Globalization and Market Power*

Catherine Fuss[a] Lorenzo Trimarchi[†b] Daniele Verdini[‡c]

[a] *National Bank of Belgium*

[b] *Université de Namur*

[c] *Université Catholique de Louvain, FNRS*

[PRELIMINARY VERSION, PLEASE DO NOT CITE]

May 1, 2022

Abstract

Recent decades have been characterized by a surge in firms' market power both in the U.S. and the EU. In this paper, we study the role played by globalization in determining the observed evolution of markups and other measures of market power. We use detail firm-level balance sheet and trade data for Belgian manufacturing over the period 2000-2015. We provide evidences of the role played by the rising trade exposure to China on various measures of market power. We estimate a positive effect on aggregate markups in the relatively more exposed industries that explain up to a fourth of the aggregate markups evolution over the period. We further provide evidences of increasing market concentration and markup dispersion going along increasing aggregate productivity. These changes are not driven by reallocation between firms, but by within adjustments of the incumbents. Overall, these evidences point to a winner-take-all type of rational behind the observed increase in market power.

Keywords: Globalization, Market Power, Markups, China Shock

JEL Classification: D22, D24, F14, L11

*We are grateful to Jan Eeckhout, Ariell Reshef, Gonzague Vannoorenberghe for their comments and suggestions. Verdini gratefully acknowledge the financial support from the Fonds National de la Recherche Scientifique (FNRS). The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bank of Belgium

†*E-mail*: lorenzo.trimarchi@unamur.be

‡*E-mail*: daniele.verdini@uclouvain.be

1 Introduction

Recent years have witnessed a growing concern, among academics and policy-makers, about the U.S. and the EU state of competition (Syverson, 2019). A whole set of evidences, ranging from higher market concentration to wider price-to-cost ratios, suggest that market power has been on the rise across sectors over the last forty years, with gloomy consequences for both business dynamism and workers conditions.[1] A key aspect, still under debate, concerns the determinants of the observed evolution of market power, which understanding is pivotal in order to design an effective policy.

Various hypothesis have been put forward. Autor et al. (2020) are the main proponents of the "superstar firms" hypothesis, according to which the observed increase in concentration and market power is driven by few large firms characterized by high productivity. The consolidation of a dominant position, in this case, goes along with greater innovation, higher cost efficiency and lower prices, and is therefore the result of a healthy competition dynamics. On the other side of the spectrum, Covarrubias et al. (2020), Gutiérrez and Philippon (2018), Grullon et al. (2019) and Philippon (2019) are the proponents of the "declining competition" hypothesis. In their view, antitrust enforcement, especially in the U.S., has been ill-suited to contrast the incumbents' consolidation in the markets, in particular through M&As. Moreover, by investing enormously in lobbying activities, these same firms have prevented competitors from entering the market with the result of generating distorted competition and limited business dynamisms. A somewhat middle ground explanation is proposed by Crouzet and Eberly (2019), De Ridder (2021), and Eeckhout (2021) who advocate for the "intangible assets" hypothesis. They show how industry leaders invest more in intangible technologies, marketing, and R&D in order to gain a competitive edge over their competitors. However, while intangible assets allow firms to cut on their marginal costs, they simultaneously generate higher entry barriers, through network effects and scale economies, weakening future competition.

In this paper, we focus on a fourth one, the "globalization" hypothesis. In particular, we ask to what extent and through which mechanisms the recent wave of globalization has generated the observed patterns of concentrations, markups, and profits. It is well-established that international trade, by fostering competition and increasing market size, can affect the domestic market structure in the presence of firm heterogeneity and distortions. There are at least two mechanisms that can explain the relationship between trade openness and market power. By opening up

[1]For a cross-country comparison of the evolution of market power, see among others De Loecker and Eeckhout (2018), Díez et al. (2021), and Calligaris et al. (2018). For a specific analysis of the US, see Autor et al. (2020), De Loecker et al. (2020), and Eggertsson et al. (2021). For the EU, see Affeldt et al. (2021).

to trade, domestic firms face tougher domestic competition that induce unproductive, low-markup firms to exit, however the high productive firms surviving in the market expand their production by charging lower prices, with an overall reduction in the domestic level and distribution of markups and positive welfare effects (Melitz and Ottaviano, 2008).[2] On top of inducing pro-competitive effects in prices, trade liberalizations also allow firms to get access to cheaper intermediate inputs and consequently leverage on the reduction of costs to actually raise markups. This is shown by De Loecker et al. (2016), in the context of the 1991 India's trade liberalization, in which the fall of trade barriers was accompanied by higher intermediate imports, costs reduction, but also relative higher product-level markups. When the overall price decrease is relatively lower compared to the cost reduction, hence when the pass-through is incomplete, firms can benefit by both charging lower prices and higher markups.

We provide empirical evidences of the importance of competition in determining the observed market power structure across industries and firms. Using detail firm-level balance sheet data for Belgian manufacturing over the period 2000-2015, we are able to characterize the evolution of various measures of market power. In particular, production and sales data allows to compute the Herfindhal-Hirschman Index (HHI) and different levels of concentration ratios (CR) at the 4-digit NACE industry. We think of Belgium as an interesting case for several reasons. The first one is that Belgium is a developed market economy, characterized by a high degree of labor protection. It is also a country heavily relying on trade, make it one of the few examples of small-open economies, and as documented in Mion and Zhu (2013), it experienced a major increase in import competition from China, but not much from other low-income countries. A long tradition in the empirical industrial organization has emphasized how concentration *per se* can be misleading to understand the extent of market power, for this reason, we rely on state-of-the-art techniques in production function estimation developed by Ackerberg et al (2015) and De Loecker and Warzynski (2012), to retrieve firm-level measures of prices over marginal costs. This enables us to study the relationship between markups and competition at a finer degree than

