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VNIVERSITAT DE VALÈNCIA

Departamento de Estructura Económica (Economía Aplicada II), Facultad de Economía, Universitat de València
Avda dels Tarongers, s/n, 46022 – Valencia, Spain
Phone +34 96 382 83 49 / Fax +34 96 382 83 54
http://www.estructuraeconomica.es
e-mail: investigacion.estructura@uv.es

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Dolores Añón Higón*; Ioannis Bournakis†

Abstract

We examine the relationship between firms' participation in global value chains (GVCs) and price markups. We use data from 14,316 firms in six European countries obtained from AMADEUS data linked to the EFIGE project. There is substantial heterogeneity between countries and industries in terms of firm-specific time variant markups. After controlling for sample selection bias using coarsened exact matching (CEM), we find that firms involved in exporting produced-to-order goods and importing service and material inputs have between a three and four percent markup premium relative to non-trading firms. Our results remain robust to alternative definitions of GVC participation, different data matching techniques (Propensity Score Matching) and different markup estimates. Our findings contribute to the scarce but increasingly significant literature on markup heterogeneity and provide ample opportunities for designing industrial policies.

Keywords: Markup, TFP, GVC participation, EFIGE Data, Coarsened Exact Matching, Propensity Score Matching.

* *Department of Applied Economics II and ERI-CES, Faculty of Economics, Universitat de València, Avda. Tarongers, s/n, 46022 Valencia (Spain); e-mail:* m.dolores.anon@uv.es. *ORCID*: orcid.org/0000-0003-2468-9490. Dolores acknowledges financial support from Grant ECO2017-86793-R funded by MCIN/AEI/ 10.13039/501100011033 and by "ERDF A way of making Europe", and from Grant PROMETEO/2019/095 funded by Generalitat Valenciana. Usual caveats apply.

† *SKEMA Business School. Avenue Willy Brandt. 59777 Euralille, France. E-mail*: ioannis.bournakis@skema.edu.

1. Introduction

The evolution of markups, the difference between price and marginal cost, provides insights into various aspects, including market structure, consumer welfare, labour demand, and new capital investment. Despite the significant welfare implications of this topic, there is surprisingly limited evidence regarding the factors that influence markup heterogeneity across industries and over time. The existing empirical evidence regarding the evolution of markups varies and remains highly inconclusive.

On the one hand, De Loecker et al. (2020) and Calligaris et al. (2018) document a substantial increase in markups in the USA and OECD and, to a lesser extent, in non-OECD countries. These studies attribute the increasing trend in markups primarily to firms already positioned in the top percentile of the markup distribution. Conversely, for firms in the bottom percentile, markups tend to remain relatively stable. The observed factors contributing to this pattern include a low entry rate of new firms owing to high entry barriers (De Loecker et al., 2020), quality upgrading (Chen and Juvenal, 2019), and an increased reliance on digitalized assets. De Loecker (2012) found that exporters tend to charge a higher markup, while imports can also increase markups if the imported materials upgrade the quality of the final product (Hornok and Muraközy, 2019). Firms that use intensively digital assets are protected by intellectual property rights that allow them to re-use these assets with zero marginal cost which leads faster to increased returns and higher profitability.

On the other hand, Gradzewicz and Muck (2023), Weche and Wambach (2021), Caselli and Schiavo (2020), and Weche (2018) present evidence of a notable decline in firm markups within European and Emerging countries. Unlike De Loecker's (2020) findings for the US, Weche and Wambach (2021) highlight that the substantial decrease in markups among European firms during the 2007/2008 financial crisis was succeeded by a markup increase. Notably, this increase is not solely driven by firms at the upper percentile of the distribution but is instead a result of an uptick in the median markup. Among the factors emphasised in the studies that document a fall in markups over the last two decades are the increasing engagement of firms in globalised production, international trade, and foreign investment. Gradzewicz and Muck (2023) find that Polish firms participating in Global value chains over the period 2002-2016 charge lower markups. This is because the international fragmentation and outsourcing of production enable manufacturing firms to improve efficiency and pass on these gains to final prices. Weche (2018) identifies increased competition from import penetration as the primary factor driving the reduction in markups among European firms. Caselli and Schiavo (2020) document a similar result, noting reduced markups in French firms attributed to the upsurge in Chinese imports.

The previous literature reveals substantial cross-country differences in the evolution of markups. Still, there is also considerable markup heterogeneity within countries and across firms

(Weche, 2018). This aspect warrants deeper exploration, given that the present state of literature tends to focus on specific product markets (Koppenberg and Hirsch, 2022; Sckokai et al., 2013) or country case studies (Mydland et al., 2022), thereby lacking comprehensive firm-level evidence across a broader panel of countries. Our study addresses this gap by examining how firms' participation in global value chains (GVCs) influences their markup for a sample of European countries. This is particularly pertinent given that the dispersion in firms' markups has been partly attributed to extensive GVC activities (Antràs, 2020; De Loecker et al., 2020; Gradzewicz and Muck, 2023).

Trade models with heterogeneous firms predict that GVC participants (through exports or imports) are more productive and set higher profit margins (Melitz and Ottaviano, 2008). This markup premium may be due to reasons other than self-selection (Antrás, 2020). GVC exporters and GVC importers may set higher markups if the first group becomes more efficient by exporting to global suppliers (i.e., learning by exporting gains) and the second group exploits cost savings by importing cheaper inputs. Both groups only partially pass on these gains to prices meaning essentially higher markups[1]. Furthermore, importing higher-quality inputs can enhance the overall quality of the final product for GVC importers, leading to an outward rotation of the demand curve and thus higher markups (Bas and Strauss-Kahn, 2015).

World Bank (2020) tests the relationship between GVC participation and markups but relies on a measure of trade status to proxy for GVC participation. This is problematic as not all trading firms are embedded in GVCs. We enrich the limited but increasingly significant literature on markup heterogeneity, by providing robust evidence from a large sample of 14316 European firms drawn from the EFIGE dataset. We accomplish our research objective by using the methodology of De Loecker and Warzynski (2012) (DLW, henceforth) to estimate firms' markups and define GVC firms as those that export produced-to-order goods and import services and material inputs. These firm-level categories represent the nearest counterpart to country/sector GVC trade, as they include trade flows across at least two countries (Antràs, 2020). To identify the relationship between GVC and markups, several empirical challenges must be addressed to ensure that the revealed pattern is robust to unobserved measurement errors and endogeneity bias. First, despite using an approach to markup derivation that does not rely on specific assumptions about demand and market conduct, measurement errors might still exist. Second, there are unobserved firm-specific idiosyncrasies that make domestic firms with significant market power more likely to participate in GVC trade. In this case, there are feedback effects between market power and GVC involvement, which complicates inferences about whether GVC firms charge higher markups. In our analysis, we mitigate possible sources of endogeneity and selection bias between markups and GVC trade by applying coarsened exact matching (CEM) and, for robustness, propensity

[1] Adversely, the higher degree of competition in foreign markets may affect the pricing strategy of exporters, making them lower their difference between marginal cost and final price (Hornok and Muraközy, 2019).

score matching (PSM) techniques. Using CEM and PSM, we can create a control group that is similar to the treatment group to understand whether GVC participation impacts firms' markups (Iacus et al., 2012). Although PSM has been one of the most widely used methodologies to deal with self-selection bias, CEM usually outperforms PSM (King and Nielsen, 2019). Therefore, the CEM method is chosen as the preferred matching method for the main specifications of the present study. However, PSM results will also be presented to strengthen our empirical findings. To further enhance the robustness of our baseline results, we conduct additional tests by exploring the relationship between GVC participation and markups through an alternative markup estimation method. Our final set of robustness checks involves investigating the relationship between the markup premium and GVC activity using alternative definitions of the latter. In this regard, we first follow Gopalan et al. (2022) and Thang and La (2022) in adopting a narrower definition of GVC participation that represents GVC status when a firm is a two-way trader (i.e., exporting produced-to-order goods and importing services and material inputs simultaneously) and owns a quality certificate.

