatment variable to the Input Gap treatment variable. I report results for this alternative in Appendix 1.2, which also suggests towards using first differences, firm-specific trends, and the manufacturing/non-manufacturing split. However, this approach is limited in its identification if, as I suspect, firms face both a pro-competitive and anti-competitive effect. The straightforward remedy is to conduct the same analysis with both Gap and Input Gap. Here I present a selection of results using both the Gap and Input Gap in a preferred specification. I also test the alternate ways to construct the Input Gap, as well as splitting the sample between manufacturing and non-manufacturing. Additional results to this approach are presented in Appendix 1.3.

Taking the clues from the previous exercise, I focus on the specification in first-differences with firm-specific time trends and year fixed effects, as in eq.(1.19) repeated below as eq.(1.38). The first difference specifications helps me deal with auto-correlation, while the firm-specific time trends seem relevant both for previous literature findings of within-firm markup trends, and empirically to precise the results. Using the year fixed effects instead of NAICS2-specific year fixed effects has the advantage of using more variation across sectors, at the cost of controlling for business cycle heterogeneity. The preferred specification will then be

$$\begin{aligned} \Delta\mu_{ist} = \quad \Delta\phi_t + \gamma_{is} \quad & + \beta_1 \left(\text{Post}_t \times \text{Gap}_s\right) \\ & + \beta_2 \left(\text{Post}_t \times \text{Input Gap}_s\right) + \Delta\epsilon_{ist} \end{aligned} \tag{38}$$

and the corresponding event study

$$\begin{aligned} \Delta\mu_{ist} = \quad \Delta\delta_t + \eta_{is} \quad & + \psi_{1t} \left(\text{Year}_t \times \text{Gap}_s\right) \\ & + \psi_{2t} \left(\text{Year}_t \times \text{Input Gap}_s\right) + \Delta u_{ist} \end{aligned} \tag{39}$$

where initially I will use Input Gap_s^{DR} as upstream measure of trade liberalization, the input gap built with weights from the Direct Requirement Matrix. Following this baseline, I compare the four different approaches to constructing the Input Gap_s with analog specifications. Across all specifications I also include versions that split into manufacturing sectors and non-manufacturing sectors, with the analog dummy structure used for the pro-competitive analysis.

3.2.2 Results - Pro-competitive and Anti-competitive

Results are presented in Table 1.7. Column 1 of Panel A presents estimated coefficients of eq.(1.38) for the Gap and Input Gap, using the base definition for the Input Gap using the direct requirement matrix. Here the pro-competitive effect seems more precisely evidenced, while the anti-competitive effect less so.

Panel B repeats the split between manufacturing and non-manufacturing. Splitting the gaps for manufacturing and non-manufacturing has the opposite effect, the pro-competitive effect is not significant, but the anti-competitive effect is clear for non-manufacturing sectors. It is not clear whether this just one effect being picked up differently in each specification, or if there are two effects that this data-set is not potent enough to statistically differentiate from zero separately.

Results are at the same time contradictory, but highlight the importance of adding both the pro-competitive and anti-competitive dimensions together. In Panel A, using both gaps helps identify the pro-competitive effect. Here firms facing a 100% gap in add-valorem tariffs decreased their markups by -0.04. With an average gap of 20.7%, the drop in markups was -0.008. From an average markups of 1.52, around 0.5%. However, here the anti-competitive effect is not statistically different from zero.

In the first column of Panel A, non-manufacturing firms facing 100% input gap increased their markup by 0.98. Given an average input gap in non-manufacturing of 2.2%, the average non-manufacturing firm increased their markups by 0.022 from an average of 1.55, around 1.4%. As before, even with this split the coefficients associated to the Gap loose in significance when adding the anti-competitive effect.