[2] Other similar mechanisms have been studied theoretically and quantitatively. The pioneering work of Brander and Krugman (1983) shows that under Cournot competition in homogeneous products, trade openness reduces unambiguously markups, but overall welfare effects depend on the extend of trade costs. Epifani and Gancia (2011) develop a industry-level monopolistic competition model of trade and show how trade liberalizations, by affecting the distribution of markups, might induce misallocation and welfare losses, in particular without free entry. Dhingra and Morrow (2019) discuss how the relationship of competition and market power in distorting the optimal allocation of resources in a monopolistic competition model with firm heterogeneity. De Blas and Russ (2015) develop predictions for an open economy Ricardian model, while Edmond et al. (2015) quantify the role of competition on markups distribution for an open economy model with Cournot competition. Finally, Arkolakis et al. (2019) quantify the welfare gains from trade in a model with variable markups.

the industry level and unveil heterogeneous effects depending on firm-specific characteristics. We identify the trade shock exploiting the surge in import from China experienced over the period 2000-2015. The empirical strategy follows Autor et al. (2013) and Acemoglu et al. (2016) and we perform the analysis at the aggregate industry level. Our results points to a positive impact of Chinese import competition on industry aggregate markups and the other measures of concentrations. Using our conservative estimates, we find that over the period Chinese competition has been responsible for one fourth of the rise of aggregate markups. We also find evidences of increasing concentration and markups dispersion within industries, along with positive effects on aggregate Total Factor Productivity (TFP).

Related Literature We contribute to several strands of literature. First, we contribute to the ongoing debate about the surge of market power in EU. Several contributions have highlighted how various measures of market power have been on the rise over the last decades. De Loecker and Eeckhout (2018) document an upward trends in the aggregate markup worldwide, especially for North America and Europe, using firm-level information for publicly listed firms across 134 countries. Overall, they estimate the aggregate price-to-marginal-cost ratio to have gone up from a 1.1 in 1980 to a 1.6 in 2016. Díez et al. (2021) perform a similar exercise using private and listed firms for a large set of countries, accounting for the 70% of World GDP. They document that over the period 2000-2015 overall markups have increased by 6% especially in advanced economies and in the service sector. In particular, the shift is driven by the top decile of the markup distribution, which is constituted mainly by publicly listed firms, and is mainly explained by within-firm increases among incumbents, rather than reallocation towards high-markup entrants. Calligaris et al. (2018) document analogous trends for OECD countries and highlight the crucial role of the digital intensive sectors. We complement their findings by estimating firm-level markups using the universe of Belgian firms and provide rational for their aggregate evolution over time.

We also contribute to the empirical literature on the relationship between trade and markups. Early evidences of the import-as-market-discipline hypothesis are Levinsohn (1993), Harrison (1994), and Krishna and Mitra (1998), concluding that trade liberalization induces reductions in estimated firm-level measured price over marginal cost.[3] Chen et al. (2009) test the predictions of Melitz and Ottaviano (2008) for seven EU countries over the period 1989-1999, and find that sector-level trade openness reduces the average markup in the short run, however in the long run

[3]For review of the methodology and findings, check Tybout (2003)

the effect of domestic openness is ambiguous and even (weakly) anti-competitive in certain cases. In this respect, Lu and Yu (2015) provide evidences of decreasing markups dispersion in the Chinese manufacturing after joining the WTO, and in the same context Brandt et al. (2017) document pro-competitive effects due to markups reductions of the incumbents.

Finally, we contribute to the literature on the China shock. Over the past decade, there has been a fierce policy and academic debate over the effects of the rise of China as the world manufacturing producer and exporter. For the U.S., Autor et al. (2013, 2016, 2021) and Pierce and Schott (2016) document how the swift rise of Chinese import penetration in the manufacturing sector has negatively affected the domestic labor market, in particular by reducing employment and job opportunities. Mion and Zhu (2013) documents similar patterns for Belgium by showing that firms upgrade their production process by becoming more skill intensive and displacing blue collar workers when facing Chinese competition.

The remainder of the paper is structured as follows: Section 2 describes the data. Section 3 and Section 4 present the main methodology and discuss the results. Section 5 concludes.

2 Data

We rely on different sources to construct our panel of Belgian manufacturing firms over the period 1996-2015. We merge together: i) the VAT Declaration, ii) the Annual Accounts, iii) the Social Security, and iii) the Transaction Trade datasets provided by the National Bank of Belgium. The VAT Declaration, collected by the Belgian tax authority, reports the consolidated balance sheet[4] information for the universe of Belgian firms over the period 1996-2015. In particular, the dataset provides information about 4-digit NACE Rev. 2 industries in which the firm has its main activity, the total yearly turnover, value added, capital stock, the number of employees in full-time equivalent (FTE), and the value of total intermediates used in production. Concerning the capital stock value, we use as definition the net value of a firm's fix assets. Annual Accounts are collected by the Central Balance Sheet Office (CBSO) of the National Bank of Belgium (NBB) and complement firm-level VAT Declaration information for the those Belgian firms above certain employment and turnover thresholds. Small firms do not need to report such information, although the conditions to meet are

[4]Consolidated balance sheets integrate information regarding all possible controlled subsidiaries of the concerned company.

quiet loose[5]. The Social Security dataset contains information about the occupation of each worker at the firm level over the period 1996-2015, in particular it allows to distinguish between blue-collar, white-collar, and managerial employees. Finally, the Transaction Trade dataset provides firm-level information on export and import at the 6-digit Harmonized System (HS) level, that we convert in order to match with the 4-digit NACE Rev. 2 industry level. Trade data are match with the main industry of activity of the firm such that firms that importing products in the same category are considered as final, and in a different category as intermediate products. All together, these datasets enable the researcher to have access to an almost comprehensive picture of the Belgian production and exchange activities. In order to estimate firm-level productivity and markups, we keep in the sample firms that report at least one unit of FTE employment over the period, hence excluding individual entrepreneurs. We further impose firms to report at least 100 euros of capital value once over the sample period. Eventually, we exclude observations with reported negative sale or negative value added, moreover we exclude outliers along various balance sheet measures.[6] Additionally, we make use of 2-digit NACE Rev. 2 industry-level deflators to convert sales and trade values in quantities, capital price deflators for the stock of capital value, intermediate price deflators for the intermediate value, and the consumer price index for wages. To construct our measures of Chinese competition, we use UN Comtrade HS 6-digit import and export data for the period 2000-2015 between Belgium and China.