In summary, our paper provides three main contributions. Firstly, we offer additional empirical evidence on the factors that influence significant variations in markups, which is a topic that has received limited attention in the literature. Our research is based on a study of a panel of 14316 firms from six European countries spanning the years 2001-2014. Secondly, we investigate how participation in global value chains (GVCs) affects firms' pricing behavior. Our analysis goes beyond the typical approach of comparing the markups of exporters and non-exporters (DLW) and those of firms exporting to different destinations (Kilinc, 2019; Chen and Juvenal, 2019). Thirdly, we highlight the potential policy implications of our findings. Our results show that globalized production has significant implications for welfare and therefore offer important insights for policymakers. Specifically, our findings imply how GVCs can lead to the reallocation of consumer and producer surplus, which has important implications for policy design and intervention.[2]

2. Data and Measurement of Variables

2.1. The Database

We use data from the EFIGE dataset provided by Bruegel. This Belgian non-profit international organisation collected survey-based data from 14,759 manufacturing firms (with 10 or more employees) in Austria, France, Germany, Hungary, Italy, Spain and the UK. We exclude Austria from the original sample due to the small number of observations. After this amendment, we have comprehensive information on the international activity of 14,316 European manufacturing enterprises. The EFIGE

[2] We also refer to Epifani and Gancia (2011) for a theoretical framework on how openness to trade affects markup distribution and induces welfare losses.

data come from a 150-question questionnaire covering six broad areas of economic activity for 2008: firm structure, labour force, innovation, internationalisation, market structure and finance (Altomonte and Aquilante, 2012; Altomonte et al., 2013). Table 1 shows the number of firms in each country in 2008.

Table 1. Number of Firms by Country in The Amadeus-EFIGE Dataset

Country	Number of firms
France	2973
Germany	2935
Hungary	488
Italy	3021
Spain	2832
United Kingdom	2067
Total	14316

The EFIGE cross-sectional survey is combined with balance sheet data from the Bureau van Dijk's Amadeus database for 2001-2014. Thus, although the EFIGE survey was conducted in 2008, the balance sheet data covers the period 2001-2014. The combined EFIGE-BvD-Amadeus database allows us to calculate markups and identify companies' GVC participation in a unified database. In particular, we obtain estimates of markups over the entire period and analyse whether GVC activity in 2008 affects markup behaviour in 2008 and beyond.

2.2. Measuring Global Value Chain (GVC) participation

We define firms based on their type of GVC involvement following Giunta et al. (2022): (a) importers of intermediate goods and/or services, and (b) exporters of intermediates[3]. EFIGE provides direct information on (a) and, we identify (b) as exporters of produced-to-order goods (i.e., firms outsourcing inputs to firms abroad). The data on produced-to-order goods are the most accurate instrument available in EFIGE for capturing vertical market relationships between suppliers and buyers within GVCs (see Veugelers et al., 2013; Giunta et al., 2022). The survey asks firms to indicate the average percentage of their sales accounted for by produced-to-order goods and their primary customer. We consider intermediate goods exporting firms to be those that respond that more than 50% of their turnover is made up of sales made according to a specific order (produced-to-order goods) from a customer located

[3] As EFIGE does not distinguish between exports of intermediate and final goods, we use the information on produced-to-order goods to classify as supplier exporters, firms whose turnover is mainly determined by producing to order for other firms located abroad (Cainelli et al., 2018).

abroad. We also differentiate single (importer or supply exporter) from dual (supply exporters and importers) GVC firms.

Table 2 shows the distribution of GVC firms by participation in 2008. Non-traders represent 41% of the firms in the sample. Traders may not always participate in GVCs. Accordingly, non-GVC firms that export only to the end market (Giunta et al. 2022) represent 16.5% of firms in the sample. Looking at GVC firms, 28% operate as single-GVC and 18.4% as dual-GVC traders. These percentages remain stable for the matched sample in which treated firms (i.e., GVC firms) are matched to untreated firms (i.e., non-GVC firms) on a series of firm characteristics.

Table 2. Firms by trade mode and GVC participation in 2008 (%).

	No-traders	Non-GVC trader	Single-GVC firm	Dual-GVC firm
Total sample	41.10%	16.53%	28.02%	18.36%
Matched sample[a]	40.54%	15.22%	28.63%	15.61%

Note: Authors' calculations from EFIGE data. No-traders are firms that neither export nor import. Non-GVC traders are those that export to the end market. Single-GVC firms are sole exporters of produced-to-order goods to other firms abroad (i.e., supplier exporter) or are sole importers. Dual-GVC firms act as both supplier exporter and importer. [a] Matched sample with CEM.

2.3. Measuring Markups

We measure markups using the DLW methodology. Contrary to previous approaches that assume specific demand conditions (Berry et al. 1995; Berry et al. 2004) and dual cost function estimation approaches (Morrison, 1993, 1994; Chirink and Fazzari, 1994; Galeotti and Schiantarelli, 1998),[4] the DWL approach derives time-variant price markups from the estimation of the production function. The DWL methodology builds on Hall (1988) by measuring at each point in time the wedge between the observed input share to revenue and the estimated elasticity of this input to output. DLW only assumes cost minimizer producers and the existence of at least one freely adjusted input (in our case, labour) without specifying any structural demand form. An expression of markup μ_{it} of firm *i* in period *t* is then given by (our panel includes a country index *c* but is suppressed for readability): [5]

[4] See De Loecker and Scott (2016) for a study that compares markups between demand and production estimation approaches.

[5] Cost minimising behaviour implies that firms equalise the output elasticity of input *J*, θ_{it}^{J}, to $\frac{1}{MC_{it}} \frac{P_{it}^{J} X_{it}^{J}}{P_{it} Y_{it}}$, where *MC* is marginal cost and the second ratio indicates the revenue share of variable input *J*.

$$\mu_{it} = \frac{\theta_{it}^J}{s_{it}^J} \tag{1}$$

where θ_{it}^J is the output elasticity with respect to input *J*, and s_{it}^J is the input *J's* revenue share, $s_{it}^J = \frac{P_{it}^J X_{it}^J}{P_{it} Y_{it}}$.

Our data allow us to use labour and intermediate inputs - under a gross output product function- for calculating markup in equation (1). While treating labour as a flexible input that can be easily adjusted without incurring costs is also debatable (Van Heuvelen et al. 2021)[6], there is a trade-off between applying a gross output production function with intermediate inputs as a flexible input and being able to accurately identify the coefficients of the factors of production (DLW)[7]. From the perspective of this study, participation in GVCs affects primarily the adjustment costs of intermediate inputs and therefore leads to biased markup estimates based on intermediate inputs (Gradzewicz and Mućk, 2022). Taking these considerations into account, we have chosen labour for the identification of markup estimates.

To recover the output elasticity with respect to labour, we estimate a baseline Cobb-Douglas value-added production function of the form:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it} \tag{2}$$

Where y_{it} is the logarithm of real value added, l_{it} is labour, and k_{it} is physical capital. Parameter ω_{it} is the firm's productivity, which is assumed to be observable by the firm but not by the econometrician; and ε_{it} is a standard statistical error term. All input parameters are assumed to be industry-specific and time-invariant. Labour is a flexible input free of adjustment costs and capital is fixed. Hence, we are interested in estimating the output elasticity with respect to labour ($\hat{\beta}_l$).[8]

To obtain unbiased estimates of the output elasticities $\hat{\beta}$s in (2), we need to control for unobservables, as set out by Olley and Pakes (1996) and Levinsohn and Petrin (2003)[9]. The idea behind unobservables is that OLS estimates of (2) suffer from endogeneity bias due to the correlation between input selection and ω_{it}. To deal with this issue, we apply the one-step GMM estimation of Wooldridge (2009). This approach deals both with the simultaneity bias and the identification problem discussed in

[6] Van Heuvelen et al. (2019) argue that the assumption that labour is flexible is unlikely to hold in dual labour markets such as the Netherlands. In their setup they use temporary contract workers as the flexible input while permanent workers are considered quasi-fixed. Unfortunately, we lack data on fixed and temporary workers and their wages to implement their method. In our data, Spain is also characterised by a dual labour market. Therefore, as a robustness check, we will exclude Spain from the sample as a robustness test.
[7] As discussed in Ackerberg et al. (2015), it is difficult to identify the coefficients of labor and material separately in a gross output production function, as the two variables are often correlated.
[8] Unfortunately, we have no information on how a firm's markup varies across products and markets, as we do not have cost and sales data at the firm–product–market level.
[9] We use the *prodest* Stata command developed by Rovigatti and Mollisi (2018).