Table 7: Pro-Competitive and Anti-Competitive Effect

	(1) DR	(2) LR	(3) DRAR	(4) LRAR
Panel A: All Sectors				
Gap	-0.04**	-0.04**	-0.03*	-0.03*
	(0.02)	(0.02)	(0.02)	(0.02)
Input Gap	0.06	0.01	-0.03	-0.03
	(0.08)	(0.02)	(0.05)	(0.07)
Observations	15,334	15,334	15,334	15,334
Panel B: Manufacturing				
Gap	-0.01	-0.00	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Input Gap	0.07	0.02	-0.04	-0.03
	(0.07)	(0.01)	(0.05)	(0.07)
Non Manufacturing				
Gap	0.01	0.05	0.31	0.31
	(0.15)	(0.13)	(0.22)	(0.22)
Input Gap	0.98***	0.45***	0.30*	0.38**
	(0.25)	(0.10)	(0.15)	(0.18)
Observations	15,334	15,334	15,334	15,334

*** $p<0.01$, ** $p<0.05$, * $p<0.1$ All columns with Firm FE and Year FE. Standard errors are clustered by sector. Each coefficient pair in Panels A are the result of a different estimation. Coefficients in columns of Panel B-C are the result of the same estimation.

One reason the effects could be confused together is the upstream structure I assume for the Input Gap. Broadly speaking, there are two main dimensions in the which they differ, scale and sector structure. With respect to scale, if the Gap affects 100% of sales, the Direct Requirement Input Gap scales exposure down by the use of inputs in the cost structure. The Leontief

Requirement Input Gap also scales exposure down, but by the full indirect effect. The re-scaled versions of each re-scales by transforming the weights so they add to one. With respect to sector structure, the Direct Requirement Input Gap takes inputs only one sector upstream, while the Leontief Requirement takes the full indirect effect. In both, inputs coming from the firm's own sector or very similar sectors have high weights. The adjusted versions adjusts for this by setting weights of the same NAICS3 sector group as the firm to zero.

With that aim, I re-estimate eq.(1.38) in columns (2-4) of Panel A using the alternate definitions for the Input Gap presented in section 1.2.1.2. Here, no version of the Input Gap yields coefficients statistically different from zero. Even more, although Input Gap_s^{DR} and Input Gap_s^{LR} have positive point estimates, coefficients for the adjusted re-scaled versions have negative estimates. This is contrary to why I adjust the initial measures, the fact that own sector coefficients could have more pro-competitive effects in them.

Finally, I conduct the same analysis now splitting between manufacturing and non-manufacturing sectors. This split, which mattered for the pro-competitive effect, also makes a difference here. Results are presented in columns 2-4 in Panel B of Table 1.7. The result is similar to column 1, with the anti-competitive effects being statistically different from zero, while the opposite is true of the pro-competitive effect. As in before, the split between manufacturing and non-manufacturing matters across all versions of the Input Gap. Here all coefficients for non-manufacturing are positive, and in particular the ones associated to the Direct Requirement and Leontief Requirement are statistically different from zero at 99% confidence.

