The Anticompetitive Effect of Trade Liberalization*

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September 19, 2025

Abstract

Recent decades have been characterized by a surge in firms' market power within the global economy. In this paper, we study the role played by globalization in determining the evolution of markups in the small open economy of Belgium. Using detailed balance sheets and trade data for manufacturing firms over the period 2000-2015, we provide evidence of the role played by Chinese import competition on the evolution of various measures of market power. According to our estimates, the China shock increased aggregate markups and induced higher market concentration and markup dispersion. These changes are driven not by the reallocation of market shares towards high-markup firms but by increases within incumbents along with productivity gains. Our findings suggest that trade liberalizations can indirectly lead to anti-competitive effects if the resulting market concentration increases due to tougher competition.

Keywords: Trade Competition, Markups, China Shock, Market Power **JEL Classification:** D22, D24, F14, L11

*We are grateful to Jan Eeckhout, Giammario Impullitti, Thomas Philippon, Ariell Reshef, and Gonzague Vannoorenberghe for their comments and suggestions. We thank participants at the 21st and 23rd ETSG Conferences, the 12th International Conference in Bari, the 5th Baltic Economic Conference in Vilnius, the 1st Baltic Central Banks Conference in Riga, the 13th Annual Meetings of the Armenian Economic Association in Yerevan and seminar audiences at UCLouvain, LSE, Maastricht University, UNamur, PSE, Tilburg University, Bank of England, and TalTech. Verdini gratefully acknowledges financial support from F.S.R.-FNRS. The views expressed herein are those of the authors and do not necessarily reflect the view of the National Bank of Belgium or the European System of Central Banks.

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1 Introduction

Recent years have witnessed a growing concern, among academics and policy-makers, about market competition in Europe and the United States (Syverson, 2019). Recent studies document that concentration (e.g., Gutiérrez and Philippon, 2018) and markups (e.g., De Loecker et al., 2020) rose over the last forty years,[1] suggesting a surge in aggregate market power with potential negative consequences for business dynamism (De Loecker et al., 2021) and workers' conditions (Deb et al., 2022).

A debate is open about the possible rationales explaining the rising in market concentration and markups. Autor et al. (2020) propose the "superstar firms" hypothesis. They show that higher concentration is driven by reallocation to large and productive firms. This shift results from competitive forces turning leading firms into dominating superstars. Other studies (e.g., Philippon, 2019) propose the "declining competition" hypothesis where they associate the rise in market power with weak antitrust enforcement.[2] The main idea behind this theory is that regulatory capture by large firms generated entry barriers preventing competitors from entering the market.[3] Alternatively, the "intangible assets" hypothesis (e.g., Eeckhout, 2021) postulates that industry leaders gain a competitive edge by investing more in intangibles (e.g., patents) to increase entry barriers.[4]

The international trade literature theoretically characterizes the relationship between globalization and market structure, defining the potential implications for aggregate market power (Arkolakis et al., 2019). This paper provides an empirical test of the relationship between globalization and market power by investigating how international trade affects the evolution of market power in the Belgian manufacturing sector from 2000 to 2015. To this extent, we exploit the surge of China, as a global manufacturing power, as a quasi-natural experiment to estimate the effects of a rise in import competition (Autor et al., 2013). To address endogeneity concerns, we build an instrumental variable strategy in the spirit of Acemoglu et al. (2016) that allows

[1] In their seminal contribution, De Loecker et al. (2020) provide evidence of the rise in market power for the United States, however this pattern has been confirmed across countries and sectors (e.g., Bajgar et al., 2019; Calligaris et al., 2018; De Loecker and Eeckhout, 2018; Díez et al., 2021; and Eggertsson et al., 2021).

[2] Covarrubias et al. (2020) and Grullon et al. (2019) provide evidence of increasing concentration, associated to lower investment and business dynamism, for the United States. For a comparison with the European Union, see Gutiérrez and Philippon (2018).

[3] For a recent discussion on the political economy of antitrust enforcement, see Lancieri et al. (2022).

[4] For the U.S. context, Crouzet and Eberly (2019) provide empirical evidence of this mechanism. De Ridder (2023) propose a framework to quantify the impact of intangibles investment on productivity slowdown for the U.S. and France.

to capture variation stemming from Chinese export potential in the manufacturing sector.

In a standard trade model with firm heterogeneity and variable markups, trade openness is pro-competitive because it induces a reallocation of market shares from low-productive to high-productive firms, and forces the latter to reduce their level of markups with consequential positive welfare effects (Melitz and Ottaviano, 2008).[5] Surprisingly, our results indicate that the rise in competition driven by the China shock has a positive effect on aggregate industry-level markups and concentration, hence it is anti-competitive. In our benchmark estimates, we find that Chinese import competition explains one-fourth of the variation in aggregate markups.

Belgium is an ideal setup to study the link between globalization and market power for several reasons. First, the country is small in size and extensively reliant on international trade, making it an excellent small-open economy case study. Second, as for other developed countries, Belgium experienced a significant increase in import competition from China, as documented by Mion and Zhu (2013), but relatively less from other low-income countries. Third, the availability of detail balance sheets data allows for the estimation of firm-level markups, an essential element to understand the degree and evolution of market power. We additionally aggregate information at the industry level to compute a whole set of measures related to market power. In particular, the aggregate markup, the Herfindahl Index (HHI), the concentration ratio for the top four largest firms (CR4), and the Theil index for markup dispersion.

To retrieve markups, we employ the control function approach developed by Ackerberg et al. (2015) to estimate production functions and the optimal variable input demand condition approach popularized by De Loecker and Warzynski (2012). This approach has become standard in the industrial organization and macro literature, and builds on the insights of Hall (1986) regarding the relationship between input and output growth under imperfect competition. In particular, positive markups should be captured when the former causes a disproportional growth of the latter.[6]

[5]Many studies analyzed how product market distortions interact with international trade. The pioneering work of Brander and Krugman (1983) shows that under Cournot competition with homogeneous products, trade openness reduces markups unambiguously. However, overall welfare effects depend on the extent of trade costs. Other studies analyzes the pro-competitive effects of international trade using model of firm-level heterogeneity and monopolistic competition models (e.g., Epifani and Gancia, 2011; Dhingra and Morrow, 2019), Bertrand competition (De Blas and Russ, 2015) or Cournot competition (e.g., Edmond et al., 2015, Asturias et al., 2019). Nevertheless, Arkolakis et al. (2019) show that variable markups play a limited role in explaining gains from trade.

[6]A growing body of literature has highlighted some limitations with the current approach and has provided some extensions or refinements. Klette and Griliches (1996) highlight the importance to account for the potential correlation between output prices and firms' input choices, namely the input

Our empirical model aims to test how the cross-industry variation in the rise of Chinese import exposure affected the evolution of markups. However, OLS estimates might suffer from an omitted variable bias. For instance, a sector's unobservable positive demand shock might induce a simultaneous increase in markups and imports. Therefore, building upon Acemoglu et al. (2016), we construct an instrumental variable (IV) using sector-level Chinese import data for eight other high-income economies to identify the impact of the China shock. In our strategy, the identifying assumption requires cross-country sectoral demand for Chinese imports to be uncorrelated.[7]

We test the empirical model over two sub-periods, 2000-08 and 2008-15, and on the stacked version to account for short- and long-term impacts. The 2SLS estimates indicate that sectors relatively more exposed to Chinese import competition experienced increasing markups. In line with the insights of Chen et al. (2009), we find this anti-competitive effect to prevail in the second part of our sample period, suggesting that market structure adjustments realize in the long-run. We also inquire about potential drivers behind the rise in markups by applying the dynamic aggregate decomposition strategy proposed by Melitz and Polanec (2015). Our results are explained by firms' average increase in markup rather than a reallocation of market shares towards high-markup firms. Oppositely, we find evidence of a negative effect on markups on the reallocation and exit margins suggesting the presence of pro-competitive effects that are too weak to compensate for the rise in the within-firm component.

Additionally, we find a positive impact on sector-level Total Factor Productivity (TFP) in the second period, suggesting a comovement between markups and productivity, as in De Ridder (2023). To explain the increase in markups, we test the impact of the China shock on industry concentration. We find that the increase in China import competition raises market concentration, suggesting that exposure to Chinese competition increases incumbents' market power. To understand the potential implication

price bias. Following the critique, several works have proposed the use of output and input quantities to generate unbiased estimates of the input elasticities (Foster et al., 2008; De Loecker, 2011; Garcia-Marin and Voigtländer, 2019; Bond et al., 2020; Doraszelski and Jaumandreu, 2021). Grieco et al. (2016) propose a framework to estimate production functions when input quantities are not observed that relies on the CES production function. An additional aspect concerns the lack of independent variation in input expenditure that can potentially hinder the identification of input elasticities in the ACF framework. To circumvent the issue, Gandhi et al. (2020) propose to rely on factor share and a non-parametric estimation derived from the flexible input first-order condition.

[7] Identification strategies using shift-share designs have been under scrutiny because of potential issues in the exogeneity assumption of the instrument, either because of the shift or the share component. These studies raise a concern with the use of shift-share in an international trade context when the exogenous variation does not come from tariff changes (Adão et al., 2019; Goldsmith-Pinkham et al., 2020; and Borusyak et al., 2022). Moreover, Adão et al. (2023) highlight the importance of using a theory-based shift-shares to account for the general equilibrium effects of the "China shock".

of trade for resource misallocation, we assess the impact of the China shock on the evolution of markup dispersion.[8] In this respect, we estimate a positive effect suggesting a potential worsening of allocative efficiency in the period 2008-2015. Overall, our findings suggest that Chinese import competition only impacts the market structure in the long run.

Related Literature. Our paper relates to several strands of the literature. First, we contribute to the ongoing debate on the rise of market power. In their pioneering contribution, De Loecker et al. (2020) are the first to systematically document a steady rise in markups since the 80s for the U.S. economy.[9] According to their estimates, the rise in market power is induced by a reallocation of market shares toward high-markup and large firms. This result is consistent with the "superstar firm" hypothesis (Autor et al., 2020). The evidence about industry concentration also confirms the rise in market power. Covarrubias et al. (2020) and Grullon et al. (2019) show increasing concentration in U.S. markets, but the evidence for European countries is mixed.[10] We contribute to this literature by providing systematic evidence on the role of international competition in explaining the surge in market power.