Ackerberg *et al.* (2015)[10]. The key assumption is that the demand for materials m_{it} is monotonic and strictly increasing in productivity, and, under certain conditions, it can be inverted to obtain:

$$\omega_{it} = m_t^{-1}(k_{it}, m_{it}, z_{it}) = h_t(k_{it}, m_{it}, z_{it}) \tag{3}$$

where additional control variables that affect the demand for intermediates are captured by the vector z_{it}[11]. Then, substituting into (2) we get the first equation to estimate:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + h_t(k_{it}, m_{it}, z_{it}) + \varepsilon_{it} \tag{4}$$

given $h_t(.)$ is an unknown function, which we proxy by a higher order polynomial in its arguments, this results in β_k in (2) being non-identified. Hence, identifying β_k requires an additional equation that deals with the law of motion of productivity, ω_{it}. Therefore, we assume that productivity follows a first-order Markovian process:

$$\omega_{it} = g(\omega_{it-1}) + \xi_{it} \tag{5}$$

where ξ_{it} represents productivity innovation. In sum, productivity can be expressed as follows: $\omega_{it} = h_t(k_{it}, m_{it}, z_{it}) = g(h(k_{it-1}, m_{it-1}, z_{it-1})) + \xi_{it}$. The second equation to estimate under the Wooldridge (2009) approach has the following form:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + g\big(h(k_{it-1}, m_{it-1}, z_{it-1})\big) + \eta_{it} \tag{6}$$

where $\eta_{it} = \xi_{it} + \varepsilon_{it}$

To estimate β_l and β_k parametrically, the unknown functions g (.,.) and f(.) are approximated by a third-order polynomial. Following Wooldridge (2009), equations (4) and (6) are estimated jointly at the two-digit sector level (NACE Rev.2 industry classification) in a GMM setup using the moment

[10] Ackerberg et al. (2015) highlight that if labour is chosen before production takes place, the coefficient on labour cannot be identified. Apart from avoiding the functional dependence problem in the first stage, the joint estimation approach in Wooldridge (2009) is also more efficient than two-step control function approaches.

[11] In the vector z, we include country dummies.

conditions outlined in Levinsohn and Petrin (2003)[12]. Therefore, the coefficient estimates are industry-specific, which controls for the potential heterogeneity of production technologies across industries. With the estimated elasticities at hand, firm-specific TFP estimates are obtained as residuals from $\widehat{\omega}_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it}$. Finally, we compute the markups in expression (1) using the estimate of the output elasticity of labour, $\hat{\beta}_l$. To allow for unanticipated shocks to output and measurement error, we adopt $y_{it} = y_{it}^{*} + \varepsilon_{it}$ (lowercase letters to represent logarithms). This error captures the differences between the expected output, given the information set of the producer, and the actual realization. Thus, we correct the markup formula by eliminating measurement errors as follows:

$$\hat{\mu}_{it} = \frac{\widehat{\theta}_{jt}^{l}}{s_{it}^{l}} \exp\left(-\hat{\varepsilon}_{it}\right) \tag{7}$$

where $\hat{\varepsilon}_{it}$ is the estimated residual from the first stage regression in the control function approach, and s_{it}^{l} is the labour expenditure share which is observed in the data. Finally, following standard practice, we winorize the resulting distribution at the 1st and 99th percentile to control for outliers (Foster et al., 2022)[13].

Our estimates for baseline markup follow the Wooldridge (2009) method for estimating the value-added Cobb-Douglas production function. However, we have found that using markup estimates derived from the Ackerberg et al. (2015) method (ACF) yields similar econometric results, as outlined in Appendix A.1. Additionally, we have observed that our results remain robust even when we use a gross output instead of a value-added production function and when we consider alternative functional forms of the production function, such as the translog production function, which is more flexible than the Cobb-Douglas.

For estimating (2), value added (y_{it}) is defined as operating revenue (OPRE) minus costs of materials (MATE), capital stock (k_{it}) is measured by the book value of fixed assets (FIAS), labour (l_{it}) is measured by the number of employees (EMPL), and wages are measured by staff remuneration (STAF). We deflate nominal euro values of operating revenue, material costs and fixed assets using a 2-digit NACE industry production price index (2005=100) from Eurostat. To estimate (2), we remove observations from the sample with missing and negative values for fixed assets, operating revenue, and cost of materials. Table A.2 in the Appendix shows summary statistics of the deflated variables used for estimating (2) and calculating markups.

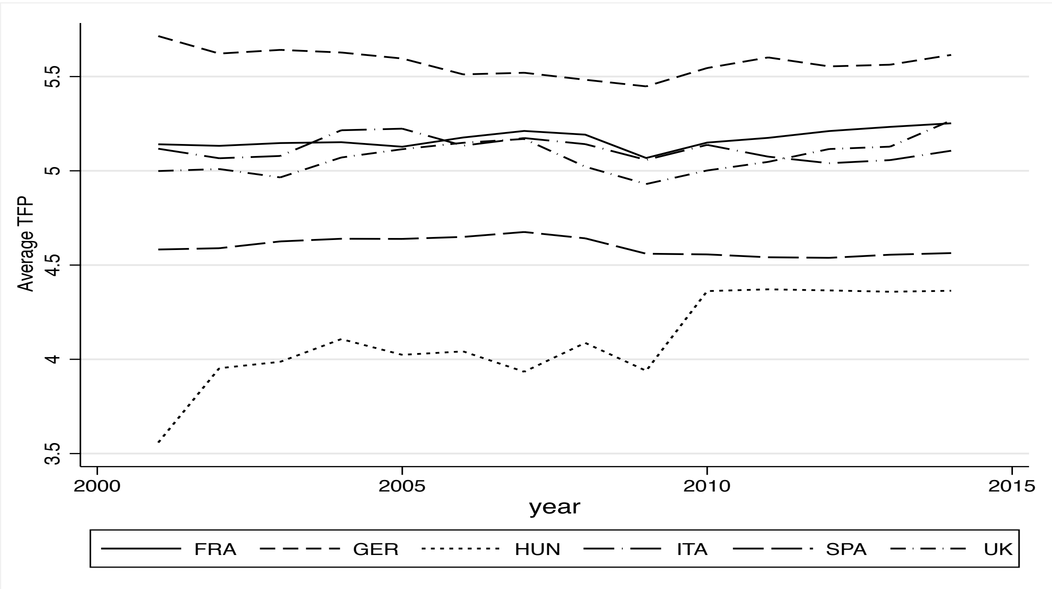
[12] The standard semi-parametric estimators use a two-step estimation procedure to obtain estimates of input elasticities (Olley and Pakes,1996; Levinsohn and Petrin, 2003, Ackerberg et al., 2015). Wooldridge's method uses a system estimation instead. Still, it takes into account the Ackerberg et al. (2015) critique, that if labour is partly hired before productivity is known, the coefficient on labour will not be correctly identified in the first step of the estimation.

[13] Including the outliers leads to similar findings on aggregate markup trends (results available upon request).

2.4 Descriptive Evidence

Following the calculation of TFP and markups, this section shows graphical evidence of how these variables evolve across industries and over time. Figure 1A displays the average country TFP trend from 2001-2014[14]. A few remarks from this graph deserve further attention. First, German firms are the leading productivity performers throughout the period, followed by French and Italian firms. Not surprisingly, Hungarian firms are at the bottom of the distribution. After a period of modest convergence, they maintain a stable (still lagging relative to the mean) TFP after 2010. UK firms experienced a considerable decline in 2007-08, which more likely represents adverse effects from the global financial crisis associated with the US subprime crisis of 2008. Turning to TFP performance by sector, in Figure A2, there are no substantial productivity differentials across industries, however, there are sectors with exceptional performance relative to the average (the reference line). These are the pharmaceuticals, electrical equipment, electronics, repairs, printing and coke.