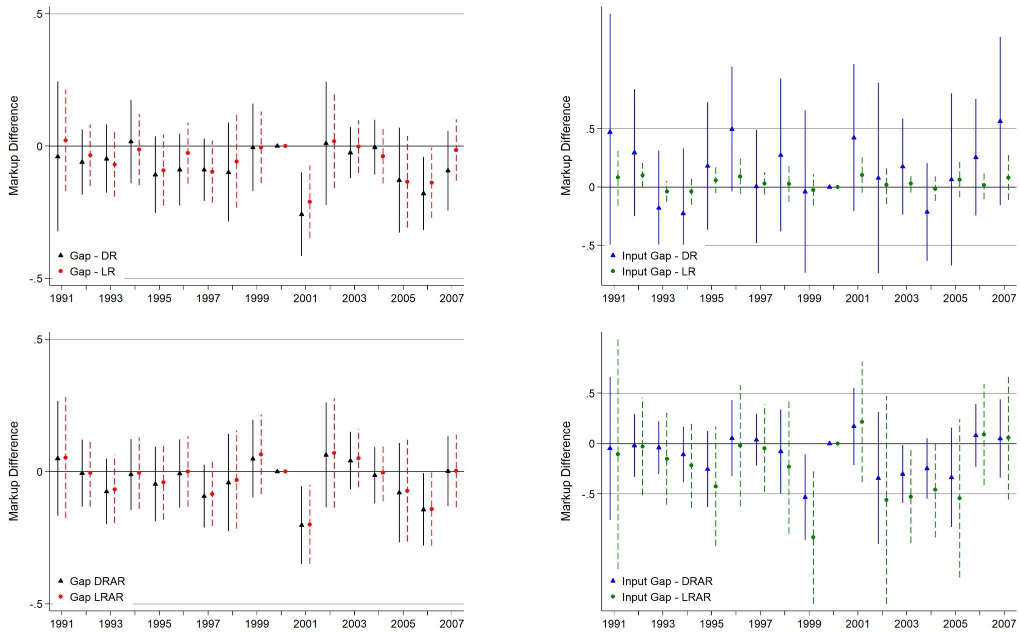

Figure 6: Alternate Input Gaps - Event Studies

To consider the alternate measures more carefully, in Figure 1.6 I present the corresponding event studies. The event studies on the left side of Figure 1.6 corresponding to the Gap are very similar across all specifications, and similar to previous results in Figure 1.4 without the input Gap. This suggests changing the definition of the Input Gap is not affecting the estimation of pro-competitive effects. Event studies corresponding to the Input Gap however are quite different. Comparing first the Direct Requirement with the Leontief Requirement, one can appreciate how the scale effects operates into the coefficients and confidence intervals. Similarly, comparing the adjusted re-scaled versions remedies scale issues, but the difference in sector structure makes the magnitude of exposure larger in the case of full Leontief Requirements. No results for the Input Gap is conclusive, and the last two are even counter-intuitive.

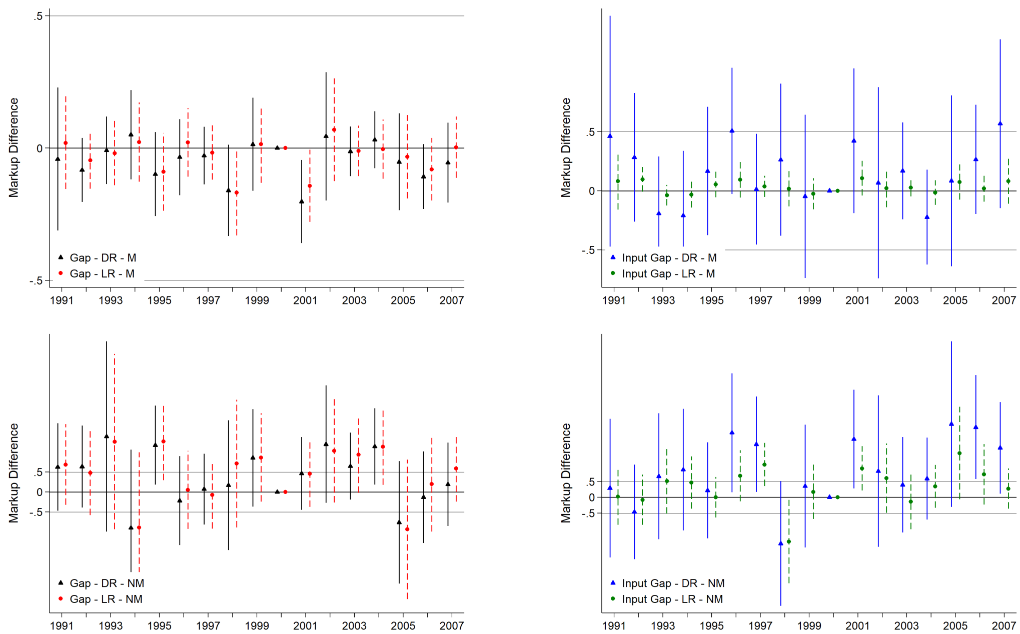

Figure 7: Alternate Gaps Manuf/non-Manuf - Event Studies

Figure 1.7 displays the corresponding event studies for manufacturing and non-manufacturing sectors, using the Direct Requirement and Leontief Requirement definitions of the Input Gap. Graph on the left suggest the pro-competitive effect operated mostly in manufacturing (top left), different from the processes happening in non-manufacturing (bottom left). On the right hand graphs the anti-competitive effect seems to operate on both sectors, but is more clearly distinguishable from null in non-manufacturing, possibly because there is no pro-competitive effect operating on those sectors. To Finalize, Figure 1.8 presents the event studies for regressions using Input $\text{Gap}_s^{\text{DRAR}}$ and Input $\text{Gap}_s^{\text{LRAR}}$, split between manufacturing and non-manufacturing.