We also contribute to the empirical literature on the relationship between import competition and markups. Early empirical evidence finds that trade liberalization reduces markups (Levinsohn, 1993; Harrison, 1994; Krishna and Mitra, 1998).[11] Recently, Impullitti and Kazmi (2022) exploit Spain's accession to the European Customs Union as an exogenous competition shock. They show that pro-competitive effects are weaker in sectors characterized by high entry barriers, suggesting that the domestic market structure plays a role in determining the benefits of a trade liberalization. More generally, trade liberalization can affect firms both on the input and the output sides. Chen et al. (2009) test the predictions of Melitz and Ottaviano (2008) for seven EU countries over the period 1989-1999. They find that trade openness reduces the average industry markup in the short run; however, in the long run, the effect of import competition is ambiguous and even (weakly) anti-competitive. De Loecker

[8]As discussed in Epifani and Gancia (2011), dispersion in aggregate industry markups induces intersectoral misallocation. This is due to the fact that high-markup sectors underproduce and low-markup sectors overproduce with respect to the socially optimal quantity. Moreover, they show that trade liberalization might generate pro-competitive losses by increasing markup dispersion.

[9]This pattern has been confirmed across countries worldwide (De Loecker and Eeckhout, 2018; Díez et al., 2021).

[10]Bajgar et al. (2019) and Affeldt et al. (2021) find a pattern of increasing concentration across major EU countries and geographically defined products, especially in the service sector. Conversely, using aggregate data from KLEMS, Cavalleri et al. (2019) find no evidence of rising concentration and markups for the four biggest European economies.

[11]For a review on the "import-as-market-discipline" hypothesis see Tybout (2003)

et al. (2016) exploit the 1991 Indian trade liberalization episode and find that lower output tariffs put downward pressure on markups, while lower input tariffs increase them. This result provides evidence of an incomplete pass-through for input cost shocks.[12]

Closely related to our paper, Aghion et al. (2021) exploit the Chinese accession to WTO as an exogenous shock to pin down the competition effect French firms' performance and innovation. They distinguish the effect driven by direct competition in the output market from the input cost shock and find a negative impact of tougher competition on firm-level sales, employment, and innovation. Compared to their work, we focus on the import competition channel and its effect on firms' markups in the manufacturing sectors of Belgium, a small open economy. In the context of Belgium, De Loecker et al. (2014) provide evidence of increasing profit margins induced by Chinese competition due to a strong reduction in marginal costs. that However, they only consider a subset of manufacturing firms and perform the analysis at the firm level, not accounting for the aggregate implications of the shock. Compare to them, we highlight how increasing concentration from tougher competition can also lead to a rise in markups.

Finally, we contribute to the literature on the China shock. Several studies document how the swift rise of Chinese import competition in the U.S. manufacturing sector has negatively affected the domestic labor market.[13] Moving beyond the labor market implications, Bloom et al. (2016) use the termination of the Multi-Fiber Agreement to assess the impact of import exposure on productivity and innovation of the European textile sector. We contribute to this line of research by showing how import competition from China impacted the Belgian manufacturing market structure, markups, and productivity across all manufacturing sectors.

Outline. The remainder of the paper is structured as follows: Section 2 describes the data sources. Section 3 presents the main theoretical and empirical methodology. Section 4 discusses the liberalization episode and the source of variations used in

[12]The literature also addresses the impact of export liberalization on market power and markups. De Loecker and Warzynski (2012) show that exporters charge higher markups and firms increase markups upon entry in international markets. In the context of China, Lu and Yu (2015) provide evidence of decreasing markup dispersion among Chinese manufacturing firms after the Chinese accession to the World Trade Organization (WTO), which is consistent with the idea that competition reduces misallocation in the economy. Brandt et al. (2017) document pro-competitive effects of Chinese trade liberalization on domestic firms through the reduction of incumbents' markups.

[13]See Autor et al. (2016) for a literature review on the China shock. Specifically, see Mion and Zhu (2013) for the Belgian manufacturing sector.

the empirical analysis. Sections 5 presents the industry-level empirical results and discuss the mechanisms at play. Finally, Section 6 concludes.

2 Data

In our analysis, we construct a panel of Belgian manufacturing firms over the 1996-2015 period by combining balance-sheet information with trade data at the firm level. Additionally, we compute a measure of exposure to Chinese import competition and the relative instrument using aggregate trade data.

Balance sheet data are retrieved from the Annual Accounts and the VAT declarations provided by the Central Balance Sheet Office of the National Bank of Belgium and the Belgian Ministry of Finance (*SPF Finance*). The Annual Accounts report balance sheet information for the universe of Belgian firms. In particular, the dataset provides yearly information about firms' 4-digit NACE Rev. 2 (NACE4) industry code, the total turnover (Y), value added (VA), fixed (K) and intangible (INT) capital, the number of full-time equivalent (FTE) employees (L), the wage bill (WB) and the value of total intermediates (M) used in production. All nominal values are deflated and reported in real terms. Concerning the capital stock, we use as definition the net value of a firm's fix assets. The VAT Declarations are collected by the Belgian tax authority and complement firm-level information about turnover and intermediate inputs for those Belgian firms below certain employment, turnover, and total assets thresholds.[14] Finally, we extract information about workers' occupations at the firm level from the Social Security data. These information allows to distinguish between blue-collar and white-collar employees that we use to build beginning-of-the-period controls at the firm and industry levels.

Information on international trade at the firm and industry level is collected from the Transaction Trade dataset of the National Bank of Belgium and the United Nations Comtrade database. Transaction Trade data provide firm-level information about export and import at the 6-digit Harmonized System (HS) product level. From UN Comtrade, we collect trade data at the 6-digit HS product classification from 1996 to 2015 that we match to the corresponding NACE4 industry level. Appendix A details

[14] A firm is not required to fill the complete form if it has not met more than one of the following threshold in the last two financial years: *i*) an annual average workforce of 50 employees quantified in FTE; *ii*) a total turnover (excluding VAT) of 7.3 million euro; *iii*) a balance sheet total of 3.65 million euro. Note that, firms reporting an annual average workforce above 100 units in FTE are always required to fill the form.

our matching procedure to link HS6 product categories to the corresponding NACE4 industry code.

Table 1: Summary Statistics for Manufacturing Firms over the Period 1996-2015

			Percentiles				
	Mean	*St. Dev.*	*p5*	*p25*	*p50*	*p75*	*p95*
Panel A: Full Sample							
Sales (Y)	13.02	135.00	0.15	0.41	1.11	3.87	35.93
Capital Stock (K)	2.02	16.99	0.00	0.06	0.23	0.73	5.61
Intangibles (INT)	0.45	24.52	0.00	0.00	0.00	0.00	0.14
Intermediate Inputs (M)	10.71	157.53	0.07	0.23	0.69	2.70	27.41
Employment in FTE (L)	37.94	192.82	1.40	7.20	21.60	60.05	127.30
Wage Bill (WB)	1.94	12.84	0.03	0.09	0.24	0.80	5.94
Panel B: Only Firms in Trade							
Sales	27.40	199.19	0.65	1.47	3.95	11.80	39.93
Capital Stock	4.10	25.01	0.02	0.17	0.60	1.86	12.79
Intangibles	0.98	36.35	0.00	0.00	0.00	0.01	0.49
Intermediate Inputs	22.39	204.48	0.23	0.98	2.78	8.71	67.21
Employment in FTE	74.56	281.03	2.00	7.60	19.80	48.45	272.00
Wage Bill	3.95	18.82	0.06	0.26	0.75	2.08	13.97
Export	17.32	138.54	0.00	0.00	0.56	4.75	54.20
Import	11.83	112.30	0.00	0.01	0.66	3.18	33.25

Notes: The full sample contains 195,118 firm-year observation, for 21,597 firms. The sample with only trading firms counts 93,601 firm-year observations, for 12.354 firms. Among these, 4.112 firms sourced at least once from China over the period. The table reports firm-level output and factors of production used later in the estimation procedure. Sales, capital, intermediates, wage bill, and trade are expressed in million of euros, employment is in full-time equivalent. All nominal variables are deflated as described in Appendix B.

We perform a data cleaning routine to correct our sample from data misreporting. The details of our data cleaning procedure are reported in Appendix B. In particular, we drop any observation reporting negative values for sales, value-added, or total assets from the original sample. The final sample contains 195,118 firm-year observations identifying 21,597 unique firms over 184 manufacturing industries for the 1996-2015 period. Table 1 shows the summary statistics. Panel A reports total sales, the stock of fixed and intangible capital, the amounts of intermediate inputs purchased, the level of employment in FTE, and the total wage bill for all firms. Looking at the variables' distribution, the skewed nature of the manufacturing sector along all dimensions emerges, with roughly half a standard deviation separating the firm at the 75th compared to the one at the 95th percentile. Panel B reports information for the 12,354 firms involved in international trade. These are, on average, larger and more capital-intensive than their domestic counterparts. We will consider this information for estimating markups and productivity by introducing controls for the firm's export activity.

3 Methodology

3.1 Markups Estimation

A key issue for our empirical strategy is to choose an appropriate measure of firms' market power. A natural candidate is the price-to-marginal cost ratio, namely the price markup. This ratio measures the wedge between the price level charged by firms in a world of perfect competition with no distortions and the observed one.[15] However, despite the extensive access to production price data, it is hardly feasible to retrieve information about firms' marginal costs.[16]

For this reason, we follow the markup estimation methodology developed by De Loecker and Warzynski (2012) that builds on the insights of Hall (1986) and relies on the use of available firm-level balance sheet data. The intuition is that, with perfect competitive markets, input cost shares should be equal to the output elasticity of its respective input. Therefore, any price deviation from this benchmark should be considered as a result of firm market power. Furthermore, this methodology is flexible enough to encompass various market structures and it does not require to impose a specific demand system.[17]

[15] Price markups can be the result of both demand and supply forces, and various model generate positive markups at the equilibrium. Models featuring dynamic Bertrand-Nash competition or static Cournot competition deliver predictions for the level of markups due to firms' market power. Therefore, under certain conditions, the distribution of price markup in the economy is a sufficient statistics to evaluate the extent of market power

[16] A notable exception is Garcia-Marin and Voigtländer (2019), in which the authors have accessible product level information on prices and marginal costs of production for the Chilean manufacturing firms.

