Universidad de Oviedo

Analyzing Horizontal and Vertical Integration from a Macroeconomic Perspective

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RESUMEN DEL CONTENIDO DE TESIS DOCTORAL

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RESUMEN (en español)

El estudio del poder de mercado ha recibido una considerable atención en los últimos tiempos debido a los avances recientes en la estimación del markup, un proxy comúnmente utilizado para describir el poder de mercado. Estos nuevos avances han permitido estimar el markup utilizando la función de producción en lugar de las funciones de costo, facilitando considerablemente la estimación.

Trabajos recientes han utilizado dicha metodología para calcular el markup y han encontrado que los markups han estado aumentando casi continuamente desde la década de 1980. Este desarrollo es preocupante, ya que el aumento del poder de mercado está relacionado con numerosos desarrollos económicos negativos. A pesar de las graves complicaciones económicas que el aumento del poder de mercado implica, hay relativamente pocos estudios que lo analicen en profundidad.

El enfoque tradicional ha sido utilizar microdatos a nivel de empresa para estimar el markup de cada empresa en un período de tiempo. Sin embargo, los microdatos a menudo no están disponibles para ciertos países e industrias, ya que requieren información sobre todas las empresas que operan en un mercado.

En nuestros trabajos de investigación, diseñamos una metodología alternativa basada en un procedimiento de estimación utilizando la Entropía Máxima Generalizada, para obtener estimaciones del markup utilizando datos macroeconómicos contenidos en las tablas input-output. Con esta metodología, podemos calcular el markup para la Industria de Alimentos Primarios (que comprende agricultura, caza, pesca y explotación forestal) para 170 países en el mundo, siendo los primeros en hacerlo.

Encontramos que varias regiones del mundo, incluyendo África y Asia, tienen markups en aumento. Otras regiones, como Europa y América del Norte, tienen markups estables y sin cambios. En América del Sur se observa una disminución en los markups.

Finalmente, identificamos determinantes causales de los markups desde una perspectiva macroeconómica y encontramos que la presencia de las Cadenas Globales de Valor, o la fragmentación internacional del proceso de producción, reduce significativamente y de manera causal los markups.

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RESUMEN (en inglés)

The study of market power has garnered considerable attention in recent times due to recent advances in the estimation of the markup, a proxy commonly used to describe market power. These new advances have allowed to estimate the markup using production function instead of cost functions, thereby facilitating the estimation considerably.

Recent papers have used said methodology to calculate the markup and have found that the markups have been increasing nearly continuously since the 1980s. This development is worrisome as rising market power is connected to numerous negative economic developments. In spite of the grace economic complications rising market power has, there is relatively few research papers that study this in-depth.

The traditional approach has been to use firm-level micro-data to estimate the markup for each firm at a time period. However, micro-data is often unavailable for certain countries and industries, as it requires information on al firms operating in a market.

In our research papers, we devise an alternate methodology based on an estimation procedure using Generalized Maximum Entropy, to derive estimates of the markup using macroeconomic data contained within input-output tables. With this methodology, we can calculate the markup for the Primary Foods Industry (comprising agriculture, hunting, fishing, and logging) for 170 countries in the world, being the first ones in doing so.

We find that several regions in the world, including Africa and Asia have rising markups. Other regions including Europe and North America have stable, non-changing markups. South America is found to have decreasing markups.

We finally find causal determinants of markups from a macroeconomic perspective, and find that the presence of Global Value Chains, or the international fragmentation of the production process, reduces markups significantly and causally.

SR. PRESIDENTE DE LA COMISIÓN ACADÉMICA DEL PROGRAMA DE DOCTORADO EN Oviedo, a 12 de junio de 2024

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Lista de los artículos usados para la disertación en formato de compendio de publicaciones

A continuación se presenta la lista de los artículos publicados utilizados para la disertación. Se indica el nombre de los artículos, coautores, el nombre de la revista, DOI, el año de publicación, y el factor de impacto según la Journal Citation Reports (JCR):

1. **Estimating market power for the European manufacturing industry between 2000 and 2014**.
   Autores: Adrián Rodríguez del Valle y Esteban Fernández Vázquez
   Revista: Empirica, Journal of European Economics
   Factor de impacto de la revista: 1,3 (2022) – Q3
   DOI: https://doi.org/10.1007/s10663-022-09559-4
   Año de publicación: 2023

2. **Analyzing market power of the agricultural industry in Asia**
   Autores: Adrián Rodríguez del Valle y Esteban Fernández Vázquez
   Revista: Economic Analysis and Policy
   Factor de impacto de la revista: 6,5 (2024) – Q1
   DOI: https://doi.org/10.1016/j.eap.2023.12.010
   Año de publicación: 2024

3. **Global Markup Estimates for the Primary Foods Industry**
   Autores: Adrián Rodríguez del Valle y Esteban Fernández Vázquez
   Revista: Data in Brief
   Factor de impacto de la revista: 1,2 (2024) – Q3
   DOI: https://doi.org/10.1016/j.dib.2024.110495
   Año de publicación: 2024

Contents

Capítulo 1

Introducción (Español)

El poder de mercado (monopolístico) es una parte integral de la realidad económica. A menudo es un resultado natural de las estrategias de maximización de beneficios de las empresas y se ve como una recompensa al riesgo asumido por los emprendedores al construir y dirigir la empresa.[1] Los emprendedores buscan aumentar su poder de mercado para disminuir su riesgo mientras operan en los mercados y, por lo tanto, aumentar la probabilidad de supervivencia económica.