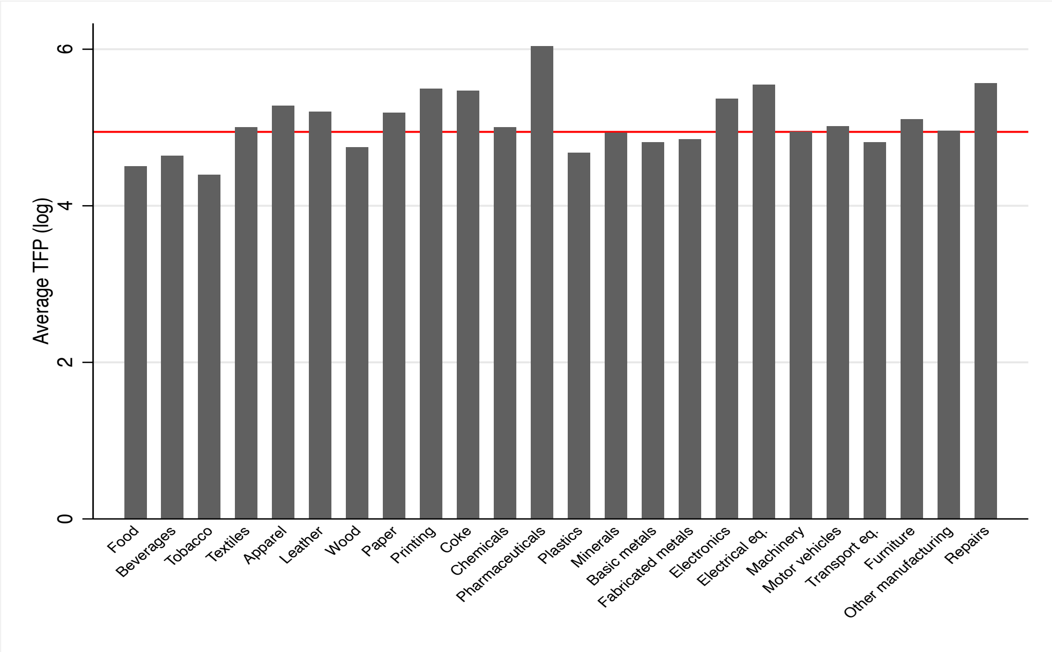
Figure 1A. Average TFP by Country, 2001-2014.



Notes: TFP is calculated using the Wooldridge (2009) methodology from a Cobb-Douglas value added production function by a 2-digit industry. The sample includes 14,316 firms from France, Germany, Hungary, Italy, Spain and the UK.

[14] Notice that only data on markups and TFP since 2008 will be used for the main analysis.

Figure 1B. Average TFP by Two-Digit NACE Rev.2 Sector, 2001-2014

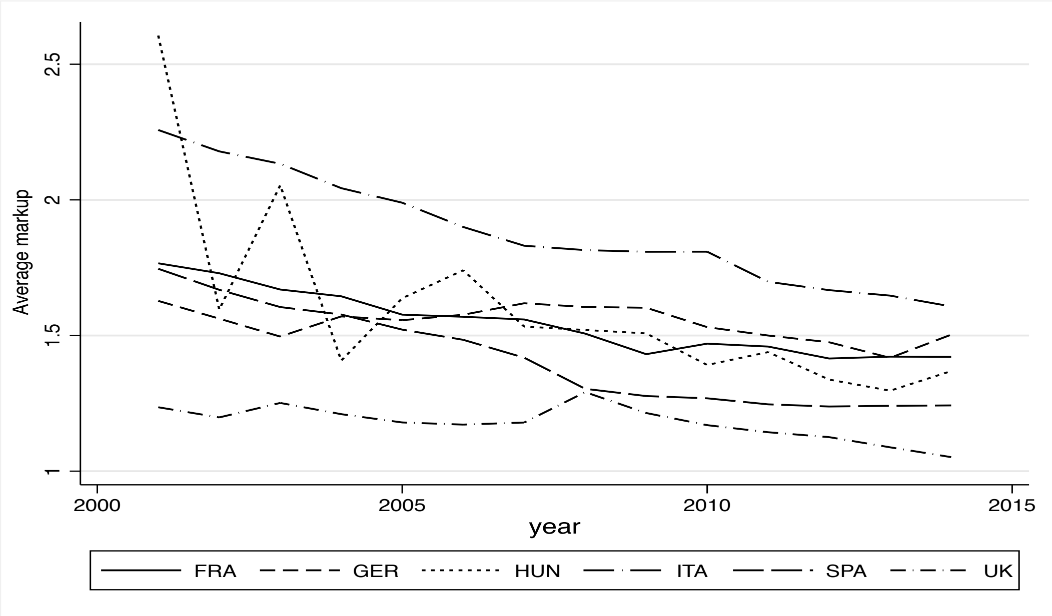


Notes: TFP is calculated using the Wooldridge (2009) methodology from a Cobb-Douglas value added production function by a 2-digit industry. The sample includes 14,316 firms from 24 Manufacturing 2-digit industries over the period 2001-2014.

Figure 2A shows the evolution of markups during 2001-2014. Values close to one indicate market conditions close to perfect competition. The mean and medium sample values is 1.61 and 1.48, respectively, which indicates European firms' substantial market power. This pattern varies across countries and over time. UK firms maintained very low markups, close to one, particularly since the Great Recession when a downward trend started. In Germany, there is a downward trend up to 2005, which more likely reflects policies of wage stagnation implanted in the 2000s and associated competitiveness gains (Dustmann et al., 2014) but an upward trend is also evident since then up to 2009, to drop to its lowest level in 2013. Italian firms charge the highest markups with German and French firms following.

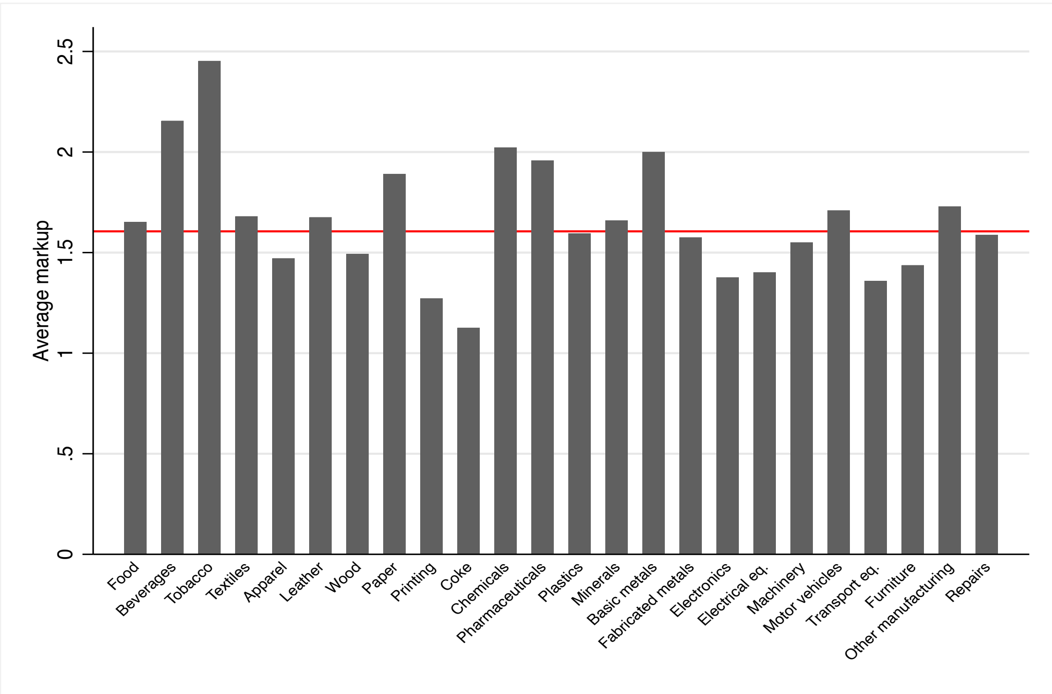
At this point, it is useful to compare our results with other findings in the related literature. This will place the current market power figures of this large group of European firms in a comparative context. In the seminal DWL study, the markup of Slovenian firms is documented between 1.10 and 1.28, depending on the specification used. Christopoulou and Vermeulen (2012) reported an average markup of 1.37 for a group of Eurozone countries over the period 1981-2004, albeit at the sectoral level.

Figure 2A. Average Markups by Country, 2001-2014



Note: Markups are calculated using the DLW (2012) methodology. The sample includes 14,316 firms from France, Germany, Hungary, Italy, Spain and the UK.