Overall, our sample contains 195,118 firm-year observations identifying 21,597 unique firms over 194 manufacturing industries during the period 1997-2015. Table 1 shows summary statistics for the whole sample. Panel A reports total sales, the stock of fix and intangible capital, the amount of intermediate inputs purchased, the level of employment in FTE and the total wage bill for all firms. Looking at the distribution across different percentiles, it emerges the skewed nature of the manufacturing sector along all dimensions, 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 the domestic counterparts. We will take into account these information for the estimation of markups and productivities, by introducing

[5]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.

[6]Outliers are defined using the distributions of the logarithm of input-output ratios (*i.e.* sales/-capital, sales/intermediates, sales/employment) In particular, we trim observations lying outside the distance between the median and three times the interquartile range of the distribution.

Table 1: Summary Statistics for Manufacturing Firms over the Period 1997-2015

			Percentiles				
	Mean	*St. Dev.*	*p5*	*p25*	*p50*	*p75*	*p95*
Panel A: Full Sample							
Sales (Y)	12.68	87.65	0.24	0.59	1.49	4.88	39.27
Capital Stock (K)	2.18	15.81	0.02	0.11	0.33	0.98	6.82
Intangibles (I)	2.18	15.81	0.02	0.11	0.33	0.98	6.82
Intermediate Inputs (M)	10.04	77.28	0.12	0.35	0.99	3.50	30.37
Employment in FTE (L)	41.72	200.32	1.70	3.75	8.80	25.00	142.80
Wage Bill (WB)	41.72	200.32	1.70	3.75	8.80	25.00	142.80
Panel B: Only Firms in Trade							
Sales	25.09	125.35	0.54	1.80	4.62	13.07	84.29
Capital Stock	4.16	22.65	0.05	0.27	0.79	2.28	14.03
Intangibles	2.18	15.81	0.02	0.11	0.33	0.98	6.82
Intermediate Inputs	20.03	110.71	0.33	1.24	3.31	9.83	67.68
Employment in FTE	78.17	284.41	2.80	9.00	22.00	53.10	282.40
Wage Bill	41.72	200.32	1.70	3.75	8.80	25.00	142.80
Total Trade	26.92	185.28	0.00	0.25	1.85	9.23	92.18
Export	16.71	120.03	0.00	0.00	0.69	5.39	57.17
Import	10.20	69.72	0.00	0.02	0.77	3.51	33.24
Import from China	0.18	2.26	0.00	0.00	0.00	0.00	0.32

Note: The full sample contains 195,118 firm-year observation, for 21,597 firms. The sample with only trading firms counts, instead, 93,601 firm-year observations, for 12.354 firms. Among these, 4.112 firms source at least once from China over the period. We exclude outliers observations, these are defined as observations outside the distance between the median and five times the interquartile range of the distribution of interest (Y/L, Y/K, Y/M). The table reports firm-level output and factors of production used later in the estimation procedure. Sales, capital, intermediates, and trade are expressed in million of euros, employment is in full-time equivalent. All nominal variables are deflated: sales and trade values by the production price index (PPI); capital by capital price deflators; intermediates by the intermediate price deflators.

controls for the export activity of the firm.

3 Methodology

Theory of Markups

To study the effect of competition on the level of firms' market power in the economy, we need to choose an appropriate measure. A natural candidate is the price-to-marginal cost ratio, namely the price markup. This index measures the wedge between the price level expected under perfect competition and the observed one. The distribution of price markup in the economy would be a sufficient statistics to evaluate the extent of market power. However, despite the extensive access to production price data, it is hardly possible to retrieve information about firms' marginal costs.[7] For this reason, we follow the methodology developed by De Loecker and Warzynski (2012) to estimate markups, that builds on the insights of Hall (1986) and relies on the use of available firm-level balance sheet data. The idea is that, in a general perfectly competitive setup, input cost shares should be equal to the respective input revenue share determined by the input elasticity, therefore any deviation could be considered deviations from the firm competitive price setting. Additionally, this methodology is flexible enough to encompass various product market structures, and it does not require to impose and estimate any demand system.[8]

We consider a firm i in sector j producing at time t. For simplicity we omit subscript j, since the empirical framework holds symmetrically for every sector.[9] The production function reads:

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

where Q_{it} denotes gross output, $F_{it}(\cdot)$ the production function defined over labor, L_{it}, capital, K_{it}, intermediates, M_{it}, and ω_{it} the productivity shock. Production function, $F_{it}(\cdot)$, is continuous and twice differentiable in its arguments, (TOCHECK: from gandhi navarro rivers (2021) it is also strictly concave in M_{it}). The level of inputs used in production need not to be chosen at each and every period. Plenty of evidences point to the fact that some inputs in production adjust very slowly, as it is

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

[8] Recent works moved critiques to the markup estimation methodology. Doraszelski and Jaumandreu (2020) highlight how first-stage misspecification can induce severe biases to the estimated measure of markup, while Bond et al. (2021) 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. (2021) 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.