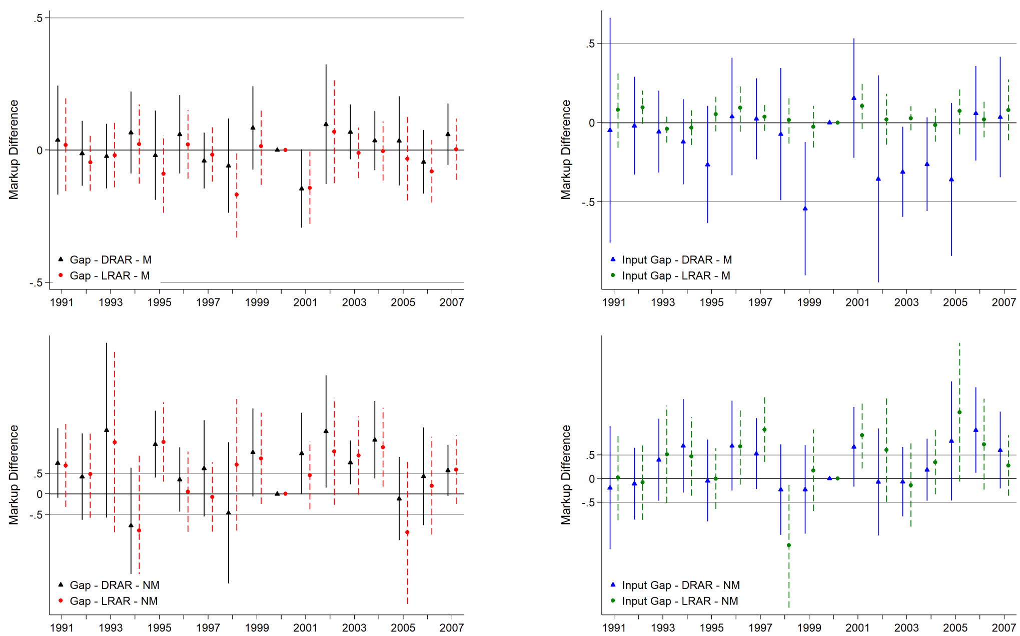

Figure 8: Alternate Gaps Manuf/non-Manuf - Event Studies

Again, the coefficients for non-manufacturing Input Gap align with the expected results, while those for the Gap align in manufacturing. Additional results can be found in Appendix 1.3.

4 Conclusion

In this paper I use three empirical approaches, difference-in-difference, event studies, and stacked difference, to uncover the pro-competitive and anti-competitive effect of imports on domestic markups. I find firms facing a 100% gap in add-valorem tariffs decreased their markups by 0.03. The average gap was 20.7%, so the average drop in markups was 0.006 from an average markups of 1.52, around 0.4%. Likewise, non-manufacturing firms facing 100% input gap increased their markup by 0.98. The average input gap in non-manufacturing was 2.2%, so on average firms increased their markups by 0.022 from an average of 1.55, around 1.4%. I cannot reject the input gap to be null for manufacturing. However, these results come from separate specifications, as disentangling the pro-competitive and anti-competitive from each other and from the business cycle is an inherent challenge of this problem.

Along with the difficulties faced, a number of improvements can be made on my approach. First, these results do not take into account entry or exit of firms, nor weight for size of the firms. They focus on the simple average of firms listed in my sample every year between from 1991 to 2007. Taking weighted averages of markups or weighting the regressions by firm size would be another informative approach, although answering a slightly different question liked to heterogeneity and reallocation. Similarly, changes in markups could induce exit of firms affected, like a pro-competitivepurification effect, and the converse could be true for entry. Testing these complementary effects would of course require using the unbalanced panel. Also, as mentioned before, listing and de-listing is not the same as entry and exit, but making that switch would require a whole different data-set.

I focus on the PNTR Gaps, but other approaches can be used to identify the China Shock. For example, there are a number of strategies using on the participation of imports in domestic supply, accompanied of appropriate instruments. One could also test the effects of trade liberalization in general, using the participation of all imports in supply, although again a solution for endogeneity would be required for identification. 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. A similar approach in a different context could help identify the effects, if the episode was also quasi-exogenous and data allowed to construct markups.

Markups are an interesting object to analyze given its role in competition, but are difficult to measure. Other strategies are easier to measure, but face different trade-offs. For example, measuring the direct response of prices is crucial, but because both the pro-competitive and the anti-competitive effects coexist with a drop of prices, the sign would not be enough to discuss the competitive effects, requiring separate measures or assumptions about the price-cost pass-through and demand elasticities. Another possible approach is to use equity market responses to trade shocks. In particular for the anti-competitive effect, one would expect a firm's profitability to increase after an episode of trade liberalization affecting their inputs. But this requires controlling for all other variables that affect profitability of the firm. Other metrics of firm performance, like expansions or contraction of firm size, changes in quality, or product menu, would also signal how trade increases or decreases pressure from competition on firms, appropriately controlling for confounding elements.