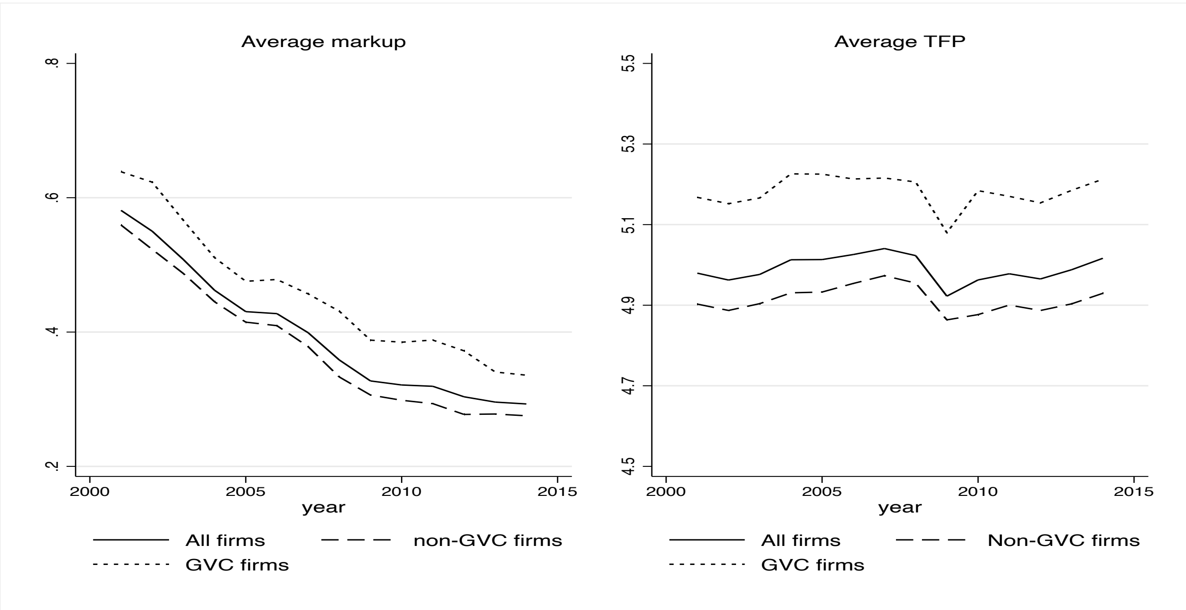
Figure 2B. Average markup by *T*wo-Digit NACE Rev. 2 Sector, 2001-2014



Note: Markup is calculated using the DLW (2012) methodology. Bars show the average markup by 2-digit sector, while a solid horizontal line reflects the overall average markup.

Our data therefore indicate that European firms had considerably higher markups in the last two decades. De Loecker and Eeckhout (2018) demonstrate that the average markups in the US are higher than those in the EU. However, they also observe an upward trend in markups in both regions over time. In contrast, Gutierrez and Philippon (2018) reveal an increase in markups in the US, while stable or decreasing trends were noted in Europe. Weche (2018) find decreasing markups for a sample of European firms during the period 2006-2013. Similar observations were made by van Heuvelen et al. (2021) for firms in the Netherlands, Mañez et al. (2020) for Spanish manufacturing firms, and Gradzewicz and Mućk (2022) for firms in Poland. Consequently, previous research provides support for the declining trend in markups in European countries at the beginning of the century, as is also documented in Figure 2A. When looking at the sectoral perspective, only the coke and tobacco industries have competitive output prices. Industries with high markups, close to or above two, include beverages, tobacco, chemicals, pharmaceuticals, and basic metals. Finally, before estimating the markup equation, we illustrate in Figure 3 that GVC firms are more productive and charge higher markups than their non-GVC counterparts.

Figure 3. Markup and TFP Differences between GVC and non-GVC



Note: Markup is calculated using the DLW (2012) methodology and TFP is estimated using a Cobb-Douglas value-added production function and the Wooldridge (2009) method, as described in section 3.2. Both markups and TFP are in logarithms.

3. Econometric Methodology

Following previous descriptive evidence, GVC firms are expected to be more productive, setting higher markups than their non-participating counterparts even before entering GVCs. Moreover, other unobservable country and industry characteristics may condition a firm's capacity to participate in GVC, which impacts its markup. Due to this, the probability of being a GVC firm is not random, requiring systematic treatment of selection bias, and hence mitigating causal inference concerns. To address this, we apply the coarsened exact matching[15] (CEM) method by matching treated (GVC firms) and untreated firms (non-GVC firms) on a series of covariates. CEM, which outperforms other matching propensity score techniques (Ripollone et al., 2020), allows covariate imbalances between control and treatment groups to be reduced (Iacus et al., 2012).

Table 3: Matching Covariates and Multivariate L1 Distances.

Matching covariates	Description
size	Number of employees. Bandwidths are <20 employees, 20–49, 50-249, 250 and over.
age	Year of firm's birth. Bandwidths are before the 1980s, 1980–1989, 1990–1999, 2000–2009
LP	Average level of labour productivity between 2002 and 2007. Coarsened into 5 equally spaced cut points
foreign	= 1 if at least 50% of capital shares belong to a foreign shareholder, 0 otherwise
product	= 1 if it carries out any product innovation, 0 otherwise
process	= 1 if it carries out any process innovation, 0 otherwise
industry	Grouped into Pavitt's (1984) sectors: economies of scale, high-tech, specialized, traditional, and other
country	France, Germany, Italy, Spain, Hungary

	All sample		**CEM Matched sample**	
	L1	mean	L1	mean
size	.154	0.343	5.1e-15	-3.4e-14
age	.107	-.249	2.5e-15	1.0e-14
LP	.033	-12.188	.04206	-1.0827
product	.146	0.146	5.9e-15	6.8e-15
process	.067	0.068	6.7e-15	9.3e-15
foreign	.088	0.088	1.8e-15	5.1e-16
industry	.096	-0.091	4.5e-15	-3.2e-14
country	.198	-0.273	3.3e-15	-5.6e-14
Multivariate L1 distance	0.521		0.247	
Number of observations	14,316	11,026 non-GVC 3,390 GVC	10,879	8,066 non-GVC 2,813 GVC

Source: own elaboration from EFIGE-Amadeus.

The CEM algorithm temporally coarsens (or categorizes) covariates into predetermined set width groups and matches firms based on the coarsened bins in addition to other categorical variables. Here, we coarsen firm size (<20 employees, 20–49, 50-249, 250 and over); firm's birth (born before the 1980s, 1980–1989, 1990–1999, 2000–2009); the average level of productivity between 2002 and 2007 (coarsened into 5 equally spaced cut points); product innovation status; process innovation status;

[15] Recent studies employing the CEM procedure to construct matched samples include Korpi and Starck (2015), Teruel et al. (2022), Wen and Zhao (2021), among others.

foreign ownership; country; and Pavitt sector (Pavitt, 1984). We choose them as they are closely related to GVC participation decisions and maximize matches.

The upper section of Table 2 presents the definition of the covariates, while the lower section shows the efficacy of matching, as the global imbalance is reduced after matching. Out of 11,026 observations of untreated firms, 8,066 belong to the matched sample. From the 3,290 observations of treated firms, the CEM procedure finds 2813 matched observations. To assess matching quality, Table 2 (lower section) reports the univariate and multivariate L1 imbalance statistics for the sample before and after CEM. The imbalance statistics measure how covariates differ between treatment and control groups, with higher values representing less balance. The reduction in both univariate and multivariant L1 distance confirms improved balance after matching. After removing unmatched observations, a "matched" sample becomes available for post-matching analysis.

Because information on trade activity is only available for 2008, we estimate a cross-section specification. Hence, using the matched sample, we provide OLS estimates for the relationship between markups and GVC participation as described by the following baseline specification:

$$\ln\mu_i = \alpha_2 + \beta_1 D_i^{GVC} + Z'_i\gamma + \sum \delta_{jc} + \varepsilon_i \qquad (8)$$

where D_i^{GVC} takes the value 1 if the firm participates in GVCs and zero otherwise. Hence, subscript represents the percentage markup premia for GVC traders with respect to the baseline category of non-GVC firms[16]. Vector Z_i controls for other firm characteristics relevant to markup, including total factor productivity (*TFP*), size (*size*), age (*age*), foreign multinationals (*foreign*), domestic (*domestic*) multinationals, centralized decision-making (*centralized*), process innovation (*process*), product innovation (*product*), and market concentration (*concentration*). Table 3 presents variable definitions and summary statistics. Finally, δ_{jc} represents country-industry interaction fixed effects, and ε_i is the error term.

[16] The reference category depends on whether non-GVC exporters are included. In that case, the reference category includes non-traders and importers of final goods.

Table 4. Variable Definition and Descriptive Statistics

Variable	Description	Mean	Std. Dev.
TFP	TFP in logs	5.023	0.638
size	number of employees (log)	3.609	1.066
age	number of years since birth (log)	3.184	0.779
domestic	=1 if at least 50% of capital shares belong to a domestic owner with at least one subsidiary abroad, 0 otherwise.	0.054	0.225
foreign	= 1 if at least 50% of capital shares belong to a foreign shareholder, 0 otherwise.	0.132	0.339
centralised	= 1 if decision-making is mainly centralised by the CEO/owner, 0 otherwise	0.693	0.461
product	= 1 if it carries out a product innovation, 0 otherwise	0.482	0.500
process	= 1 if it carries out a process innovation, 0 otherwise	0.457	0.498
concentration	Market concentration	0.210	0.208

Note: summary statistics refer to 2008.