[9] 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.

the case for capital. This is crucial since the markup identification strategy proposed by De Loecker and Warzynski (2012) relies on the firm's capability to flexibility adjust at least one of the production inputs.

Following the literature, we assume capital to be a dynamic input in production, in other words, it is subjected to a high degree of adjustment costs, conversely intermediate inputs can be freely adjust at each period t. This latter assumption is key to identify markups. Labor needs further digression. In their seminal paper, De Loecker and Warzynski (2012) assume labor to be flexible enough to be considered as a variable input. In their setup, they consider the outcome of Slovenian firms during the transition period of the Nineties, when they moved from a state-guided to a market-driven economy. Given the labor market dynamism at that moment, their assumption seems an appropriate simplification. The Belgian economy, however, is characterized by a more rigid labor market, hence the same assumption would be hardly justifiable. 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 light of these evidences, we assume labor to be a dynamic input in production like capital.

Firm i at time t faces a cost-minimization problem of which the associated Lagrangian reads:

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

where w_{it}, r_{it}, and p_{it}^{M} 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 of the variable inputs, which in this case coincide with the one for intermediates:

$$\frac{\partial \mathcal{L}_{it}}{\partial M_{it}} = p_{it}^{M} - \lambda_{it}\frac{\partial Q_{it}(\cdot)}{\partial M_{it}} = 0. \tag{2}$$

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:

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

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:

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

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.

The nice feature of computing markups in this theoretical framework is that only two parameters are sufficient. 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 estimation procedures to correctly pinpoint input elasticities by controlling for unobserved productivity shocks.

Production Function Estimation

The production function estimation literature provides two frameworks to estimate output elasticities and productivities: the dynamic panel method proposed by Arellano and Bond (1991), Blundell and Bond (1998; 2000), and the control function approach proposed by Olley and Pakes (1996) and extended by Levinsohn and Petrin (2003), Wooldridge (2009), Ackerberg, Caves, and Frazer (2015) (ACF, hereafter), and Gandhi, Navarro, and Rivers (2020). We rely on the second approach, in particular, we follow the procedure developed by ACF.

We make the assumption that productivity is Hicks neutral with respect to production inputs, that the set of common technology parameters evolve over time, and that $F_{it}(\cdot)$ is translog in its arguments. Hence, we can rewrite eq. (1) as follows:

$$q_{it} = f_{it}(l_{it}, k_{it}, m_{it}; \beta_t) + \omega_{it} + \epsilon_{it}, \tag{4}$$

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, hence potentially correlated to the level inputs of production, while ϵ_{it} is the unanticipated productivity shock assumed to be independent and identically distributed. The technological parameters, β_t, are common to all firms within an industry. The core of the identification revolves around the solution of the bias generated by the simultaneous determination of the level of productivity and the inputs level. The restrictions imposed on eq. (3) allow to apply the methodology developed by ACF.

In order to have consistent estimates of the βs, output and inputs need to be expressed in physical quantities. Since we only have access to their counterparts in values, we use industry-level deflators to correct for prices. We estimate equation (4) at the two-digit NACE industry level.

In estimating equation (4) by OLS, we might not account for the endogeneity of the productivity parameter , ω_{it}, hence biasing the βs. It is well known, since the work of Marschak and Andrews (1944), that ω_{it} should not be considered as exogenous with respect to the firm, since firms are expected to be aware of their productivity level when choosing the inputs of production, hence we should expect them to make the input bundle choice accordingly. If this is the case, the correlation between inputs and productivity levels would turn positive, biasing the resulting OLS estimation.

To solve this problem, the empirical IO literature has developed a theoretical framework allowing, under certain assumptions to isolate and identify productivity shocks along with input elasticities. As considered in ACF, under strict monotonicity of the intermediate input demand with respect to the productivity shock, it is possible to invert the function to identify the parameter ω_{it}. Taking the following general form for the intermediate demand:

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

with $\mathbf{z_{it}}$ a vector of additional determinants of the optimal input demand choice[10]. Assuming m_{it} to be invertible, it is possible to retrieve productivity as a function of all the other observable variables.

$$\omega_{it} = \omega_t(l_{it}, k_{it}, m_{it}, \mathbf{z_{it}}), \tag{6}$$

It is then possible to form moment condition to estimate the output elasticity and productivity, under the assumption of ω_{it} following a Markov process[11] and using a specific functional form for the production function.

In particular, we assume the production function to be translog in capital, labor, and the intermediate input:

$$\begin{aligned} q_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2 \\ + \beta_{lk} l_{it} + \beta_{km} k_{it} + \beta_{km} l m_{it} + \beta_{lmk} l_{it} k_{it} m_{it} \end{aligned} \tag{7}$$

Table 2 reports the estimated output elasticities and markups at the aggregate industry level. The reported coefficients are averages across the full sample period

[10] We choose to add as additional controls 2-digit sector dummies and the export status of the firm.
[11] We specify it to be a AR(1) process.

Table 2: Output Elasticities and Markups at Broad NACE Sector

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

Note: The sample contains 184,742 firm-year observation, for 21,099 firms. We estimate output elasticities and markups using the algorithm from De Loecker Warzynski (2015). We assume a firm-level translog production function and we treat capital and labor as predetermined. To account for changes in the production technology over time, we estimate the output elasticities over 5-year rolling windows. 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. Broad NACE Rev. 2 are aggregated as follows: *Food, Beverages, and Tobacco* (NACE 10, 11, 12); *Textile, Wearing Apparels, and Leather Products* (NACE 13, 14, 15); *Wood, Paper Products, and Printing* (NACE 16, 17, 18); *Chemicals and Pharmaceutical* (NACE 20, 21); *Computer, Electronics, and Optical Products* (NACE 24, 25); *Vehicles and Transport Equipment* (NACE 29, 30); *Furniture, Other Manufacturing, and Repairing* (NACE 31, 32, 33).

and feature sizeable variation within and across industries.