Theory suggests both competitive effects should operate on firms, and this paper provides evidence to that respect on both pro-competitive and anti-competitive effects. More evidence is required, but also quantitative model estimations, to grasp the weight these mechanism have on welfare.

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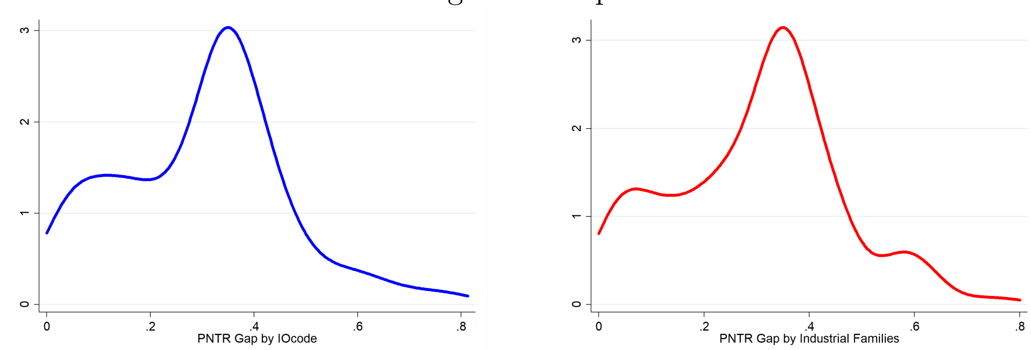
5 Gap Comparison

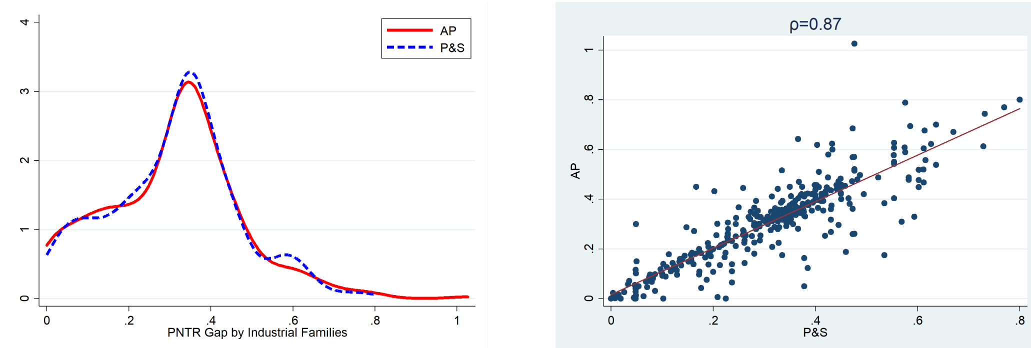
To check my procedure in construct the gaps is sound, I compare them with use with those used in Pierce and Schott [2016], publicly available for download by the authors. For a number of reasons, the resulting gaps do not match exactly. First, they focus on manufacturing gaps only, whereas I have gaps 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 9: 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 10: Compare



6 Anti-competitive Effect

Here I present the results analog to the pro-competitive analysis of Section 1.3.1, but switching the treatment variable from Gap_s to Input Gap_s. As also discussed in Section 1.3.1, these have a number of shortcomings, but I report them for completeness. Starting with estimations for specifications with Markup in levels in Table A.1

Table 8: Markup Level and Input Gap

	All Sectors				Manufacturing/Not Manufacturing			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Input Gap DR	-0.63**	-0.62	0.00	0.35				
	(0.32)	(0.54)	(0.35)	(0.27)				
Input Gap DR Manuf.					-0.50*	-0.65	0.07	0.18
					(0.29)	(0.57)	(0.35)	(0.23)
Input Gap DR Not Manuf.					0.73	-0.25	0.77	2.83**
					(1.00)	(1.37)	(0.93)	(1.25)
Year FE	No	No	Yes	No	Yes	No	Yes	No
Year*NAICS2 FE	No	Yes	No	Yes	No	Yes	No	Yes
Firm Trend	No	No	Yes	Yes	No	No	Yes	Yes
Average Markup	1.52							
Observations	15,334	15,334	15,334	15,334	15,334	15,334	15,334	15,334
R-Squared	0.80	0.81	0.89	0.90	0.80	0.81	0.89	0.90