[17] Recent works raised several critiques to the markup estimation methodology. Doraszelski and Jaumandreu (2021) highlight how first-stage misspecification can induce severe biases to the estimated measure of markup, while Bond et al. (2020) points to the necessity to have a quantity and not revenue based estimation of the production function. We cannot exclude these aspects to play a role in our setting, however De Ridder et al. (2023) show that the revenue-based markup measure is only biased in levels, but not in its dispersion and correlation to other firm-level measures of profitability.

We consider a firm i at time t with the following production function:[18]

$$Q_{it} = F_{it}(L_{it}, K_{it}, M_{it}, \Omega_{it}), \tag{1}$$

where Q_{it} denotes gross output, $F_{it}(\cdot)$ the production function defined over labor, L_{it}, capital, K_{it}, intermediates, M_{it}, and the productivity shock, Ω_{it} . We assume the production function, $F_{it}(\cdot)$, to be continuous and twice differentiable in its arguments. The markups identification strategy proposed by De Loecker and Warzynski (2012) relies on the firm's capability to flexibility adjust at least one of the inputs in production. Plenty of evidence points to the fact that firms' input choices are subject to adjustment costs, as in the case of capital due to the its durable nature, or the case of labor due to labor market regulation. Following the literature, we assume capital to be a dynamic input in production, conversely intermediate inputs can be freely adjusted at each period t. Variation in the firm use of intermediate inputs is key to identify markups. Given that the Belgian economy is characterized by a rigid labor market, we do not assume labor to be flexible, differently from De Loecker and Warzynski (2012).[19]

As shown by De Loecker and Warzynski (2012), we can derive from the minimization problem of equation (1) the following expression for markups:

$$\mu_{it} = \theta_{it}^{M} (\alpha_{it}^{M})^{-1}, \tag{2}$$

where θ_{it}^{M} is the output elasticity of intermediate inputs, and α_{it}^{M} is the share of intermediate input expenditures on total sales. A revision of the theoretical model can be found in Appendix C, here it is sufficient to highlight how the main advantage of framework is to allow the estimate of markups by mean of only two parameters.

Firm-level balance sheet data contain the necessary information to compute α_{it}^{M}, conversely θ_{it}^{M} is not readily available and must be estimated. The empirical literature on production function estimation provides a wide range of alternative procedures to correctly pinpoint input elasticities by controlling for unobserved productivity

[18]For simplicity, we omit the industry subscript, since the empirical framework holds symmetrically for every sector. Note that this does not mean that across sectors input shares are the same. The model allows different sectors to produce using different inputs mix.

[19]As discussed in Konings and Marcolin (2014), Belgium has a centralized hierarchical system of collective bargaining for wages, in particular they show that productivity-wage differential are significant and strongly persistent, indicating the extent of rigidity in which Belgian firms operate. In addition, Dhyne et al. (2015) provide evidence of high adjustment cost for net labor changes in the context of Belgium. In light of this evidence, we assume labor to be a dynamic input in production like capital.

shocks. To retrieve the parameter θ_{it}^{M}, the key challenge in estimating production functions is to deal with the endogeneity of the productivity to the input choices. Thus, we estimate the production function using the control function methodology proposed by Ackerberg et al. (2015).[20]

Production function estimation is performed for each aggregate manufacturing sector, in particular we bring to the data a log-linearized version of equation (1):

$$q_{it} = f_{it}(l_{it}, k_{it}, m_{it}; \beta) + \omega_{it} + \varepsilon_{it}, \tag{3}$$

where the production function $f_{it}(\cdot)$ is assumed to be translog, ω_{it} is the Hicks neutral productivity level observed by the firm, potentially correlated to the level of the inputs in production, while ε_{it} is the unanticipated productivity shock assumed to be independent and identically distributed across firms. A limitation in our setup is the need for more data on quantities that can induce a price bias in the estimates. However, De Ridder et al. (2022) show that this bias is attenuated when studying markup changes over time, which is the focus of our empirical exercise. Appendix D presents the production function methodology in detail, with an exposition of the set of assumptions and the identification strategy.

Table 2 reports the estimated output elasticities and markups at the aggregate industry level. The reported coefficients are averages across the entire sample period and feature sizeable variation within and across industries. We find intermediate inputs to generate higher marginal revenues for labor and capital, with values ranging between 0.70 and 0.75 for the former and around 0.05 and 0.25 for the latter. Notice that elasticities do not necessarily sum up to one since we are not imposing constant returns to scale.

Figure F.1 and F.2 in Appendix F show the evolution of the aggregate markup respectively revenue-weighted and unweighted. Figure F.3 shows the evolution of the distribution of firm-level markups for the years 2000, 2008, and 2015. All the figures show an increase in the markups, both in the aggregate and in the dispersion.

[20]It is well known, since the work of Marschak and Andrews (1944), that productivity should not be considered as exogenous with respect to the firm, since the latter makes choices about the optimal input mix taking productivity into account. In such context, the correlation between inputs and productivity levels is expected to be positive, hence introducing a bias in the resulting OLS estimation. To solve for this problem, the production function estimation literature provides two frameworks to estimate output elasticities and productivities: the dynamic panel method proposed by Arellano and Bond (1991), and Blundell and Bond (1998; 2000), and control function approach proposed first by Olley and Pakes (1996) and lately extended by Levinsohn and Petrin (2003), Wooldridge (2009), Ackerberg et al. (2015), and Gandhi et al. (2020).

Table 2: Output Elasticities and Markups at Broad NACE Sector

Industry	Output Elasticities of			Markup			Firms
	Capital	*Labor*	*Intermediates*	*Median*	*Mean*	*Sd. Dev.*	
Food, Beverages, and Tobacco	0.05	0.25	0.71	1.11	1.12	0.26	5,109
Textile, Wearing Apparels, and Leather Products	0.05	0.23	0.72	1.02	1.11	0.33	2,187
Wood, Paper Products, and Printing	0.05	0.22	0.71	1.07	1.12	0.29	4,134
Chemicals and Pharmaceutical	0.07	0.31	0.75	0.97	1.02	0.28	888
Rubber and Plastic Products	0.04	0.23	0.74	0.95	1.02	0.31	926
Other Non-Metallic Mineral Products	0.05	0.24	0.71	1.05	1.09	0.24	1,477
Basic and Fabricated Metal Products	0.05	0.21	0.71	1.10	1.14	0.30	5,559
Computer, Electronics, and Optical Products	0.06	0.26	0.70	1.01	1.06	0.29	464
Electrical Equipment	0.06	0.26	0.74	1.22	1.28	0.32	576
Machinery and Equipment n.e.c.	0.06	0.25	0.70	1.12	1.17	0.26	1,578
Vehicles and Transport Equipment	0.06	0.25	0.75	1.04	1.10	0.30	457
Furniture, Other Manufacturing, and Repairing	0.04	0.21	0.72	1.16	1.23	0.33	3,262

Notes: Estimation is performed on the sub-sample that went through the second round of cleaning as described in Appendix A. We estimate output elasticities and markups using the algorithm from De Loecker Warzynski (2012). We assume a firm-level translog production function and we treat capital and labor as predetermined. Firm-level markup is calculated as the ratio between the intermediate output elasticity and the relative revenue share, the latter corrected for the first stage error.

3.2 Aggregate Markup Decomposition

As described in Table 2, we observe a considerable heterogeneity in markups within sectors and across firms. To investigate the mechanism behind aggregate changes, we decompose them into changes in the within-firm average markup, the reallocation of market shares across firms, and the entry/exit of competitors in the market following the decomposition by Melitz and Polanec (2015).[21] As shown in Appendix E, it is possible to express the change in the aggregate markup between the two periods as:

$$\Delta M_j = \Delta \bar{M}_{c,jt} + \Delta \text{cov}_{c,jt} + s_{e,j2}(M_{e,j2} - M_{c,j2}) + s_{x,j1}(M_{c,j1} - M_{x,j1}), \tag{4}$$

where $\Delta \bar{M}_{c,jt}$ defines the change of aggregate markup coming from the sector-level shift in the average firm markup over the period, $\Delta \text{cov}_{c,jt}$ the change due to the reallocation of market shares between firms, and $s_{e,j2}(M_{e,j2} - M_{c,j2})$ and $s_{x,j1}(M_{c,j1} - M_{x,j1})$ respectively the contribution from entrants and exiters.

[21] In their paper, Melitz and Polanec (2015 extend the standard Olley and Pakes (1996) static decomposition to account for aggregate productivity changes over time. In doing so, it allows to identify the contribution of entry and exit. Despite being developed to study aggregate productivity changes, it is conceptually the same for various other firm-level measures, see for example Autor et al. (2020) for an application to the evolution of the labor share. With respect to the productivity literature, however, the structural interpretation do differs, since comovements between market shares and markups do not pertain to the same class of theoretical models.

We compute the dynamic decomposition for the entire period 2000-2015 and for the two subperiods 2000-2008 and 2008-2015. For any pair of periods t and $t+1$, we define the group of *incumbents* as firms reporting a positive market share in both t and $t+1$, the group of *entrants* as firms reporting no market share in t and positive market share in $t+1$, and the group of *exiters* as firms reporting positive market share in t, but no market share in $t+1$.

Figure F.4 in Appendix F shows the decomposition of the aggregate markup growth (dark blue) for the two sub-periods, 1995-2008 and 2008-2015, and the entire 2000-2015 period. First, we can see that the aggregate markup level rose by 9% over the period. Roughly, a 90% increase over the 1995-2015 period is due to the within-firm component. Reallocation of market share between firms accounts for less than 10%, even though the sign is negative in the first period, meaning that market shares were relocated to low-markup firms between 2000 and 2008. On the opposite, the effect is positive in the second half and dominates over the full sample period.