China Shock

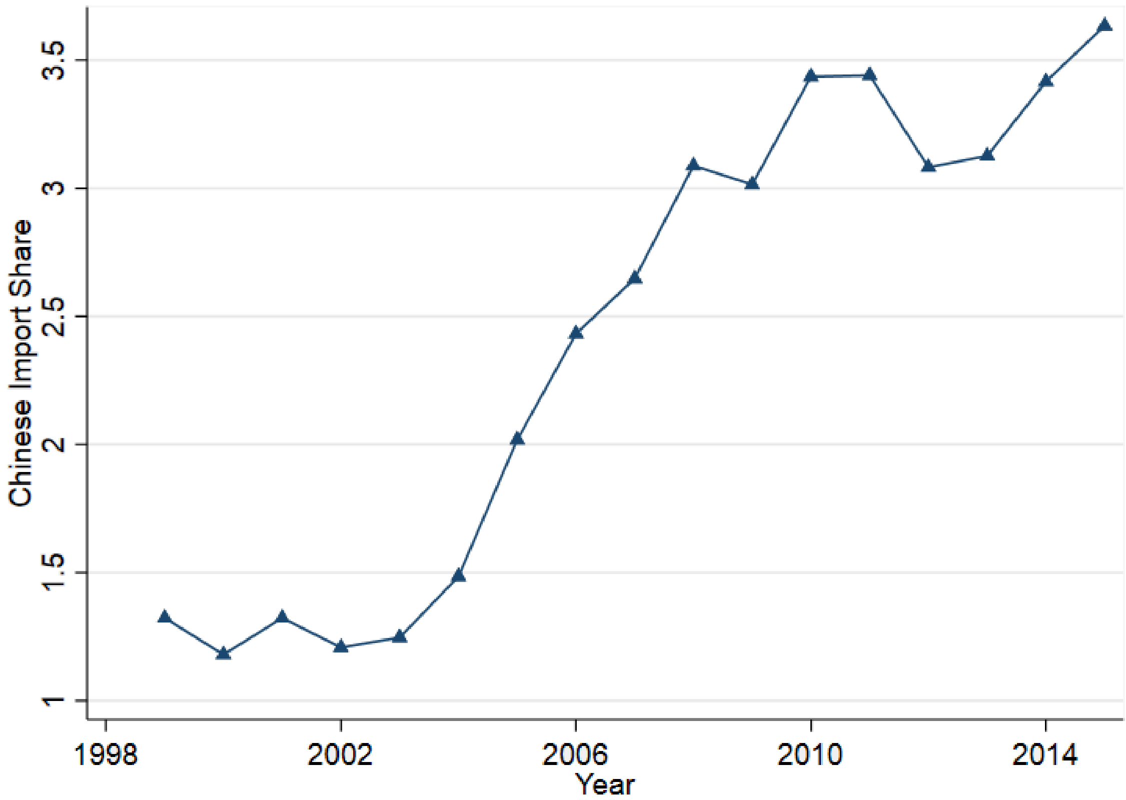
We examine the degree of import competition for the 184 Belgian 4-digit NACE industries, over our sample period 2000-2015. We follow Mion and Zhu (2013) and define our measure of import exposure as the industry-level change in Chinese import share[12] weighted by the beginning-of-the-period industry imports and production values:

$$\Delta IS_{j,\tau}^{BECH} = 100 \times \frac{\Delta M_{j,\tau}^{bc}}{Q_{j,1999} + M_{j,1999}}, \tag{8}$$

[12]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 $\Delta M^{bc}_{j,\tau}$ is the change in Chinese imports values in industry j over the period $\tau \in \{2000-2008; 2008-2015\}$, and $Q_{j,1999}$ and $M_{j,1999}$ are respectively Belgian total production and imports in industry j at the beginning of the period. Variation in $\Delta IS^{bc}_{j,\tau}$ across industries stem from their reliance to intermediate inputs and final products in the production process. In particular, import-intensive industries are expected to be relatively more affected by the surge in trade with China. To get a sense of the importance of the shock for the Belgian economy, Figure 1 reports the aggregate evolution of our measure of Chinese import competition over the sample period. While in 2000 the share of Chinese import on total production and import was slightly above 1%, by 2010 it was more than 2 times larger, plateauing since.

Figure 1: Evolution of Chinese Import Share, Manufacturing



Note: 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.

We follow Autor, Dorn, and Hanson (2021) in quantifying the cumulative effect of the China shock on various measure of market power and productivity, by estimating a first-difference model over progressively longer time horizons. In particular, the regression model reads:

$$\Delta Y_{jt} \;=\; \beta_1 \,\Delta IS^{BECH}_{jt} \;+\; \gamma \mathbf{X_{jt}} + \;\gamma_j \;+\; \delta_t \;+\; \varepsilon_{jt}$$

where $\Delta Y_{j,t+h}$ is the log change of the dependant variable of interest over the period $t \in 2000$ to $t+h$, with $h \in [2000, 2008, 2015]$, γ_j and δ_t are respectively the year and industry fixed effects, and the vector $\mathbf{X_{jt}}$ contains the levels and trends in 1999 on various industry-level controls such as employment, the labor share, the share of production workers, the capital-to-labor ratio, the value added labor productivity, and the Herfindahl index as measure of concentration.

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), and rely on their IV strategy that aim at capturing the Chinese comparative advantage rise 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[13]:

$$\Delta IS^{oc}_{j,\tau} = 100 \times \frac{\Delta M^{oc}_{j,\tau}}{Q_{j,1998} + M_{j,1998}}, \tag{9}$$

where $M^{oc}_{j,\tau}$ is computed as an average of imports of other eight high-income countries from China, and $Q_{j,1999}$ and $M_{j,1999}$ are again computed using Belgian production and import data.