All columns with Firm FE

Standard errors in parentheses, clustered by sector

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The specifications with Markup in first differences in Table A.2

Table 9: Markup Difference and Input Gap

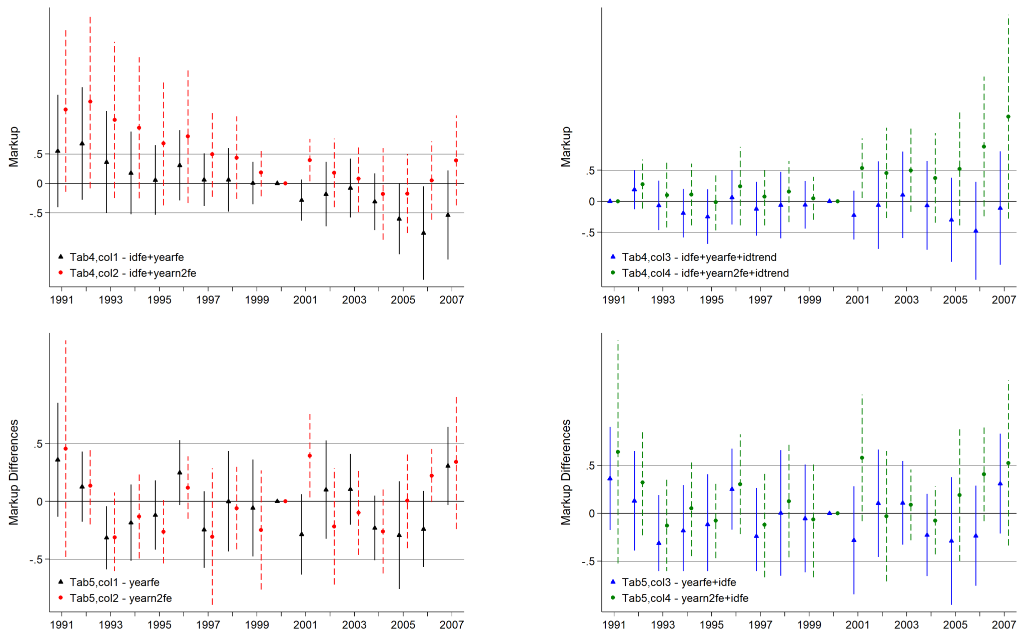
	All Sectors				Manufacturing/Not Manufacturing			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Input Gap DR	-0.08	0.06	-0.06	0.13*				
	(0.05)	(0.06)	(0.07)	(0.08)				
Input Gap DR Manuf.					-0.00	0.05	0.04	0.11
					(0.04)	(0.06)	(0.06)	(0.08)
Input Gap DR Not Manuf.					0.69***	0.18	1.01***	0.43*
					(0.17)	(0.18)	(0.20)	(0.25)
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Year*NAICS2 FE	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Average Markup Dif.								
Observations	15,334	15,334	15,334	15,334	15,334	15,334	15,334	15,334
R-Squared	0.00	0.03	0.03	0.05	0.00	0.03	0.03	0.05