The role played by the extensive margin is minor, and the net effect of entry and exit is negative overall, suggesting that what matters is the high-markup firms exiting the market. This result is intuitive: firms entering the market account for a tiny fraction of the total market share in general while exiting firms might come from more consolidated positions. Another reason for the lack of action in terms of entry and exit is the lack of business dynamism in the Belgian manufacturing sector, as highlighted in Figure F.5, with a share of entry and exit firms well below 10% each year since the beginning of the sample.

3.3 Other Measures of Market Power

We construct concentration and within-industry markup dispersion measures to understand the mechanism behind markup changes.

Concentration Indexes. Concentration measures are widely used to infer the degree of market competition. As discussed in Covarrubias et al. (2019), concentration is not a sufficient statistics about the functioning of the market. In particular, high concentration can be associated with high entry barriers and incumbents' anti-competitive behaviors. However, it can also result from competition between market leaders that devote most of their revenues to capital investments and innovation.[22]

[22]Standard Cournot model of competition delivers equilibrium outcomes relating positively a firm market share with its markup and market power, as in Brander and Krugman (1983); however, models of innovation and endogenous growth might generate a negative correlation between the two measures,

In our setup, we address this potential ambivalence by analyzing the evolution of concentration and markups. This allows to get a better understanding of the type of concentration arising from the market structure. We propose two measures of concentration. As first measure, we define the Herfindhal index for industry j at time t as:

$$\text{HHI}_{jt} = \sum_i (s_{i,jt})^2, \tag{5}$$

where $s_{i,jt}$ is firm i share of total sales in both domestic and foreign industry j at time t. The measure ranges between $1/J$, when market shares are evenly distributed across incumbents, and 1, in the case in which sales are concentrated in the hand of a unique firm. Second, we also define the concentration ratio for the four largest incumbents as:

$$\text{CR4}_{jt} = \sum_{i=1}^{4} (s_{i,jt})^2, \tag{6}$$

for which i takes the top four values of firms' sales ranking.

Misallocation. To analyze the potential efficiency loss determined by the presence of market power, we construct a measure of industry dispersion of markups. From a theoretical point of view, the greater the dispersion of markups, the higher the efficiency losses due to misallocation. This result is theoretically driven by the presence of high-markup firms producing below their optimal level and low-markup firms producing above.[23] In this paper, we measure the markup dispersion by the Theil index. For industry j at time t, we define:

$$\text{Theil}_{jt} = \frac{1}{N} \sum_i \frac{\mu_{ijt}}{\bar{\mu}_{jt}} ln \left(\frac{\mu_{ijt}}{\bar{\mu}_{jt}} \right). \tag{7}$$

where N is the mass of firms, μ_{ijt} is firm's i estimated markup, and $\bar{\mu}_{jt}$ is the within-industry average markup level. The measure ranges between 0, for the case of no dispersion, and $\ln(N)$, for the case of maximum dispersion.

as in Aghion et al. (2005).

[23] See Lerner (1934) for a broader discussion and Epifani and Gancia (2011) and Dhingra and Morrow (2019) for more recent theoretical insights.

4 Exploiting the "China Shock"

To identify an international trade shock to the Belgian economy, we exploit the remarkable surge of China as a world manufacturing producer and exporter. The rising Chinese role in world trade is well suited for being used as a quasi-natural trade shock due to a concurrence of various factors, as extensively discussed in various seminal works (Autor et al., 2013; 2016). First, among the key drivers explaining the progressive increase of trade flows originating from China, there is a policy change, namely its accession to the WTO in 2001. This implied not only massive cuts in trade barriers with the Western economies, but also the reduction of uncertainty in those industries for which low tariffs were already put in place.[24] Second, both the trade liberalization and the massive induced migration from the rural areas of the West to the urban areas of the East allowed China to build a comparative advantage in the labor-intensive manufacturing industries, in which it eventually specialized. Finally, the realized shift in trade patterns was swift and largely unanticipated. In addition, evidence suggests that Belgium was largely exposed to the shock over the course of the last two decades. In particular, Mion and Zhu (2013) show that despite the increase in imports of Chinese products starting in the 2000s, Belgium did not experience a similar change in trade patterns with other low-income economies. This aspect is important for the validity of our empirical analysis.

Import Exposure. We examine the degree of import exposure for the 184 Belgian 4-digit NACE industries, over our sample period 2000-2015. We follow Mion and Zhu (2013) and define our measure of import exposure as the industry-level change in Chinese import share[25] weighted by the beginning-of-the-period industry imports and production values:

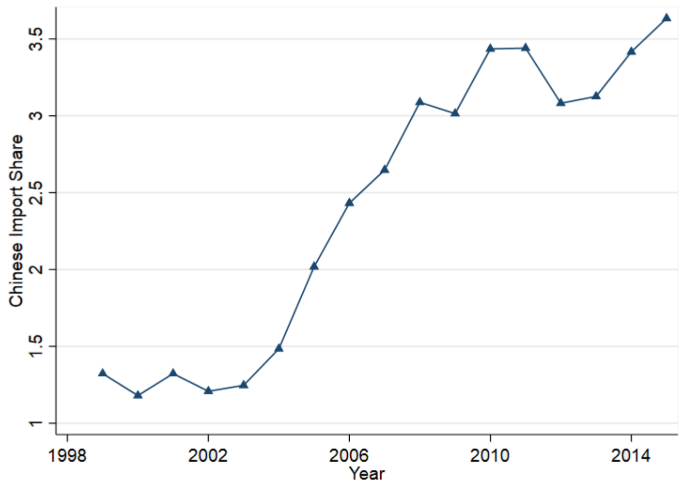
$$\Delta IS_{j,t}^{BECH} = 100 \times \frac{\Delta M_{j,t}^{BECH}}{Q_{j,2000} + M_{j,2000}}, \tag{8}$$

[24]Pierce and Schott (2016) Pierce and Schott (2016) discuss at length how this was a crucial factor for the trade relationship of China with the U.S. since the status for Normal Trade Relationships (NTR) had to be renewed for China every year since the '80, and became permanent only at the end of the 2000.

[25]Conversely to the standard import penetration measures proposed in Autor, Dorn, and Hanson (2013) or Acemoglu et al. (2016), import shares do not include aggregate export values at the denominator. Being Belgium the host of the second largest European port, Antwerp, it is characterized, in a few 4-digit industries, by larger exports with respect to the sum of imports and production, causing import penetration to be negative.

where $\Delta M^{BECH}_{j,t}$ is the long-run change in Chinese imports values in industry j, while $Q_{j,2000}$ and $M_{j,2000}$ are respectively Belgian total production and total imports in industry j at the beginning of the period. Variation in $\Delta IS^{BECH}_{j,t}$ across industries stems from variation in local industry openness to international imports in the base year, which arises from differential specialization in manufacturing and in import-intensive industries within manufacturing. In particular, import-intensive industries are expected to be relatively more exposed by the surge in trade with China.

Figure 1: Evolution of Chinese Import Share, Manufacturing



Notes: The figure show the evolution of aggregate Chinese import share in the manufacturing sector over the period 2000-2015. Import data comes from Comtrade, while production data from our constructed Belgian firm-level dataset.

To understand the importance of the China shock for the Belgian economy, Figure 1 reports the evolution of our aggregate measure of Chinese import exposure over the sample period. While in 2000, the share of the Chinese import on total production and imports was slightly above 1%, by 2010, it was more than two times larger, plateauing since. This figure shows that the rise in trade exposure in Belgium lags a few years after China's accession to the WTO, with the surge only happening from 2004 onward.

Endogeneity. It is important to recognize that OLS estimates might suffer from an omitted variable bias. To fix ideas, consider Figure 1 and the potential determinants behind the rise in Chinese import exposure over the decade. Chinese firms might become relatively more productive and be able to compete in various Belgian manufacturing sectors at the expense of local competitors. At the same time, however, some industries might experience a general expansion in sales induced by a change in consumers' preferences simultaneously raising demand for local and foreign producers. In the first case, we should expect a negative relationship between local firms' prices and imports from China. Conversely, in the second case, domestic firms would be able to exploit the rise in demand by potentially increasing prices introducing a mechanical correlation between markups and foreign imports.

To reduce concern about potential endogeneity arising from firms' optimization of their sourcing strategies, we follow the industry-level identification proposed by Acemoglu et al. (2016). We rely on an instrumental variable strategy that aims at capturing the variation in the rise of Chinese import share stemming from the country specialization in their comparative advantage over the period. In particular, we regress our measure of import exposure on the same measure constructed using import changes between China and other eight high-income economies:[26]

$$\Delta IS_{jt}^{OTCH} = 100 \times \frac{\Delta M_{jt}^{OTCH}}{Q_{j,1996} + M_{j,1996}}, \tag{9}$$

where $\Delta M_{j,\tau}^{oc}$ is now the long-run change in the average Chinese import value from the other eight high-income economies, and $Q_{j,1996}$ and $M_{j,1996}$ are again computed using Belgian production and import data, but in 1996, in order to avoid mechanical correlation between the share components of the two measures.

The identification by means of the proposed IV is valid as long as the change in the Belgian import exposure is not predicted by a simultaneous rise in sector-level demand across the other 8 high-income economies. For example, if over the period all Chinese trading partners experience a rise in demand for the automotive sector, the exclusion restriction would not be satisfied and the identification would not be possible. In our setup, however, this should be less of a concern due to the degree of disaggregation at which we estimate the empirical model. Compared to (Autor et al., 2013), 4-digit NACE industry provides greater cross-industry variation to exploit and a lower risk for potential mechanic correlation between countries' demands.