The core of our inquire is to assess the impact of the surge of China on several indicators of market power in the domestic Belgian manufacturing sector.

3.1 Dynamic Decomposition and Concentration Measures

Identifying the determinants of the evolution of market power is crucial for the development of well-suited policies. Before turning to the identification, however, it is possible to gather relevant information about the underlying mechanisms driving the observed changes in markups by looking at firms' dynamics at the industry level. In order to do so, we apply the methodology developed by Melitz and Polanec (2015) to quantify the relative contribution of different groups of firms to the aggregate markup. In particular, by extending Olley and Pakes (1996) (OP, hereafter), their

[13]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.

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

Note: 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.

decomposition allows to attribute the changes in the aggregate markup to the contribution of three different groups: the incumbent, the entering, and the exiting firms.[14] For the incumbents, we also disentangle the *within* component, that accounts for the average increase of markups across firms, from the *reallocation* component, that accounts for the role of those firms gaining market shares. Consider the aggregate level of markup in industry j at time t for a specific group $G \in \{c, e, x\}$:

$$M_{G,jt} = \sum_{i \in G} s_{ijt} \mu_{ijt},$$

where s_{ijt} defines the market share of firm i belonging to group G and μ_{ijt} its associated level of price markup. Consider a simple scenario made of two periods, the

[14]For any pair of periods t and $t+1$, an *incumbent* is defined as a firm having a positive market share in both t and $t+1$, an *entrant* as a firm having no market share in t and positive share in $t+1$, and an *exiter* as a firm having positive market share in t and no market share in $t+1$.

aggregate markup in the first period will be given by the weighted sum of markups of all firms plus the markup of those firms that will exit the market in the following period, while in the second period, the aggregate markup will be given by those firms that survived plus the markup of the new ones in the industry. Formally:

$$M_1 = s_{c,j1}M_{c,j1} + s_{x,j1}M_{x,j1} = M_{c,j1} + s_{x,j1}(M_{x,j1} - M_{c,j1}),$$
$$M_2 = s_{c,j2}M_{c,j2} + s_{e,j2}M_{e,j2} = M_{c,j2} + s_{e,j2}(M_{e,j2} - M_{c,j2}),$$

where simplification arises from the fact that: $s_{c,j1} = 1 - s_{x,j1}$ and $s_{c,j2} = 1 - s_{e,j2}$. Melitz and Polanec (2015) define the change in aggregate markup[15] as the difference between M_2 and M_1:

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

Let's define by $\Delta a_{ijt} = a_{ijt} - \bar{a}_{G,jt}$ the distance between firm i's idiosyncratic value of a and the average industry one, it is possible to apply the OP decomposition for the aggregate level of markup in industry j at time t for a specific group G 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:

$$\begin{aligned} M_{G,jt} &= N_{G,jt}\bar{s}_{G,jt}\bar{\mu}_{G,jt} + \sum_{i \in G} \Delta s_{ijt} \Delta \mu_{ijt}, \\ &= \bar{M}_{G,jt} + \mathrm{cov}_{G,jt}. \end{aligned}$$

Such decomposition allows to retrieved the previously discussed *within*, $\bar{M}_{G,jt}$, and *between*, $\mathrm{cov}_{G,jt}$, components. Using the same logic, we can express the change in aggregate markup as:

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

where $\Delta \bar{M}_{c,jt}$ defines the change in the *within* component of aggregate markup of the incumbents across the two periods, $\Delta \mathrm{cov}_{c,jt}$ the change in the *between* component of

[15]The original paper applied the decomposition to productivity, conceptually it is the same for markups, however the structural interpretation do differs, since comovement between market shares and market power do not pertain to the same class of theoretical models describing comovement between market share and productivity.

the incumbents, $s_{e,j2}(M_{e,j2} - M_{c,j2})$ the firms' entry component, and $s_{x,j1}(M_{x,j1} - M_{c,j1})$ the firms' exit component.

Along with the estimated measures of markups, we provide standard concentrations measures and a measure of within-industry dispersion. We define the Herfindhal index for industry j at time t as:

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

where $s_{i,jt}$ is the firm i sales in industry j at time t. The measure ranges between 1/J, for perfect equality, and 1, at which we have the concentration of all sales in only one firm. We further define the concentration ratio for the four largest firms within sector, or CR4, as:

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

To get a sense of within-industry misallocation, we compute the Theil index of markups as:

$$\text{Theil}_t = \frac{1}{N} \sum_i \frac{\mu_{it}}{\bar{\mu}_t} log \left(\frac{\mu_{it}}{\bar{\mu}_t} \right).$$

The measure ranges between 0, for no dispersion, and the logarithm of the number of firms, which defines the maximum level of dispersion. The higher the dispersion the higher the extent of the misallocation and the possible welfare losses driven by market power.

4 Results

Table 3: Baseline Effect of Chinese Import Share on the Industry-Level Aggregate Markup

	$\Delta\, Markups$			
	(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	2001-2015	2001-2015	2001-08	2008-15
KP F-Stat	11.909	5.928	33.569	8.929
Obs.	368	368	184	184

Note: The table reports the estimated coefficients for equation (8). The dependent variable is defined as the stacked difference in the Chinese import share over the periods 2000-2008 and 2008-2015. Standard errors are cluster at the ZE level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3 reports the baseline results of the stacked difference estimation on the aggregate industry-level markup. Column (1) is our preferred specification, were we control for 2-digit industry and time fixed effects. We add pre-sample period controls on sales, concentration, labor productivity, capital intensity and skill composition at the industry level. The effect is positive and significant at the 1 percent. The instrument's F-stat is above 10. The effect is stronger when looking at column (2), where we control for 4-digit industry fixed effects. When looking at the two sub-periods, the effect is driven by the second one.