Standard errors in parentheses, clustered by sector

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

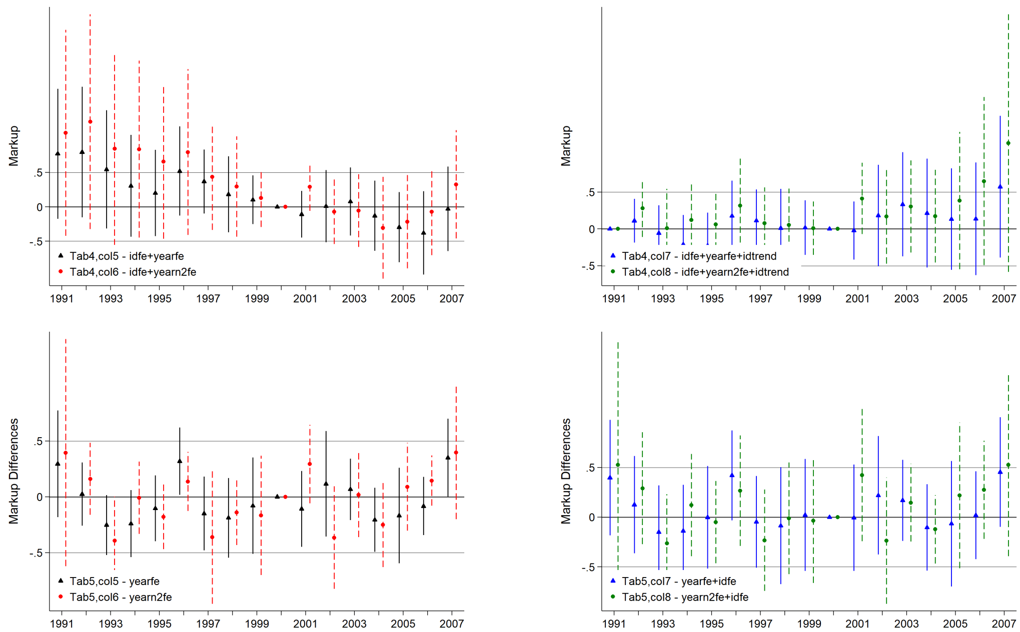
And the corresponding event studies in Figure A.3

Figure 11: Anti-Competitive - Event Studies



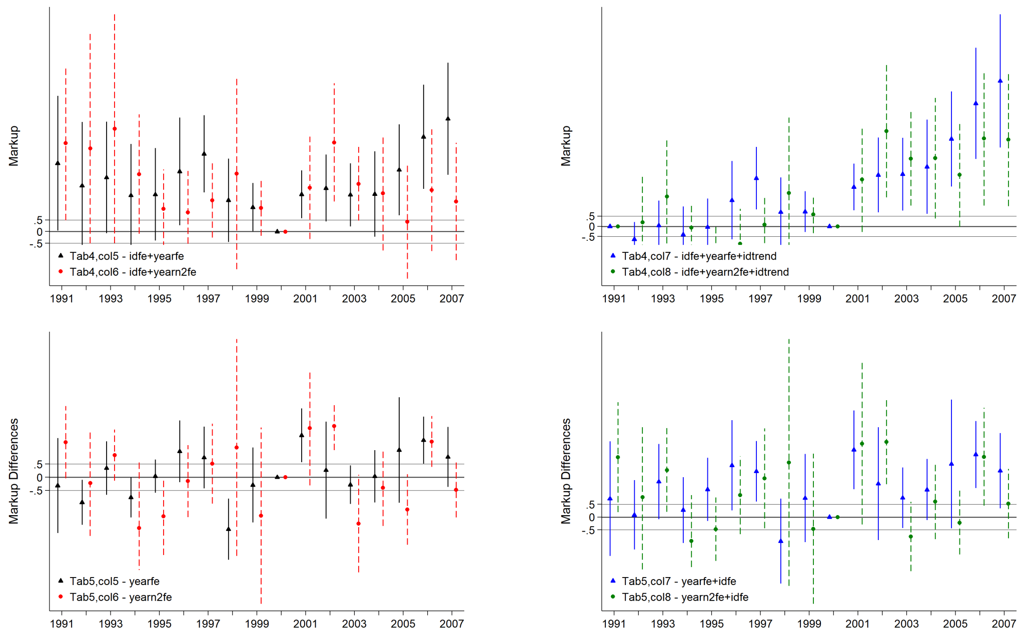
The event study for the specification that splits manufacturing presented in Figure A.4

Figure 12: Anti-competitive in Manufacturing - Event Studies



and for non-manufacturing in Figure A.5

Figure 13: Anti-competitive in non-Manufacturing - Event Studies



Finally, the estimation for the stacked differences specification in Table A.3

Table 10: Markup Stacked Differences and Input Gap

	All Sectors				Manufacturing/Not Manufacturing			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Input Gap DR	-0.12*	-0.06	-0.08	0.00				
	(0.07)	(0.05)	(0.09)	(0.07)				
Input Gap DR Manuf.					-0.13**	-0.04	-0.09	0.05
					(0.06)	(0.04)	(0.08)	(0.07)
Input Gap DR Not Manuf.					-0.24	-0.40**	-0.22	-0.59**
					(0.20)	(0.16)	(0.31)	(0.27)
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Year*NAICS2 FE	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Average Markup Dif.								
Observations	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804
R-Squared	0.00	0.04	0.35	0.37	0.00	0.04	0.35	0.37