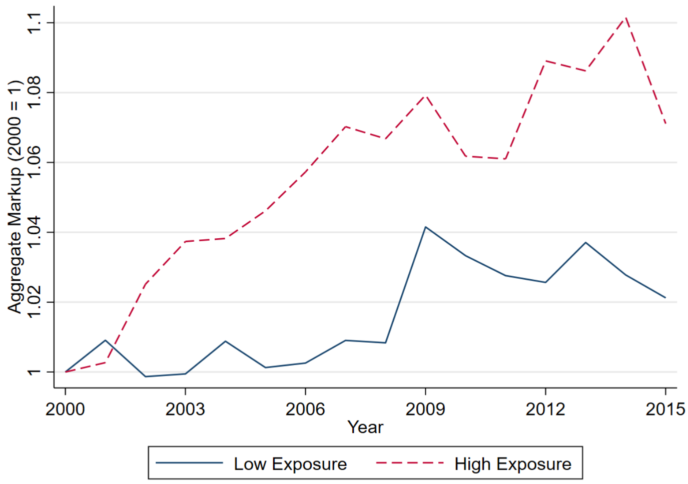
5 Results

Graphical Results. To motivate our empirical strategy, in Figure 2 we plot the evolution of weighted aggregate markups for two sub-sample of industries over

[26] These comparison countries are Australia, Canada, Denmark, Israel, Japan, New Zealand, Sweden, United Kingdom. We ensure to avoid the selection of Euro countries and the United States since their inclusion might weaken the exclusion restriction.

the period 2000-2015. On the one hand, the dashed red line represents the revenue-weighted aggregate markup for those industries facing an above-the-median change in Chinese import share; on the other, the solid blue line represents the same measure for those industries below the median of the exposure. As it is apparent, industries that are relatively more exposed to the China shock experience higher aggregate markup growth over time. Interestingly, specifically for 2000, this is not the case, with much of the action taking place in the years following China's accession to the WTO. This suggestive evidence excludes the presence of pre-trends that could potentially invalidate the analysis.

Figure 2: Evolution of the Aggregate Markup, by Exposure to Chinese Competition



Notes: The figure show the evolution of the aggregate markup for the manufacturing sector. The red dashed line identifies all sectors above the median in terms of exposure, and in blue all sectors below the median.

Nonetheless, this is just motivating evidence, since the observed increase in the aggregate markups might be due to endogenous factors determining the increase in the Chinese import share at the industry level. Intuitively, any cost reduction shock experienced by firms importing from China might translate into a higher price-to-marginal cost ratio. For this reason, we need to rely on the aforementioned identification strategy in order to disentangle a firm's endogenous sourcing behavior from the pure supply-driven import shock from China.

Industry-Level Analysis In the baseline model, we want to test the aggregate industry-level effect of the rise in imports from China, therefore we estimate the following specification:

$$\Delta\,\text{Markup}_{j,t} \;=\; \beta_1\,\Delta\,IS^{BECH}_{j,t} \;+\; \mathbf{X'_{j,2000}}\,\gamma + \;\delta_j \;+\; \delta_t \;+\; \varepsilon_{j,t}. \tag{10}$$

The dependent variable is $\Delta\text{Markup}_{j,t}$, denoting the (log) difference of the aggregate industry-level markup. The key variable of interest is $\Delta\,IS^{BECH}_{j,t}$, the change in industry-level exposure to Chinese import, instrumented by $\Delta\,IS^{OTCH}_{j,t}$. The dummy variables δ_j and δ_t are the industry and year fixed effects and capture respectively time-invariant characteristics across industries and common yearly shocks affecting the Belgian manufacturing, finally $\mathbf{X_{j,2000}}$ is a vector containing beginning-of-the-period controls at the aggregate industry level. These controls aim at capturing structural differences between industries before the realization of the shocks, therefore we include the capital-to-labor ratio, the labor share, the share of blue-collar workers, the value added labor productivity, and the Herfindahl index for market concentration. To control for heteroskedasticity and potential serial correlation of the error term, $\varepsilon_{j,t}$, we cluster at the 3-digit NACE industry level. Moreover, we weight regressions by the industry-level volume of sales at the beginning-of-the-period.

Baseline Results. Table 4 reports the results for our baseline regression in equation 14. In column (1), the first row reports the 2SLS estimates for the stacked differences of the two sub-periods, 2000-2008 and 2008-2015. In this specification, we include industry fixed effects defined at 2-digit NACE level and the set of beginning-of-the-period controls. We estimate our coefficient to be positive and significant at the 1% with a point estimate equal to 0.038. In this estimate, the Kleibergen-Paap (KP) F-statistics is higher than 10, indicating sufficient predictive power for our instrument. In column (2), we include 4-digit NACE fixed effects. This specification controls for all potential industry-level confounding factors by exploiting variation over time within the same industry. The effect is larger in this second specification; however, the instrument is weaker, with the KP F-statistics close to 6. One important aspect for the weaker identification is the fact that we are only relying on variation over the two sub-periods. Despite being very demanding on the data, we are reassured by the direction and magnitude of the estimated coefficient.

Furthermore, we split our sample in two sub-periods 2000-2008 and 2008-2015 to see if our results are stable before and after the Global Financial Crisis. The results are shown in columns (3) and (4). According to these estimates, surprisingly, the markup adjustment is realized in the second sub-period. One possible explanation is the late realization of the China shock, as shown in Figure 1, that might have contributed to dampen the impact in the first half of our sample period. However, our findings are in line with Chen et al. (2009), who also find anti-competitive effects of trade liberalization realizing in the long-run, rather than in the short-run.

Table 3: Industry-Level Chinese Import Competition, Markups

	Δ Markups			
	(1)	(2)	(3)	(4)
$\Delta\, IS_{jt}^{BECH}$	0.038***	0.051***	-0.000	0.053***
	(0.014)	(0.020)	(0.004)	(0.016)
First Stage				
$\Delta\, IS_{jt}^{OTCH}$	0.008***	0.010**	0.012***	0.03***
	(0.002)	(0.004)	(0.002)	(0.001)
Year FE	✓	✓		
NACE 2 FE	✓		✓	✓
NACE 4 FE		✓		
Controls	✓		✓	✓
Span	2000-15	2000-15	2000-08	2008-15
KP F-Stat	11.91	5.93	33.57	8.93
Obs.	368	368	184	184

Notes: The table reports the estimated coefficients for equation (10). The dependent variable is defined as the difference in the Chinese import share over the periods 2000-2008 and 2008-2015, and is windsorized at the 5%. Regressions are weighted by beginning-of-the-period sales. Standard errors, in parentheses, are cluster at the 3-digit NACE industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We provide two robustness check to our baseline exercise. Table G.1 in Appendix G reports the effect of Chinese import competition on the evolution of industry-level EBITDA which captures whether the raise in markups was associated to larger aggregate profits from firms in these markets. Moreover, to address potential concerns related to biases in the estimation of the output elasticities of input, we show the baseline results for the intermediate-to-sales ratio only. The signs of coefficients are in line with the baseline results.

Two aspects are noteworthy to highlight, first, as from Figure Figure 1, the rise in the Chinese import share takes place from 2004 onward, meaning that the cumulative effect might start to become significant relatively further in time; second, this might simply suggest a certain degree of sluggishness in markup adjustment over time, in particular this might due to the specific mechanism underlying the process. We will inquire the potential sources of the aggregate markup variation over time in the next section. Coming back to our estimates, taking our preferred specification in column (1), we have that a one standard deviation increment in Chinese import exposure increases the aggregate markups by 0.07.

Overall, the empirical results show a positive relationship between the Chinese import shock and the evolution of aggregate industry-level markups. We can rationalize this finding with the model proposed by Impullitti and Kazmi (2022). Although direct competition forces domestic firms to squeeze markups by reducing their residual demand, the increase in concentration might generate a counteracting force sufficient to overturn the initial pro-competitive effect.[27]

Decomposition. Table 4 presents the decomposition results as illustrated by equation (6). Columns (1) to (3) look at the reallocation effect, which captures how the distribution of market shares has changed across high- or low-markup firms. The estimated coefficients are always negative but significant only when looking at the stacked difference. This result indicates that low markup firms increase market shares when exposed to Chinese competition. Columns (4) to (6) look at the within effect, which identifies changes in aggregate markups due to the average change in the unweighted aggregate markup. According to these estimates, the China shock induces a strong reaction in incumbent firms to push their average charged markup upward during our sample period. This effect stems from the second period of our sample. Similar to Díez et al. (2021), we find that changes in aggregate markups are explained by changes in the average markups, while the reallocation effect is negative.[28]

Table 5 reports the results for the two sub-periods and the stacked difference specification for the entry and exit components. Columns (1) to (3) look at the aggregate effect of new entrants. The estimated coefficients are always positive but almost significant only for the second stacked period, for which the p-value is around 0.13. This result indicates a negligible effect on firms that enter the market. Columns (4) to (6) look at the aggregate effect of exiting firms. Contrarily to the entry component, we estimate a negative impact of Chinese import competition that is weakly significant over the

[27] In the case of unilateral trade liberalization, the presence of anti-competitive effects is confirmed by Melitz and Ottaviano (2008). In their model, however, the mechanism generating the result is the disproportionally higher entry rate of firms in the non-liberalizing country. In the same spirit, Parenti (2018) shows that trade liberalization leads to anti-competitive effects if large foreign firms enters the domestic market at the expenses of the small domestic ones.

[28] According to their findings, this upward shift is driven by firms in the top decile of the markup distribution and is explained by an average increase in markups among incumbents rather than reallocation towards high-markup firms. Similarly, Calligaris et al. (2018) document analogous trends for OECD countries and highlight the crucial role of the digital-intensive sectors.

Table 4: Industry-Level Chinese Import Competition, Decomposition I

	Δ Reallocation			Δ Within		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIS_{jt}^{BECH}	-0.003	-0.017	-0.007**	0.003	0.070***	0.046***
	(0.003)	(0.012)	(0.004)	(0.003)	(0.025)	(0.015)
Year FE			✓			✓
NACE 2 FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Span	2000-08	2008-15	2000-15	2000-08	2008-15	2000-15
KP F-Stat	33.569	8.929	11.909	33.569	8.929	11.909
Obs.	184	184	368	184	184	368

Notes: The table reports the estimated coefficients for equation (11). The dependent variable is defined as the difference in the Chinese import share over the periods 2000-2008 and 2008-2015, and is windsorized at the 5%. Regressions are weighted by beginning-of-the-period sales. Standard errors are cluster at the 3-digit NACE industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

sample period and almost significant in the second sub-period (i.e., p-value equal to 0.12). This evidence suggests pro-competitive forces that must be sufficiently large in magnitude to overturn the within-component effect.