To further investigate the relative importance of the type of GVC involvement in markups, we estimate the expression:

$$\ln\mu_i = \alpha_2 + \beta_1 D_i^{non-GVC} + \beta_2 D_i^{single-GVC} + \beta_3 D_i^{dual-GVC} + \gamma Z_i + \sum \delta_{jc} + \varepsilon_i \qquad (9)$$

where the $D_i^{non-GVC}$ represents if firm i exports to the end market; $D_i^{single-GVC}$ takes the value 1 if firm i participates either only through exports, imports of materials, or imports of services and zero otherwise; $D_i^{dual-GVC}$ takes the value 1 if it participates simultaneously through exports and imports.

4. Results

4.1 Baseline Results

Table 4 shows OLS estimates of equations (3) and (4). We report the GVC participation coefficients. Column (1) displays the results for the full sample, while the remaining columns show the results for the CEM sample. Results in columns (1) and (2) are very similar suggesting that GVC firms charge on average a 2% higher markup than non-GVC firms. In this vein, the integration with foreign suppliers and final producers facilitates both the adoption of advanced technologies (i.e., learning by exporting gains) and (or) cheaper inputs aimed at increasing efficiency leading to higher markups.

As non-GVC firms include traders, column (3) controls also for non-GVC exporters (i.e., firms serving the end market). Results show that GVC and non-GVC exporters have a markup premium over non-traders. However, the difference in markups between GVC firms and non-GVC exporters is not considered as statistically significant. In column (4) the dependent variable is the firm's average markup over the period 2008-2014. The results indicate that GVC firms maintain this markup premium over time. In column (5) we deal with any remaining concern on the potential endogeneity of GVC participation. We do this by employing a two-stage least square (2SLS) instrumental variable (IV) approach. We build an instrument for firms' GVC participation in 2008 by using questions posed to firms about their preceding trade activities. Specifically, firms in the survey were queried about whether, before 2008, they had purchased any services or any intermediate goods from abroad or whether they had exported any of their products. Responses indicating consistent or regular engagement in these activities are used to construct the instrument, which strongly predicts GVC participation in 2008[17]. Moreover, it appears to be a strong instrument as it passes both tests for weak instruments. As shown in column (5), the Kleibergen-Paap F-statistic (3178.9), as well as the Cragg-Donald Wald F-statistic (4912.7), both surpass the Stock-Yogo 10% critical values (Stock and Yogo, 2005). Turning to the second-stage regression results, the results in column (5) suggest that the markup premium of GVC relative to non-GVC firms is about 7%, slightly higher than that of the equivalent OLS estimates of column (3).

Table 5. The impact of GVC participation on firm's markups

Dep. Var.	Markup[a] (1)	Markup[b] (2)	Markup[b] (3)	Markup[b]$_{08\text{-}14}$ (4)	Markup[b] (5)
GVC	0.022**	0.023**	0.038***	0.030**	0.074***
	(0.011)	(0.012)	(0.013)	(0.012)	(0.017)
Non GVC exporter			0.047***	0.049***	0.064***
			(0.016)	(0.015)	(0.017)
Controls	yes	yes	yes	yes	yes
Industry-Country FE	yes	yes	yes	yes	yes
Observations	5140	4272	4272	4347	4272
Adjusted R^2	0.282	0.275	0.276	0.305	0.275
Estimation method	OLS	OLS	OLS	OLS	2SLS
Kleibergen-Paap rk F-statistic					3178.8
Cragg-Donald F-statistic					4912.6
Log-likelihood	-1365	-1118	-1113	-902	-1117

Notes: The dependent variable is the $\ln\mu_i$ estimated from a Cobb-Douglas value-added production function. Standard errors clustered at the firm level are in parentheses. [a] and [b] refer to total and CEM samples. The control variables enter with one lag and include *TFP*, *size*, *age*, *foreign mne*, *domestic mne*, *centralized*, *process*, *product*, and *concentration.* *, **, and *** indicate significance at the 10%, 5%, and 1% respectively. OLS stands for ordinary least squares, while 2SLS refers to two-stage least squares estimation.

[17] Results from the first-stage regression are not reported but are available upon request.

In Table 6, we seek to shed light on how different types of GVC involvement influence markups. To this end, we estimate equation (9). In column (1), we observe that a firm with a single GVC mode charges lower markups than one with both modes, although these differences are not statistically significant. This result persists over time, as shown in column (2). Similarly, no statistically significant differences in markups are found between GVC importers of materials, GVC importers of services, and GVC exporters in columns (3) and (4). Therefore, we conclude that GVC participation offers a markup premium independently of the participation type[18]. The markup premium of GVC firms is also not statistically different from that of other exporters who do not participate in GVC. Therefore, our results imply that it is internationalization and not GVC per se that confers a markup premium.

Table 6. Different types of GVC involvement and firm's markups

Dep. Var.	Markup (1)	$\text{Markup}_{08\text{-}14}$ (2)	Markup (3)	$\text{Markup}_{08\text{-}14}$ (4)
Non GVC exporter	0.076^{***}	0.075^{***}	0.041^{**}	0.043^{***}
	(0.017)	(0.016)	(0.016)	(0.015)
Single GVC	0.061^{***}	0.053^{***}		
	(0.012)	(0.012)		
Dual GVC	0.080^{***}	0.068^{***}	0.028^{*}	0.022
	(0.017)	(0.016)	(0.016)	(0.015)
Only exp. GVC			0.034^{**}	0.027^{*}
			(0.017)	(0.016)
Only imp. materials			0.048^{***}	0.042^{***}
			(0.012)	(0.011)
Only imp. services			0.066^{*}	0.061
			(0.040)	(0.038)
Controls	yes	yes	yes	yes
Industry-Country FE	yes	yes	yes	yes
Observations	4272	4347	4272	4347
Adjusted R^2	0.2801	0.3080	0.2790	0.3071
Log-likelihood	-1101	-891	-1103	-892

Notes: The dependent variable is the $\ln\mu_i$ estimated from a Cobb-Douglas value-added production function for 2008 in columns (1) and (3), and the average markup over the period 2008 to 2014 in columns (2) and (4), respectively. Standard errors clustered at the firm level are in parentheses. The control variables enter with one lag and include *TFP*, *size*, *age*, *foreign mne*, *domestic mne*, *centralized*, *process*, *product*, and *concentration.* *, **, and *** indicate significance at the 10%, 5%, and 1% respectively.

4.2. Robustness Checks

To assess the robustness of the above findings we perform three sensitivity checks. First, we employ an alternative definition of GVC and replicate our baseline results. In this regard, we follow previous studies (Gopalan et al., 2022; Thang and La, 2022) and use a narrower definition that considers GVC participation status when a firm participates in GVCs, as defined in the previous section, and in addition,

[18] Although not reported here, we find that more productive, larger and younger firms have higher markups. A markup premium is also associated with firms in concentrated industries and firms that make decisions centrally.

it owns a quality certificate[19]. In the definition of GVC status, quality standards are considered to enable firms to meet global quality standards (Criscuolo and Timmis, 2017; Kergroach, 2019, Thang and La, 2022). For the second robustness check, we use propensity score matching (PSM)[20] as an alternative matching methodology instead of CEM. Results from different matching methods may lead to different estimation results. PSM is a member of the class of "Equal Percent Bias Reducing" matching methods, and although it is frequently used in policy evaluation studies it is considered inferior to CEM in terms of its ability to reduce imbalance, model dependence, estimation error, bias, variance and mean square error (Iacus et al. 2012, p. 2). More specifically, we apply nearest neighbours matching with the replacement of the common support. In this method, a treatment firm is matched with one or more controls with propensity scores that are most similar. Due to the limited size of our treatment sample, we select the three nearest neighbours. We use matching with replacement, so that the same control firm may be used more than once. To achieve close balancing, we use a calliper of 0,25.