Table 4 reports results for a similar exercise, using as dependent variables the within and between components coming from the decomposition exercise. The within effect is stronger and dominates the reallocation effect, meaning that are incumbents firms that charge higher markups, without reallocation of market shares from low to high markup chargers.

Table 5 looks at the concentration measures. Results are less robust with respect

Table 4: Effect of Chinese Import Share on the Industry-Level Aggregate Markup, Decomposition

	$\Delta\, Reallocation$			$\Delta\, Within$		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIS^{BECH}_{jt}	-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	2001-08	2008-15	2001-15	2001-08	2008-15	2001-15
KP F-Stat	33.569	8.929	11.909	33.569	8.929	11.909
Obs.	184	184	368	184	184	368

Note: The table reports the estimated coefficients for equation (8). The dependent variable is defined as the stacked difference in the Chinese import share over the periods 2000-2008 and 2008-2015. Standard errors are cluster at the ZE level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 5: Effect of Chinese Import Share on the Industry-Level Aggregate Markup, Concentration

	$\Delta\, HHI$			$\Delta\, CR4$		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIS^{BECH}_{jt}	-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	2001-08	2008-15	2001-15	2001-08	2008-15	2001-15
KP F-Stat	33.569	8.929	11.909	33.569	8.929	11.909
Obs.	184	184	368	184	184	368

Note: The table reports the estimated coefficients for equation (8). The dependent variable is defined as the stacked difference in the Chinese import share over the periods 2000-2008 and 2008-2015. Standard errors are cluster at the ZE level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

to the previous tables, but overall they point to higher overall concentration over the period. This is in line with a story of rising markups due to higher market power.

Finally, in Table 6 we look at the effect on productivity and markup dispersion. Productivity is also increasing along with markups in the second period, this might

Table 6: Effect of Chinese Import Share on the Industry-Level Aggregate Markup, Other

	ΔTFP			$\Delta Theil(Markup)$		
	(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	2001-08	2008-15	2001-15	2001-08	2008-15	2001-15
KP F-Stat	33.569	8.929	11.909	33.569	8.929	11.909
Obs.	184	184	368	184	184	368

Note: The table reports the estimated coefficients for equation (8). The dependent variable is defined as the stacked difference in the Chinese import share over the periods 2000-2008 and 2008-2015. Standard errors are cluster at the ZE level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

imply that along with increasing market power, firms are also upgrading in terms of efficiency. Overall, this might point to a story of winner-take-all competition, where the most productive firms become dominant in their market and start charging higher markups. Results concerning markup dispersion point also in the same direction, with higher dispersion meaning higher distance between the leaders and the laggards in terms of ability to charge higher prices.

5 Conclusion

Recent decades have witnessed a surge in firms' market power. This paper contributes to the debate on the consequences of international trade competition on firms market power by looking at the impact of the Chinese surge in world trade on the distribution of markups and other measure of market power for the Belgian manufacturing sector over the period 2000-2015.

We use balance sheet and trade data to estimate firm level markups and productivity at the firm level, and we compute additional aggregate sector level measures of market power, as HHI and CR4 concentration measures.

We find that sectors that are relatively more exposed experience higher degree of market power in the form of higher level and dispersion of markups, higher concentration, but also higher productivity growth. These changes are not driven by reallocation between firms, but by within adjustments of the incumbents. Overall, these evidences point to a winner-take-all type of rational behind the observed increase in market power.

References

Acemoglu D., D. Autor, D. Dorn, G. Hanson, and B. Price (2016). "Import Competition and the Great US Employment Sag of the 2000s," *Journal of Labor Economics*, vol. 34(1), pp. 141-198.

Ackerberg D.A., K. Caves, and G. Frazer (2015). "Identification Properties of Recent Production Function Estimators," *Econometrica*, vol. 83(6), pp. 2411-2451.

Affeldt P., T. Duso, K. Gugler, J. Piechucka (2021). "Market Concentration in Europe: Evidence from Antitrust Markets," mimeo.

Aghion P., A. Bergeaud, M. Lequien, M. Melitz, and T. Zuber (2021). "Opposing firm-level Responses to the China Shock: Horizontal Competition Versus Vertical Relationships?," NBER Working Paper No. 29196.

Arkolakis C., A. Costinot, and A. Rodríguez-Clare (2019). "The Elusive Pro-Competitive Effects of Trade" , *Review of Economic Studies*, vol. 86(1), pp. 46-80.

Autor D., D. Dorn, and G. Hanson (2013). "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, vol. 103(6), pp. 2121-2168.

— (2016). "The China Shock: Learning from Labor Market Adjustment to Large Changes in Trades," *Annual Review of Economics*, vol. 8, pp. 205-240.

—, G. Pisano, and P. Shu (2016). "Foreign Competition and Domestic Innovation: Evidence from U.S. Patents," NBER Working Paper No. 22879.

Autor D., D. Dorn, L.F. Katz, C. Patterson, and J. Van Reenen (2020). "The Fall of the Labor Share and the Rise of Superstar Firms," *The Quarterly Journal of Economics*, vol. 135(2), pp. 645–709.

Bartelsman E., D. Haltiwanger, and S. Scarpetta (2013). "Cross-Country Differences in Productivity: The Role of Allocation and Selection," *American Economic Review*, vol. 103(1), pp. 305-334.

Bloom N., M. Draca, and J. Van Reneen (2016). "Trade Induced Technical Change? The Impact of Chinese Import on Innovation, IT and Productivity," *Review of Economic Studies*, vol. 83(1), pp. 87-117.

Caliendo L., M. Dvorkin, and F. Parro (2019). "Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock," *Econometrica*, vol. 87(3), pp. 741-835.