Table 5: Industry-Level Chinese Import Competition, Decomposition II

	Δ Entry			Δ Exit		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIS_{jt}^{BECH}	0.021	0.011†	0.002	0.003	-0.039†	-0.048*
	(0.03)	(0.007)	(0.02)	(0.02)	(0.025)	(0.015)
Year FE			✓			✓
NACE 2 FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Span	2000-08	2008-15	2000-15	2000-08	2008-15	2000-15
KP F-Stat	33.569	8.929	11.909	33.569	8.929	11.909
Obs.	184	184	368	184	184	368

Notes: The table reports the estimated coefficients for equation (11). The dependent variable is defined as the difference in the Chinese import share over the periods 2000-2008 and 2008-2015, and is windsorized at the 5%. Regressions are weighted by beginning-of-the-period sales. Standard errors are cluster at the 3-digit NACE industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, † $p < 0.15$.

Concentration. HHaving established that Chinese import exposure had an anticompetitive effect for Belgian manufacturing, we move to understand potential mechanisms behind this stylized fact. As highlighted theoretically in Impullitti and Kazmi (2022), trade liberalizations can indirectly lead to anticompetitive effects if the resulting market concentration increases due to tougher competition.
In particular they provide a general equilibrium model of oligopolistic competition with free entry. Trade liberalization has a double effect in this setup. On the one hand, more competition puts downward pressure on firms' markups. On the other, it allows surviving firms to exert a higher degree of market power as a result of the shrinking number of competitors forced to exit the market. This implies that when the concentration effect dominates the standard pro-competitive effect, markups can even increase in equilibrium. This is not the case in the standard Melitz and Ottaviano (2008) model because monopolistic competition ensures a monotonic relationship between competition and markups.
To test this potential mechanism we estimate the following equation:

$$\Delta\,\text{Concentration}_{j,t} \;=\; \beta_1\,\Delta\,IS^{BECH}_{j,t} \;+\; \mathbf{X}'_{\mathbf{j,2000}}\,\beta + \;\gamma_j \;+\; \delta_t \;+\; \varepsilon_{j,t} \tag{11}$$

where ΔConcentration$_{j,t}$ denotes the long difference of the Herfindahl index (HHI) and the concentration ratio (CR4). Table 6 reports these results. Columns (1) to (3) look at the industry-level HHI. In the first period, the effect is negative but not significant; in the second period, the estimated effect is positive and significant. The effect remains positive but not significant when looking at the stacked regressions. These results are consistent with what we find in columns from (4) to (6) concerning the concentration ratio of the four largest firms in the sector. The coefficients are positive and weakly significant in the second period and for the whole sample. This finding is consistent with the idea that large firms in relatively more exposed industries might take advantage of a more favorable position in the market and charge high markups.

Productivity. An additional mechanism through which firms gain market power is innovation.[29] If this mechanism is at play, we expect aggregate productivity to rise in sectors more exposed to Chinese import competition. We test whether industries exposed relatively more to Chinese import adjust in terms of productivity by estimating

[29]For instance, Aghion et al.(2005) propose a model where firms have the incentive to innovate in order to appropriate post-innovation rents, and this is particularly crucial to allow them to survive or *escape* competition. They show evidence for the UK, where they find an inverted U-shaped relationship between industry-level innovation and competition. Hombert and Matray (2018) provide evidence for the US and find that R&D intensive firms are affected relatively less in the sectors exposed to Chinese competition, which is due to the link between innovation and product differentiation.

Table 6: Industry-Level Chinese Import Competition, Concentration

	Δ HHI			Δ CR4		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIS_{jt}^{BECH}	-0.002	0.091**	0.014	0.004	0.038*	0.007*
	(0.003)	(0.041)	(0.010)	(0.006)	(0.023)	(0.004)
Year FE			✓			✓
NACE 2 FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Span	2000-08	2008-15	2000-15	2000-08	2008-15	2000-15
KP F-Stat	33.569	8.929	11.909	33.569	8.929	11.909
Obs.	184	184	368	184	184	368

Notes: The table reports the estimated coefficients for equation (8). The dependent variable is defined as the difference in the Chinese import share over the periods 2000-2008 and 2008-2015, and is windsorized at the 5%. Regressions are weighted by beginning-of-the-period sales. Standard errors, in parentheses, are cluster at the 3-digit NACE industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

the following model:

$$\Delta \, \mathrm{TFP}_{j,t} \; = \; \beta_1 \, \Delta \, IS_{j,t}^{BECH} \; + \; \mathbf{X}'_{\mathbf{j,2000}} \, \beta + \; \gamma_j \; + \; \delta_t \; + \; \varepsilon_{j,t} \tag{12}$$

where $\Delta\mathrm{TFP}_{j,t}$ denotes the (log) difference of Total Factor Productivity retrieved from the production function estimation. Columns (1) to (3) of Table 7 reports results on productivity. The stacked difference estimates are positive but not significant. However, we identify two opposing effects between the first and the second period. Indeed, column (1) reports a negative and weakly significant impact on TFP; on the contrary, in the second period, the effect turns positive and significant at 1%. This finding suggests a comovement of aggregate markups and productivity, which aligns with the escaping competition hypothesis of Aghion et al. (2005).

Misallocation. Finally, in columns (4) to (6) of Table 7 we report results concerning markup dispersion, and in particular the Theil index. We are particularly interested at measuring what happens to the second moment of the markup distribution across firms in order to understand the efficiency cost induced by the Chinese shock. To interpret the results, we should think of an increase in markup dispersion as a worsening of the aggregate efficiency of a sector, and this is due to the fact that greater variance implies the presence of firms charging disproportionately higher markups that

Table 7: Industry-Level Chinese Import Competition, TFP and Theil Index

	Δ TFP			Δ Theil Index		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIS_{jt}^{BECH}	-0.030*	0.358***	0.055	-0.000	0.006***	0.000
	(0.017)	(0.136)	(0.111)	(0.000)	(0.002)	(0.001)
Year FE			✓			✓
NACE 2 FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Span	2000-08	2008-15	2000-15	2000-08	2008-15	2000-15
KP F-Stat	33.569	8.929	11.909	33.569	8.929	11.909
Obs.	184	184	368	184	184	368

Notes: The table reports the estimated coefficients for equation (8). The dependent variable is defined as the difference in the Chinese import share over the periods 2000-2008 and 2008-2015, and is windsorized at the 5%. Regressions are weighted by beginning-of-the-period sales. Standard errors, in parentheses, are cluster at the 3-digit NACE industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

have potentially stronger effects for misallocation. Firms charging positive markups employ less than the optimal level of inputs to produce because the imperfectly competitive equilibrium output falls below the perfectly competitive one. Once again, we test the impact of Chinese import exposure on our measure of markup dispersion, namely the Theil index, by estimating this regression:

$$\Delta\,\text{Theil}_{j,t} \;=\; \beta_1\,\Delta\,IS_{j,t}^{BECH} \;+\; \mathbf{X}'_{\mathbf{j,2000}}\,\beta + \;\gamma_j \;+\; \delta_t \;+\; \varepsilon_{j,t} \tag{13}$$

where $\Delta\text{Theil}_{j,t}$ denotes the (log) difference of the Theil index derived in equation (9). The estimates are reported in columns (4) to (6) of Table 6 and they show that markup dispersion increases in import-exposed industries during the second period, but they are not significantly different from zero over the period. These results might suggest the potential worsening of resource allocation within industries.

6 Conclusion

Recent decades have witnessed a surge in firms' market power. In this paper, we investigate the role played by globalization, and, in particular, import competition from China, on Belgian manufacturing firms' markups and other measures of market power. Results show that sectors that experienced a relatively higher rise in Chinese competition increased markups from 2000 to 2015. This anti-competitive effect was driven by incumbent firms raising average markups, as unveiled by the proposed decomposition exercise.

We rationalize our findings by the effect that import competition had on the domestic market structure of Belgian firms, particularly by showing that concentration increased in more exposed sectors. Along with increasing markups, Chinese competition induced firms to increase their productivity, measured as Total Factor Productivity (TFP), which is suggestive of a winner-take-most type of story. Furthermore, we find an increase in markup dispersion in affected sectors, indicating that misallocation has worsened. This evidence suggests that international trade might worsen allocative efficiency and induces anti-competitive effects.

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Appendix A

Product-Industry Concordance

As explained in Section 2, UN Comtrade data are reported at the 6-digit HS product classification. Over our sample period, the HS classification is reported in four different versions: H1 in 1996, H2 in 2002, H3 in 2007, and H4 in 2012. Specifically from 2007 onward, the H3 classification is made available for all the subsequent batches of trade data. The core activity of our Belgian manufacturing firms is defined at the 4-digit NACE Rev. 2 industry classification.

Therefore, to match aggregate product-level trade data with firm-level industry information, we went through two rounds of harmonizations using the Reference And Management Of Nomenclatures (RAMON) correspondence tables provided by the European Commission. The procedure followed is reported here:

1. We harmonize over time UN Comtrade data reported in the H1 classification, for the 1996-2001 period, and in the H2 classification, for the period 2002-2006, in order to have the full sample reported in the H3 classification. When one product of the old classification is matched with multiple new ones, we assign trade values to each new category using equal weights.

2. Each H3 product category is matched with 6-digit 2008 Classification of Product by Activity (CPA) product categories. Again, if one product category is matched with multiple ones, we assign trade values to each category using equal weights.

3. Finally, 6-digit CPA 2008 classification can be aggregated up at the 4 digits level. The latter defines precisely the 4-digit NACE Rev. 2 industry classification.

Appendix B

Data Cleaning

As discussed in Section 2, we merge various firm-level datasets from the Belgian federal institutes and the National Bank of Belgium. From each source we extract all active firms over the 1996-2015 period. To select the sample, we keep firms that over the period meet the following requirements:

1. report positive values of sales and value added;
2. report positive employment, in full time equivalent (FTE), at least once;
3. report a minimum of 100 euro of physical capital stock, or tangible fixed assets, at least once;
4. report positive assets, at least once.

We limit the analysis to firms whose primary sector of activity is manufacturing. The full sample contains 195,118 firm-year observations identifying 21,597 unique firms over 184 NACE4 industries during the period 1996-2015. We construct our concentration measures and control variables from this sample.