Standard errors in parentheses, clustered by sector

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7 Pro-Competitive and Anti-competitive Effect

Here I present the analogs to Tables A.1-A.3 but adding the Input Gap. Starting with the analog for Table A.4

Table 11: Markup Level, Gap and Input Gap

	All Sectors				Manufacturing/Not Manufacturing			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gap	0.07	0.16	-0.07	-0.05				
	(0.15)	(0.16)	(0.11)	(0.15)				
Input Gap DR	-0.81*	-0.71	0.18	0.38				
	(0.47)	(0.56)	(0.35)	(0.29)				
Gap Manuf.					0.13	0.16	-0.06	-0.06
					(0.16)	(0.16)	(0.12)	(0.15)
Gap Not Manuf.					-0.01	0.06	0.90	1.18**
					(0.72)	(0.67)	(0.71)	(0.57)
Input Gap DR Manuf.					-0.80*	-0.74	0.17	0.21
					(0.47)	(0.59)	(0.34)	(0.26)
Input Gap DR Not Manuf.					1.11	-0.28	0.14	2.13*
					(1.13)	(1.41)	(1.05)	(1.18)
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Year*NAICS2 FE	No	Yes	No	Yes	No	Yes	No	Yes
Firm Trend	No	No	Yes	Yes	No	No	Yes	Yes
Average Markup	1.52							
Observations	15,334	15,334	15,334	15,334	15,334	15,334	15,334	15,334
R-Squared	0.80	0.81	0.89	0.90	0.80	0.81	0.89	0.90

All columns with Firm FE

Standard errors in parentheses, clustered by sector

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Running the same specifications in first differences, the analog to Table A.5 is

Table 12: Markup Difference, Gap and Input Gap

	All Sectors				Manufacturing/Not Manufacturing			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gap	-0.02	0.02	-0.04**	-0.00				
	(0.02)	(0.02)	(0.02)	(0.02)				
Input Gap DR	-0.03	0.04	0.06	0.14*				
	(0.06)	(0.06)	(0.08)	(0.08)				
Gap Manuf.					0.01	0.02	-0.01	-0.00
					(0.02)	(0.02)	(0.02)	(0.02)
Gap Not Manuf.					-0.03	0.01	0.01	0.08
					(0.14)	(0.11)	(0.15)	(0.15)
Input Gap DR Manuf.					-0.03	0.03	0.07	0.12
					(0.06)	(0.06)	(0.07)	(0.08)
Input Gap DR Not Manuf.					0.73***	0.18	0.98***	0.38
					(0.23)	(0.20)	(0.25)	(0.27)
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Year*NAICS2 FE	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Average Markup Dif.								
Observations	15,334	15,334	15,334	15,334	15,334	15,334	15,334	15,334
R-Squared	0.00	0.03	0.03	0.05	0.00	0.03	0.03	0.05

Standard errors in parentheses, clustered by sector

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Finally, the stacked difference specification, analog to Table A.6

Table 13: Markup Stacked Differences, Gap and Input Gap

	All Sectors				Manufacturing/Not Manufacturing			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gap	-0.00	0.01	-0.01	0.01				
	(0.02)	(0.01)	(0.03)	(0.03)				
Input Gap DR	-0.11**	-0.07	-0.06	0.00				
	(0.05)	(0.05)	(0.09)	(0.08)				
Gap Manuf.					-0.01	0.01	-0.02	0.01
					(0.01)	(0.01)	(0.03)	(0.03)
Gap Not Manuf.					-0.22	-0.10	0.33	0.29
					(0.22)	(0.09)	(0.50)	(0.30)
Input Gap DR Manuf.					-0.11**	-0.04	-0.07	0.04
					(0.05)	(0.05)	(0.09)	(0.07)
Input Gap DR Not Manuf.					-0.14	-0.35**	-0.44	-0.76*
					(0.26)	(0.17)	(0.45)	(0.41)
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Year*NAICS2 FE	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Average Markup Dif.								
Observations	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804
R-Squared	0.00	0.04	0.35	0.37	0.00	0.04	0.35	0.37

Standard errors in parentheses, clustered by sector

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$