The results of these robustness checks are presented in Table 7, where we provide OLS estimates for equation (3). We report only coefficients related to GVC participation. Columns (1) and (2) show results derived from the same specifications as those in columns (3) and (4) of Table 4, but with an alternate definition of GVC. This alternative definition includes the firm's quality certification for its products and processes. The findings align closely with those in Table 4, suggesting that GVC and non-GVC exporters have a markup premium over non-traders and maintain this premium over time. However, the difference in markups between GVC firms and non-GVC exporters is not statistically significant. Columns (3) and (4) show the results for the same specification but for the PSM sample, which is relatively small. Robustness results confirm the baseline findings. GVC firms and non-GVC exporters have markup premiums. In this case, the markup premium of non-GVC exporters is relatively larger than GVC firms, albeit the difference is not statistically significant.

Table 7. Robustness checks: GVC Participation and Markups

	CEM sample		PSM sample	
Dep. var.	$Markup^a$	$Markup^a_{08-14}$	$Markup^b$	$Markup^b_{08-14}$
	(1)	(2)	(3)	(4)
GVC^Q	0.043^{***}	0.032^{**}		
	(0.014)	(0.013)		
GVC			0.041^{***}	0.028^{**}
			(0.013)	(0.012)
Non-GVC exp	0.043^{***}	0.045^{***}	0.058^{***}	0.042^{**}
	(0.015)	(0.014)	(0.018)	(0.017)
Controls	yes	yes	yes	yes
Industry-Country FE	yes	yes	yes	yes
Observations	4272	4347	3340	3391

[19] The EFIGE survey asks firms whether they have passed a quality certification (e.g., ISO9000) test for their products or processes We use this information to create a more precise definition of a GVC firm.
[20] We use the Stata routine 'psmatch2' provided by Leuven and Sianesi (2003) to perform PSM.

Adjusted R^2	0.2762	0.3046	0.2614	0.2824
Log lik.	-1,113	-902	-809	-643

Notes: The dependent variable is the $\ln\mu_i$ in columns (1) and (3) and the average markup over the period 2008 to 2014 in columns (2) and (4), respectively. Standard errors clustered at the firm level are in parentheses. [a] and [b] refer to PSM and CEM samples, respectively. GVC^Q is a dummy that takes the value of 1 for GVC firms that have a quality certificate. The control variables enter with one lag and include *TFP*, *size*, *age*, *foreign*, *domestic mne*, *centralized*, *process*, *product*, and *concentration.* *, **, and *** indicate significance at the 10%, 5%, and 1% respectively.

In our final robustness check, we assess whether our baseline findings are reliable when we use alternative methods to estimate the production function that produces the estimate of the markup. We present these results in Table 8. To begin with, we estimate markups using a value-added production function with the Ackerberg et al. (2015) method described in Appendix A.1. We then estimate equation (8) and use the ACF markup as the dependent variable. Our findings, presented in column (1), suggest that GVC firms have a premium of about 4% over non-trading firms. In column (2), we demonstrate that our results are robust when using the Wooldridge (2009) method with markups obtained from a gross output instead of a value-added production function. We obtain a relatively larger estimated markup premium of 9% for GVC firms, compared to non-trading firms. We also consider a more flexible translog value-added production function (see Appendix A.3), from which we retrieve output elasticities and estimate markups according to equation (7). The markup premium is estimated using equation (8), and the results presented in column (3) confirm our baseline findings. Finally, we note that our markup estimates assume labour is a flexible input. However, the treatment of labour as a flexible input remains a subject of debate, particularly in dual labour markets such as the Spanish case (van Heuvelen et al., 2021). Therefore, in column (4), we exclude Spain from the sample, and our results remain robust to this exclusion. Our findings are available upon request.

Table 8. Robustness checks: alternative markup estimates

	Markup ACF_CDVA	Markup WRDG_CDGO	Markup ACF_TRVA	Markup WRDG _CDVA (without Spain)
	(1)	(2)	(3)	(4)
GVC	0.036***	0.089***	0.034***	0.046***
	(0.013)	(0.017)	(0.013)	(0.015)
Non GVC exporter	0.048***	0.074***	0.036**	0.054***
	(0.016)	(0.020)	(0.016)	(0.020)
Controls	yes	yes	yes	yes
Industry-Country FE	yes	yes	yes	yes
Observations	4,274	4,712	4,268	2,804
Adjusted R^2	0.2520	0.3459	0.3502	0.1490
Log lik.	-1120	-2882	-1075	-761
Clusters	4274	4712	4268	2804

Notes: The dependent variable is the $\ln\mu_i$. ACF_CDVA stands for markups estimated from a value-added Cobb-Douglas production function using the Ackerberg et al. (2015) method. WRDG_CDGO stands for markups estimated from a gross-output Cobb-Douglas production function using the Wooldridge (2009) method. ACF_TRVA is for markups estimated from a value-added Translog production function using the Ackerberg et al. (2015) method. WRDG_CDVA stands for markups estimated from a value-added Cobb-Douglas production function using the Wooldridge (2009) method. All specifications are estimated using the CEM sample, and in column (4) we exclude Spain from the analysis. Standard errors clustered at the firm level are in parentheses. The control variables enter with one lag and include *TFP*, *size*, *age*, *foreign*, *domestic mne*, *centralized*, *process*, *product*, and *concentration.* *, **, and *** indicate significance at the 10%, 5%, and 1% respectively.

Overall, the results of these robustness checks show that firms engaged in GVCs exhibit a greater ability to set prices above marginal costs compared to their non-trading counterparts. This finding is robust to controls for (lagged) firm productivity, suggesting that higher markups are not merely due to their greater efficiency. Nevertheless, the observed markup premium in GVC firms may not necessarily signify an increase in market power. As an example, GVC firms may be experiencing elevated markups due to significant fixed costs associated with internationalization strategies (De Loecker et al., 2020).

5. Conclusions

We explored the relationship between firms' GVC participation and markups. We use data for the period 2001-2014 for six EU countries from EFIGE-BvD Amadeus and construct estimates of time-varying and firm-specific markups using the DLW methodology. Among European firms, markups are on average 1.6, indicating that the assumption of perfect competition is widely rejected. The overarching trend reveals a decline in markups for European firms from 2001 to 2014, contrasting with evidence found in the literature for US firms over the same period. Our estimates further uncover notable variations in markups across countries and industries. Among the six European nations, UK firms emerge as the most competitive, whereas Italian firms, on average, impose the highest markups within the sample. Notably, industries such as chemicals, pharmaceuticals, beverages, tobacco, and basic metals stand out for charging markups that surpass the sample average.

The primary focus of this paper is to investigate whether Global Value Chains (GVC) contribute to the observed pattern of markup heterogeneity. By employing CEM to control for sample selection bias, our baseline econometric estimations reveal that firms engaged in GVCs exhibit a markup premium ranging from 3% to 4% compared to firms exclusively involved in domestic trade. This outcome withstands various sensitivity tests, encompassing alternative estimation methods and specifications for markup determination. Notably, the GVC premium tends to increase when gross output is considered as an output measure instead of value-added. Our findings indicate that integration into GVCs can lead to expanded market access, heightened efficiency, and opportunities for European firms to tap into markets with higher values. However, this integration also exposes firms to elevated risks and complexities, contributing to higher markups. Importantly, our analysis does not reveal evidence that the mode of GVC participation affects the markup premium. Despite these insights, it's crucial to acknowledge certain limitations in our analysis that warrant caution in interpretation. While we derive time-variant markups for the period 2001-2014, the econometric impact of GVCs on markup evolution is based on a cross-sectional specification covering only variation across firms, industries, and countries in 2008. This limitation stems from the nature of the EFIGE dataset. Therefore, future research incorporating panel data to better understand markup behavior over time is encouraged.

We conclude our discussion by highlighting policy considerations derived from the current results. While participation in Global Value Chains (GVCs) is a valuable aspect of business sustainability and should be encouraged, there is a need for policy intervention to maintain a balance between the benefits of dynamic internationalization through GVCs and potential social welfare losses from increased markups. Recognizing GVCs as a fundamental component of globalized production, effective policy intervention requires coordination among countries and international organizations. Policies should be designed to ensure that higher markups are reflective of high labor and environmental standards. In this context, labor policies should focus on promoting health and safety regulations as well as collective bargaining mechanisms. Additionally, environmental policies should be consistently enforced to enhance allocative efficiency and reduce greenhouse gas emissions. This comprehensive policy toolkit aims to make GVCs more inclusive, ensuring that the potential welfare losses from globalization are counteracted by gains that contribute to sustainable and prosperous societies.