Among others we use balance sheet information about total turnover (Y), value added (VA), fixed (K) and intangible (INT) capital, the wage bill (WB) and the value of total intermediates (M) used in production. These values are all expressed in euros, therefore we convert them in real terms using the 2-digit NACE Rev. 2 industry-level deflators provided by the National Account Statistics of the National Bank of Belgium. In particular, we use price deflators on value-added, sales and trade values, the deflator of gross fixed capital formation for capital and intangibles, intermediate price deflators for intermediate inputs, and the consumer price index for wages. Deflators base year is 2005.

In a second step, we perform an additional cleaning procedure to ensure stability of the sample for markups estimation. In particular, we require firms:

1. to report at least one employee, which excludes individual entrepreneurs;
2. to be active in at least two consecutive years, to ensure the possibility to construct one-period lag variables as instrument in the GMM estimation.

To avoid markup estimates to be driven by extreme values, we drop outliers in three key distributions: i) sales-to-capital ratio, ii) sales-to-labor ratio, and iii) sales-to-intermediate inputs ratio. The three ratios are log normalized. We define outliers as values outside the interval given by the median plus/minus three times the interquartile range of the distribution. We apply the routine for the distribution of interest at the sector-year level. This leaves the sample with 184,742 firm-year observation for 21,099 firms.

Appendix C

Firm's Cost Minimization

Let's consider a firm i in sector j producing at time t. For simplicity we omit subscript j. The production function reads:

$$Q_{it} = F_{it}(L_{it}, K_{it}, M_{it}, \Omega_{it}), \tag{C.1}$$

where Q_{it} denotes gross output, $F_{it}(\cdot)$ the production function defined over labor, L_{it}, capital, K_{it}, intermediates, M_{it}, and Ω_{it} the productivity level. We assume the production function, $F_{it}(\cdot)$, to be continuous and twice differentiable in its arguments. Firm i at time t faces the following cost minimization problem:

$$\begin{aligned} \min_{\{K_{it}, L_{it}, M_{it}\}} \quad & w_{it}L_{it} + r_{it}K_{it} + p^M_{it}M_{it}, \\ \text{s.t.:} \quad & F_{it}(L_{it}, K_{it}, M_{it}) \geq Q_{it}, \end{aligned} \tag{C.2}$$

with the associated Lagrangian reading:

$$\mathcal{L}(L_{it}, K_{it}, M_{it}, \lambda_{it}) = w_{it}L_{it} + r_{it}K_{it} + p^M_{it}M_{it} + \lambda_{it}(Q_{it} - F_{it}(\cdot)),$$

where w_{it}, r_{it}, and p^M_{it} denote the wage rate, the interest rate on capital, and the intermediate input price respectively.

To pinpoint the markup level, it is necessary to rely on the first-order condition for the variable input, which we assume to be the intermediates:

$$\frac{\partial \mathcal{L}_{it}}{\partial M_{it}} = p^M_{it} - \lambda_{it}\frac{\partial F_{it}(\cdot)}{\partial M_{it}} = 0.$$

The shadow price λ_{it} represents the marginal cost of production for any given level of total production Q_{it}. Rearranging equation (2), and multiplying both sides by $\frac{M_{it}}{Q_{it}}$, we obtain:

$$\frac{\partial F_{it}(\cdot)}{\partial M_{it}}\frac{M_{it}}{Q_{it}} = \frac{1}{\lambda_{it}}\frac{p^M_{it}M_{it}}{Q_{it}}.$$

By definition, the markup is expressed as the ratio between prices and marginal costs, hence $\mu_{it} \equiv \frac{P_{it}}{\lambda_{it}}$. By rearranging the previous equation and multiplying and dividing the right-hand side by P_{it}, we obtain a function for markups expressed as follow:

$$\mu_{it} = \theta_{it}^{M} (\alpha_{it}^{M})^{-1}, \tag{C.3}$$

where θ_{it}^{M} is the output elasticity of intermediate inputs, and α_{it}^{M} is the share of intermediate input expenditure in total sales.

As highlighted by De Loecker and Warzynski (2012), this approach has the advantage to nest various price-setting models that are common to the international trade and industrial organization literature.

Appendix D

Productivity Estimation

Consider the generic production function discussed in Section 3:

$$Q_{it} = F_{it}(L_{it}, K_{it}, M_{it}, \Omega_{it}), \tag{D.1}$$

Assumptions. We make the assumption that productivity is Hicks neutral with respect to production inputs and that $F_{it}(\cdot)$ is translog in its arguments. Production function estimation is performed for each aggregate manufacturing sector, but we omit the industry subscript to keep the notation simple. Hence, we can rewrite a log-linearized version of equation $(D.4)$ as follows:

$$q_{it} = f_{it}(l_{it}, k_{it}, m_{it}; \beta) + \omega_{it} + \varepsilon_{it}, \tag{D.2}$$

where $f_{it}(\cdot)$ is a second-order Taylor expansion of a Cobb-Douglas production function, ω_{it} is the productivity level observed by the firm, potentially correlated to the level of the inputs in production, while ε_{it} is the unanticipated productivity shock assumed to be independent and identically distributed. Formally, the assumed translog function takes the following form:

$$\begin{aligned} q_{it} = {} & \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2 \\ & + \beta_{lk} l_{it} + \beta_{km} k_{it} + \beta_{km} l m_{it} + \beta_{lmk} l_{it} k_{it} m_{it}. \end{aligned} \tag{D.3}$$

In order to have consistent estimates of the parameters we need two conditions. First, output and inputs need to be expressed in physical quantities, however, since we only have access to their counterparts in values, we use industry-level deflators to correct for prices.[30] Since such deflators capture only partially the price level, the left-hand side of equation (3) captures only a proxy for the quantity produced, which is given by $\tilde{Q}_{it} = R_{it}/P_{jt}$, with R_{it} being the firm's revenue and P_{jt} the industry-level deflator. This implies that the unobserved output price difference, $p_{it} - p_{jt}$, will end up in the residual, $\tilde{\varepsilon}_{it}$ determining an output price bias. Despite being unable to measure and correct the bias in the estimate, recent evidence in De Ridder et al. (2022) suggests that this bias is attenuated when studying the distribution of markups changes over time, which is the focus of our empirical exercise.

Second, we need to control for productivity ω_{it}, which is observable for the firm, but unobservable by the econometricians. To proxy for ω_{it}, Levinsohn and Petrin (2003), and subsequently Ackerberg et al. (2015), exploit firm level purchases of intermediate

[30] De Ridder et al. (2022) discuss how revenue-based estimations of the production function introduce critical biases for the identification of the true markup, this is particularly problematic when looking at the level. However, when looking at changes, the pairwise correlation of the log-difference of the estimated markups using revenue and quantity measures is around 0.6, which is reassuring since in our context we are going to look at markups changes over time rather than at their levels.

inputs:

$$m_{it} = m_t(l_{it}, k_{it}, \omega_{it}, \mathbf{z_{it}}), \tag{D.4}$$

where $\mathbf{z_{it}}$ is a set of firm's characteristics potentially affecting the optimal demand for the intermediate inputs. In particular, in our setup we control for the export status, e_{it}, and the firm's market share, ms_{it}. Under strict monotonicity of the intermediate input demand with respect to productivity, it is possible to invert the demand function to identify firm productivity as:

$$\omega_{it} = h_t(l_{it}, k_{it}, m_{it}, \mathbf{z_{it}}). \tag{D.5}$$

Identification. In the first stage, we estimate the predicted level of output, $\hat{\phi}_{it}$, purged by the unanticipated productivity shock, $\tilde{\varepsilon}_{it}$, by estimating the following regression:

$$\tilde{q}_{it} = \phi_{it} + \tilde{\varepsilon}_{it},$$

with $\tilde{q}_{it}$ being the deflated output variable and ϕ_{it} being given by:

$$\phi_{it} = f_{it}(\tilde{l}_{it}, \tilde{k}_{it}, \tilde{m}_{it}; \beta) + \omega_{it}.$$

In the second stage, we are going to form moment conditions from the innovation term of the dynamic productivity process to retrieve the parameters of the production function. We assume productivity, ω_{it}, to evolve according to a first-order Markov process:

$$\omega_{it} = g_t(\omega_{it-1}) + \xi_{it}, \tag{D.6}$$

with ξ_{it} being the innovation term. Productivity is computed as the wedge between the predicted output variable of the first stage, $\hat{\phi}_{it}$, and the translog production function:

$$\omega_{it}(\beta) = \hat{\phi}_{it}(\tilde{l}_{it}, \tilde{k}_{it}, \tilde{m}_{it}; \beta) - f_{it}(\tilde{l}_{it}, \tilde{k}_{it}, \tilde{m}_{it}; \beta).$$

The innovation term, $\xi_{it}(\beta)$, is estimated for a given set of βs from equation (4), by non-parametrically regressing ω_{it} on its past value. Finally, to retrieve the output elasticity of each input we form moment conditions by exploiting the orthogonality conditions between present unanticipated innovation shocks to the productivity process and the lagged values of intermediate inputs that we use as instruments. The identification hinges on intermediate input prices to be serially correlated over time. We also include both the present value of capital and labor, since we assume these to be predetermined one period ahead, therefore orthogonal to the present innovation shock:

$$\mathbb{E}\left(\xi_{it}(\beta)\ (\mathbf{X}_{it})\ \right) = 0.$$

Estimation is performed using a standard GMM procedure and we separately run regressions at a higher aggregate industry level in order to generate sufficient within variation to identify the parameters. With the vector of estimated parameters, $\hat{\beta} = \{\hat{\beta}_l, \hat{\beta}_k, \hat{\beta}_m, \hat{\beta}_{ll}, \hat{\beta}_{kk}, \hat{\beta}_{mm}, \hat{\beta}_{lk}, \hat{\beta}_{km}, \hat{\beta}_{km}, \hat{\beta}_{lmk}\}$ it is possible to retrieve the output elasticity of the intermediate input as follow:

$$\hat{\theta}_{it}^{m} = \hat{\beta}_m + 2\hat{\beta}_{mm} m_{it} + \hat{\beta}_{lm} l_{it} + \hat{\beta}_{km} k_{it} + \hat{\beta}_{lkm} l_{it} k_{it}.$$

Appendix E

Melitz Polanec Decomposition

Let's consider the aggregate level of markup in sector j at time t for a specific group $G \in \{c, e, x\}$, where c denotes the incumbents, e the entrants, and x the exiters:

$$M_{G,jt} = \sum_{i \in G} s_{ijt} \mu_{ijt}, \tag{E.1}$$

where s_{ijt} defines the market share of firm i in sector j at time t, and μ_{ijt} its associated level of price markup.