Calligaris S., C. Criscuolo, and L. Marcolin (2018). "Mark-ups in the Digital Era," OECD Science, Technology and Industry Working Paper, 2018/10.

Covarrubias M., G. Gutiérrez, and T. Philippon (2020). "From Good to Bad Concentration? U.S. Industries over the Past 30 Years," NBER *Macroeconomics Annual*, vol. 34, pp. 1-46.

Dauth W., S. Findeisen, and J. Suedekum (2014). "The Rise of the East and the Far East: German Labor Markets and Trade Integration," *Journal of the European Economic Association*, vol. 12(6), pp. 1643-1675.

De Blas B. and K.N. Russ (2015). "Understanding Markups in the Open Economy," *American Economic Journal: Macroeconomics*, vol. 7(2), pp. 157-180.

De Loecker J., J. Eeckhout and G. Unger (2020). "The Rise of Market power and the Macroeconomic Implications," *The Quarterly Journal of Economics*, vol. 135(2), pp. 561-644.

De Loecker J., P. Goldberg, A. Khandelwal, and N. Pavcnik (2016). "Prices, Markups, and Trade Reforms," *Econometrica*, vol. 84(2), pp. 445-510.

De Loecker J., C. Fuss, and J. Van Biesenbroeck (2014). "International Competition and Firm Performance: Evidence from Belgium," NBB Working Paper No. 269

De Loecker J., and F. Warzynski (2012). "Markups and Firm-Level Export Status," *American Economic Review*, vol. 102(6), pp. 2437-2471.

De Ridder M. (2021). "Market Power and Innovation in the Intangible Economy," mimeo.

Dhingra S. and J. Morrow (2019). "Monopolistic Competition and Optimum Product Diversity under Firm Heterogeneity," *Journal of Political Economy*, vol. 127(1), pp. 196-232.

Díez F.J., J. Fan, and C. Villegas-Sánchez (2021). "Global Declining Competition?," *Journal of International Economics*, 103492.

Edmond C., V. Midrigan, and D. Y. Xu (2015). "Competition, Markups, and the Gains from International Trade," *American Economic Review*, vol. 105(10), pp. 3183-3221.

Epifani P. and G. Gancia (2011). "Trade, Markup Heterogeneity and Misallocation" *Journal of International Economics*, vol. 83(1), pp. 1-13.

Feenstra R. and A. Sasahara (2018). "The 'China Shock', Exports and U.S. Employment: A Global Input-Output Analysis," *Review of International Economics*, vol. 26(...), pp. 1053-1083.

Garcia-Marin A. and N. Voigtländer (2019). "Exporting and Plant-level Efficiency Gains: It's in the Measure," *Journal of Political Economy*, vol. 127(4), pp. 1777–1825.

Gopinath G., Ş. Kalemli-Özcan, L. Karabarbounis, and C. Villegas-Sanchez (2017). "Cross-Country Differences in Productivity: The Role of Allocation and Selection," *Quarterly Journal of Economics*, vol. 132(4), pp. 1915-1967.

Grullon G., Y. Larkin, and R. Michaely (2017). "Are US Industries Becoming More Concentrated?," *Review of Finance*, vol. 23(4), pp. 697-743.

Gutiérrez G. and T. Philippon (2018). "How European Markets became Free: A Study of Institutional Drift," NBER Working Paper No. 24700.

Holmes T.J., W. Hsu, and S. Lee (2014). "Allocative Efficiency, Mark-Ups, and the Welfare Gains from Trade," *Journal of International Economics*, vol. 94(2), pp. 195-206.

Konings J. and L. Marcolin (2014). "Do Wages Reflect Labor Productivity? The Case of Belgian Regions," *IZA Journal of European Labor Studie*, vol. 3(11), pp. 1-21.

Klenow P. and A. Rodríguez-Clare (1998). "The Neoclassical Revival inGrowth Economics: Has It Gone Too Far?," *NBER Macroeconomics Annual*, B. Bernanke and J. Rotemberg, eds. Cambridge, MA: MIT Press.

Levinsohn J., and A. Petrin (2003). "Estimating Production Functions using Inputs to Control for Unobservables," *The Review of Economic Studies*, vol. 70(2), pp. 317-341.

Lu Y., and L. Yu (2015). "Trade Liberalization and Markup Dispersion: Evidence from China's WTO Accession," *American Economic Journal: Applied Economics*, vol. 7(4), pp. 221-253.

Marschak J. and W.J. Andrews (1944). "Random Simultaneous Equations and the Theory of Production" *Econometrica*, vol. 12, pp. 143-205.

Melitz M. and S. Polanec (2015). "Dynamic Olley-Pakes Productivity Decomposition with Entry and Exit" *The RAND Journal of Economics*, vol. 46(2), pp. 362-375.

Mion G. and L. Zhu (2013). "Import Competition from and Offshoring to China: a Curse or a Blessing for Firms?" *Journal of International Economics*, vol. 89(1), pp. 202-215.

Olley G. and S. Pakes (1996). "The Dynamics of Productivity in the Telecommunication Equipment," *Econometrica*, vol. 64(6), pp. 1263-1297.

Parente S.L. and E.C. Prescott (2000). "Barriers to Riches," Cambridge, MA:MIT Press.

Pierce J. and P. Schott (2016). "The Surprisingly Swift Decline of US Manufacturing Employment," *American Economic Review*, vol. 106(7), pp. 1632-1662.

Philippon T. (2019). "The Great Reversal: How America Gave Up to Free Market," Cambridge, MA:Harvard University Press.

Syverson C. (2019). "Macroeconomics and Market Power: Context, Implications, and Open Questions," *Journal of Economic Perspectives*, vol. 33(2), pp. 23-43.