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Appendix

A. Alternative Estimations of the Production Function.

The paper uses four approaches to estimate output elasticities and obtain markup estimates. The baseline approach is a Cobb-Douglas value-added production function following Wooldridge (2009), as described in section 2.3. Alternatively, we estimate a value-added production function using the Ackerberg et al. (2015) method (ACF, henceforth). Third, we estimate a gross-output Cobb-Douglas production function using Wooldridge (2009). Fourth, we estimate a value-added translog production function.

A1. The ACF Method.

The main argument of the ACF method is that the labour coefficient in equation (4) cannot be identified in the Olley and Pakes (1996) and Levinsohn and Petrin (2003) methods. Ackerberg et al. (2015) propose a two-stage method, by which equation (4) can be written as:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + h_t(k_{it}, m_{it}, z_{it}) + \varepsilon_{it} = \varphi(l_{it}, k_{it}, m_{it}, z_{it}) + \varepsilon_{it} \quad \text{(a.1)}$$

Equation (a.1) is estimated via Ordinary Least Squares and is used to separate the expected output $\widehat{\varphi}_{it}$ from the residuals. Additionally, assuming the same Markov process for productivity as described by (5) and considering that $\omega_{it} = h_t(k_{it}, l_{it}, m_{it}, z_{it})$, and $\varphi_t(k_{it}, l_{it}, m_{it}, z_{it})$, we can project ω_{it} on its lag such to get the second equation to estimate.

$$\widehat{\varphi}_{it} - \beta_l l_{it} - \beta_k k_{it} = \rho(\widehat{\varphi}_{it-1} - \beta_l l_{it-1} + \beta_k k_{it-1}) + \xi_{it} \quad \text{(a.2)}$$

In short, in the ACF method all the coefficients are estimated in the second stage using valid moment conditions and where $\widehat{\varphi}_{it-1}$ is replaced by its estimate from the first stage. Once, the estimated β_l is retrieved[21], the markup is then estimated as described in section 3.2.

Table A.1.: ACF vs. Wooldridge Markups

			Interquartile range		
Markup	Mean	s.d.	25%	50%	75%
ACF	2.080	0.831	1.495	1.924	2.479
Wooldridge	1.606	0.648	1.148	1.484	1.921

Note: The descriptive statistics show levels of markups across all manufacturing industries and countries, where we pool observations from 2010 to 2016. ACF indicates the estimation method is based on Ackerberg et al. (2015). In both, ACF and Wooldridge we have estimated a value-added Cobb-Douglas production function.

Table A.2. compares markups of the ACF and the baseline Wooldridge method. Average and medium markup estimates using the ACF method are relatively larger, as well as more skewed. Comparing the ACF with the Wooldridge markup estimates, the latter are more in line with previous findings. Nevertheless, our main findings are robust to using the ACF markups (see Table ??).

A2. The Gross Output Production Function

As in De Loecker et al. (2020), we assume for robustness the following gross-output production function:

$$q_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \omega_{it} + \varepsilon_{it} \tag{a.3}$$

where q_{it} is the logarithm of gross output and m_{it} is the logarithm of intermediate input in Wooldridge setup, the output elasticity with respect to labour equals to: $\hat{\theta}_{it}^{l} = \frac{\partial q_{it}}{\partial l_{it}} = \hat{\beta}_l$, which is obtained using the Wooldrige (2009) method. The markup is obtained as $\hat{\mu}_{it} = \frac{\widehat{\beta}_l}{s_{it}^{l}} \exp\left(-\hat{\varepsilon}_{it}\right)$, where $\hat{\varepsilon}_{it}$ is the estimated residual from the first stage regression, and s_{it}^{l} is the labour expenditure share over gross output, which is observed in the data.

A3. The Translog Production Function

Finally, an estimation of a translog value-added specification is added for robustness since it allows for a firm-specific output elasticity. Equation (2) is then replaced by:

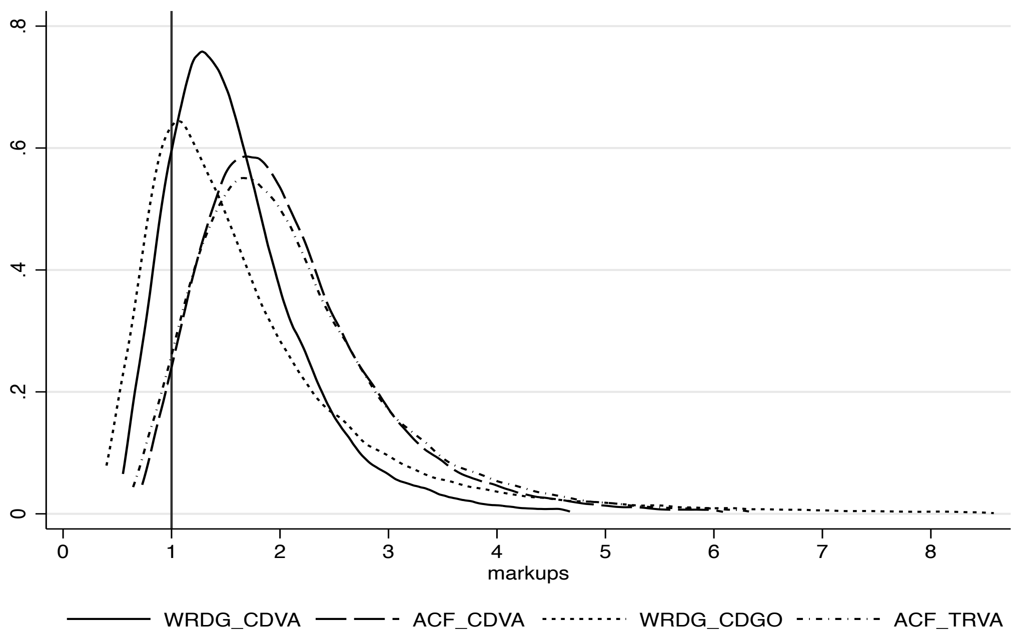
$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \omega_{it} + \varepsilon_{it} \tag{2}$$

[21] The mean (s.d) estimated output elasticities across all sectors for labour and capital are 0.812 (0.067) and 0.173 (0.042) with the ACF method. The mean (s.d.) output elasticities with the Wooldridge method are slightly smaller, 0.626 (0.060) and 0.097 (0.042).

This equation is estimated using the ACF method[22], as described above. In this setup, the output elasticity with respect to labour equals to: $\hat{\theta}_{it}^{l} = \frac{\partial lnY_{it}}{\partial lnL_{it}} = \hat{\beta}_l + \hat{\beta}_{lk}k_{it} + 2\hat{\beta}_{ll}l_{it}$.

Figure A.1 shows the distribution of markups for different setups. Markups below unit, meaning that prices are below marginal costs, make economic sense in the short term. The baseline markups, which are derived from a value-added Cobb-Douglas production function using the Wooldridge (2009) method, have a relatively narrow distribution, with most markups falling within a possible range of values (WRDG_CDVA). In the Cobb-Douglas gross output specification (WRDG_CDGO), the range of markup values is wider, and markups below one are more common, as are very high markups[23]. Markup estimates from a value-added Cobb-Douglas production function using the ACF method (ACF_CDVA) and (ACF_TRVA) sow larger markups than in the other setups. Despite these differences, our main findings are robust to using markups from different setups.

Figure A.1. Density graphs of markups



Note: WRDG_CDVA stands for markups estimated from a value-added Cobb-Douglas production function using the Wooldridge (2009) method. ACF_CDVA stands for markups estimated from a value-added Cobb-Douglas production function using the Ackerberg et al. (2015) method. WRDG_CDGO stands for markups estimated from a gross-output Cobb-Douglas production function using the Wooldridge (2009) method. ACF_TRVA is for markups estimated from a value-added Translog production function using the Ackerberg et al. (2015) method.

[22] We had difficulties in identifying output elasticities with the translog specification using the Wooldridge (2009) approach.
[23] Gandhi *et al.* (2020) show that the characteristics of interest (including markups and productivity) from a value-added production function differ from those from a gross output production function. Since we have difficulties in accurately determining the input coefficients in the gross output setup, especially the coefficient for intermediate inputs, we only consider these alternative estimates of markups in the robustness analysis.

Table A.2. Summary statistics of variables for the production function

Variable	Mean	Median	s.d.	Max.	Min
OPRE	19147	3530	111374	5931888	14
MATE	10846	1517	65302	2804406	0
FIAS	6600	767	66420	6342371	0
EMPL	85	25	439	26363	1
STAF	3369	797	21934	1266570	0

Source: Variables from EFIGE-Amadeus for the period 2001-2014, used for the estimation of a value-added translog production function.