Consider a scenario with two periods. In the first period, the aggregate markup is given by the sum of incumbents markups plus the sum of markups of those firms that will exit in the second period, both weighted by their respective group market share in the sector. In the second period, instead, the aggregate markup is given by the sum of markups of those incumbents that survived plus the sum of entrant firms' markup, both again weighted by their respective group market share. Formally:

$$\begin{aligned} M_{j1} &= s_{c,j1} M_{c,j1} + s_{x,j1} M_{x,j1} = M_{c,j1} + s_{x,j1}(M_{x,j1} - M_{c,j1}), \\ M_{j2} &= s_{c,j2} M_{c,j2} + s_{e,j2} M_{e,j2} = M_{c,j2} + s_{e,j2}(M_{e,j2} - M_{c,j2}), \end{aligned}$$

with the rearranging of the terms in the left-hand side coming from the following identities: $s_{c,j1} = 1 - s_{x,j1}$ and $s_{c,j2} = 1 - s_{e,j2}$.

The change in the aggregate markup between period one, M_1, and period two, M_2, is defined as:

$$\Delta M = M_{c,j2} - M_{c,j1} + s_{e,j2}(M_{e,j2} - M_{c,j2}) - s_{x,j1}(M_{x,j1} - M_{c,j1}).$$

It is now possible to apply the Olley and Pakes (1996) decomposition to the aggregate markups of the incumbents, by defining the distance between firm's i markup and its sector average as: $\Delta\mu_{ijt} = \mu_{ijt} - \bar{\mu}_{G,jt}$. We can then rewrite the group-specific aggregate markup in sector j at time t as:

$$M_{G,jt} = \sum_{i \in G} (\bar{s}_{G,jt} - \Delta s_{ijt})(\bar{\mu}_{G,jt} - \Delta\mu_{ijt}),$$

from which it follows:

$$M_{G,jt} = G_{jt}\bar{s}_{G,jt}\bar{\mu}_{G,jt} + \sum_{i \in G} \Delta s_{ijt}\Delta\mu_{ijt},$$
$$= \bar{M}_{G,jt} + \mathrm{cov}_{G,jt},$$

with $\bar{M}_{G,jt}$ being the average sector-level markup of incumbents, defining the *within* component, and $\mathrm{cov}_{G,jt}$ being the covariance between the change in firm-level markup and the respective change in market share, hence the *between* component. Therefore, it is possible to express the change in aggregate markup between the two periods as:

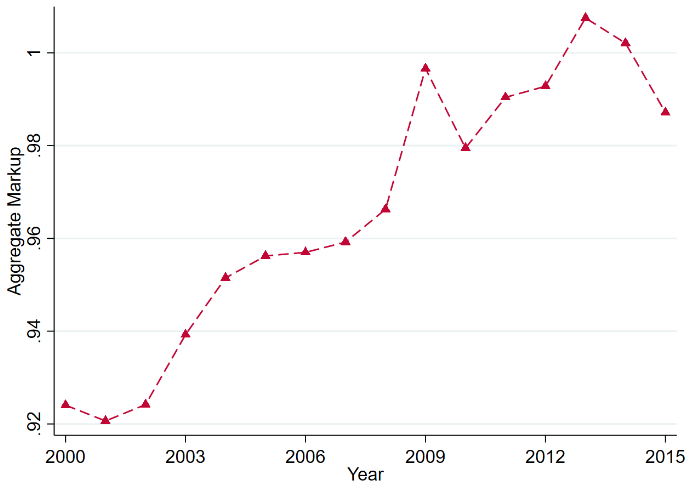
$$\Delta M_j = \Delta\bar{M}_{c,jt} + \Delta\mathrm{cov}_{c,jt} + s_{e,j2}(M_{e,j2} - M_{c,j2}) + s_{x,j1}(M_{c,j1} - M_{x,j1}), \qquad \text{(E.2)}$$

where $\Delta\bar{M}_{c,jt}$ defines the change of aggregate markup coming from the sector-level shift in the average firm markup over the period, $\Delta\mathrm{cov}_{c,jt}$ the change due to the reallocation of market shares between firms, and $s_{e,j2}(M_{e,j2} - M_{c,j2})$ and $s_{x,j1}(M_{c,j1} - M_{x,j1})$ respectively the contribution from entrants and exiters.

Appendix F

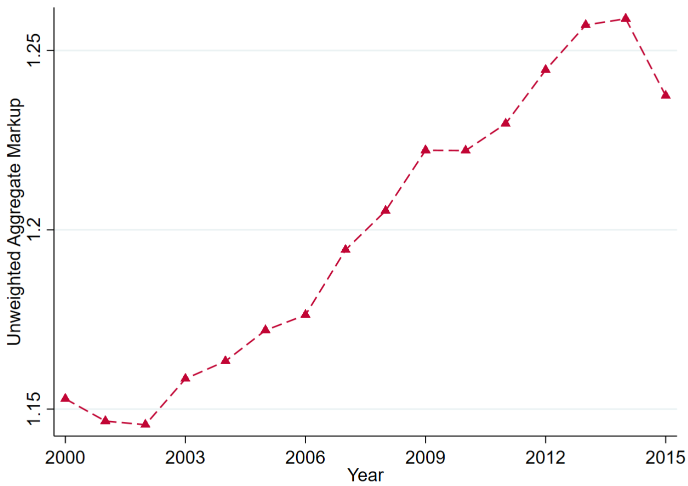
Figures

Figure F.1: Evolution of the Revenue-Weighted Aggregate Markup



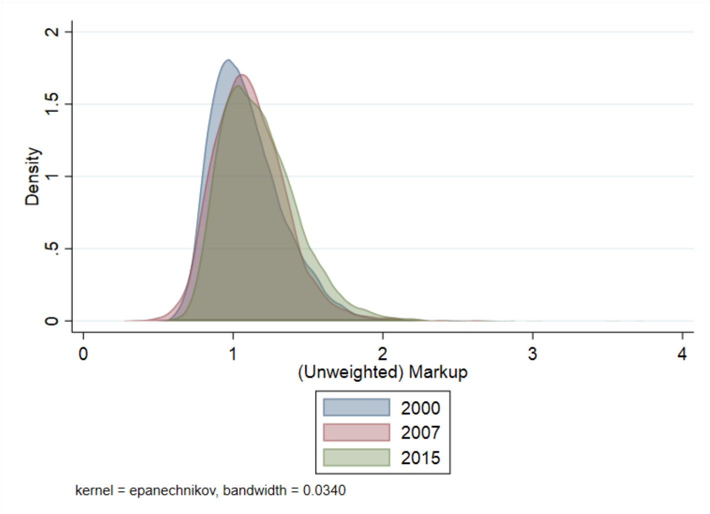
Notes: The figure show the evolution of the revenue-weighted aggregate markup for entire manufacturing sector.

Figure F.2: Evolution of the Unweighted Aggregate Markup



Notes: The figure show the evolution of the unweighted aggregate markup for entire manufacturing sector.

Figure F.3: Distribution of Firm-Level Markups

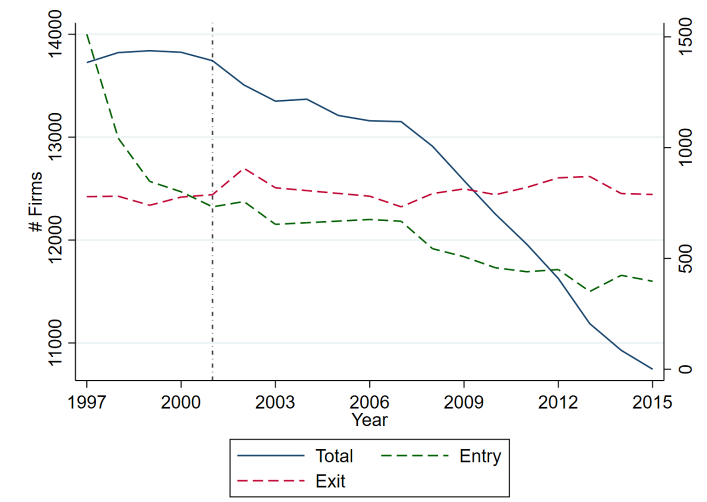


Notes: The figure show the kernel distribution of firm-level markups for entire manufacturing sector in the years 2000, 2008, and 2015.

Figure F.4: Aggregate Dynamic Decomposition of Markups

Notes: The figure show the aggregate dynamic decomposition of markups for the two subperiods, 2000-2008 and 2008-2015, and the full period 2000-2015.

Figure F.5: Firms' Entry and Exit



Notes: The solid blue line shows the evolution of the aggregate number of manufacturing firms from 2000 to 2015. The number is reported on the left y-axis. The dashed green and dashed red lines represents respectively the aggregate number of entry and exit firms in the same period. Their numbers are reported in the right y-axis.

Appendix G

Tables

Table G.1: Industry-Level Chinese Import Competition, Profitability

	Δ Y/M		Δ EBITDA	
	(1)	(2)	(3)	(4)
ΔIS_{jt}^{BECH}	0.04***	0.05**	0.41***	0.53**
	(0.15)	(0.21)	(0.15)	(0.22)
First Stage				
ΔIS_{jt}^{OTCH}	0.008***	0.010**	0.008***	0.010**
	(0.002)	(0.004)	(0.002)	(0.004)
Year FE	✓	✓	✓	✓
NACE 2 FE	✓		✓	
NACE 4 FE		✓		✓
Controls	✓		✓	
Span	2000-15	2000-15	2000-15	2000-15
KP F-Stat	11.91	5.93	11.91	5.93
Obs.	368	368	368	368

Notes: The table reports the estimated coefficients for equation (10) in stacked difference. The EBITDA is calculated as the ratio between profits, net the wage bill, and sales. The dependent variables are windsorized at the 1%. Regressions are weighted by beginning-of-the-period sales. Standard errors, in parentheses, are cluster at the 3-digit NACE industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.