En mercados que funcionan bien, la estrategia de maximización de beneficios es adicionalmente beneficiosa para la sociedad en su conjunto, debido a los efectos colaterales que se derivan de esos esfuerzos. Los efectos beneficiosos incluyen, entre otras cosas, mayores tasas de empleo, más innovación tecnológica (un motor clave del crecimiento económico) y el aumento de los ingresos de la sociedad.

No obstante, el poder de mercado también tiene el potencial de causar daño a la sociedad y generar ineficiencias en el mercado. Demasiado poder de mercado distorsiona los incentivos del mercado y revierte todos los efectos beneficiosos que se dan a la sociedad. A niveles más altos de poder de mercado, los beneficios adicionales logrados son a expensas de la sociedad en su conjunto y en beneficio de los propietarios. Mientras que en mercados que funcionan normalmente las actividades de búsqueda de beneficios aumentan el "tamaño del pastel"que beneficia a todos, en mercados distorsionados, las actividades de búsqueda de beneficios aumentan la "porción del pastel"para esos monopolistas, manteniendo el tamaño general igual.

Sin embargo, el grado de poder monopolístico en el cual dicha reversión de efectos beneficiosos a perjudiciales ocurre es, hasta la fecha, desconocido para la ciencia. El análisis del poder de mercado ha estado presente en la investigación económica desde hace unos 100 años, con ejemplos que incluyen los trabajos destacados de Lerner (1934). Sin embargo, a pesar de esta longevidad y fuerte presencia en la investigación económica, aún quedan muchos aspectos desconocidos. Esto se debe en parte a la dificultad de recopilar los datos necesarios para realizar un análisis integral de toda la economía.

[1]En otras palabras, un mayor poder de mercado de la empresa implica más beneficios para los propietarios de la empresa.

Durante la mayor parte del siglo pasado, los académicos y los responsables de políticas han asumido que el poder de mercado era constante. Aunque los académicos realizaban análisis en condiciones menos que ideales, sin poseer datos de suficiente cobertura y utilizando metodologías basadas en suposiciones muy fuertes, la evidencia sugería que el poder de mercado era más o menos invariable durante gran parte del siglo XX. No obstante, los últimos 40 años han visto algunas revoluciones.ᵉᶜonómicas profundas que han alterado sustancialmente el panorama de los mercados. Entre los cambios más importantes se encuentran el auge de las Cadenas Globales de Valor desde la década de 1980, la digitalización de la economía desde finales de la década de 1990 y el movimiento de las economías de altos ingresos[2] hacia las industrias de servicios y alejándose de la manufactura.

El término Cadenas Globales de Valor, o GVC por sus siglas en inglés, se refiere a la fragmentación internacional del proceso de producción por parte de las empresas. Antes de la década de 1980, la mayor parte de la producción tenía lugar dentro del mismo país, e incluso de la región donde se ubicaban las empresas. Esto comenzó a cambiar debido a las innovaciones tecnológicas y la introducción de políticas que apoyaban el libre comercio.

Es precisamente durante este tiempo que los académicos han encontrado un cambio en la evolución del poder de mercado de las empresas. De Loecker et al. (2020) y otros trabajos han encontrado que desde la década de 1980, el poder de mercado ha estado aumentando continuamente en los EE. UU., con la tendencia manteniéndose fuerte durante la década de 2020 (el final de su muestra) excepto durante la crisis financiera de 2008-2009. Muchos trabajos posteriores han corroborado estos hallazgos utilizando otros conjuntos de datos para otros países.

La evolución del aumento del poder de mercado es definitivamente preocupante debido a los efectos sociales perjudiciales. Los estudios han encontrado un vínculo entre el aumento del poder de mercado y: el aumento de la desigualdad de ingresos (Diez et al., 2018), la disminución de la participación laboral en los ingresos (Autor et al., 2020), la mala asignación de los factores del mercado (Baqaee and Farhi, 2017), entre otros.

A pesar de la gravedad de la tendencia, las causas exactas del aumento del poder de mercado no se entienden bien. Dado que tanto el auge de las Cadenas Globales de Valor como el aumento del poder de mercado ocurrieron en la década de 1980, esto puede verse como una causa principal. Sin embargo, el poder de mercado es estudiado por microeconomistas que dependen del uso de microdatos. Este tipo de datos limita el análisis y no puede investigar de manera efectiva la relación entre la globalización y el poder de mercado. Además, debido a la falta de disponibilidad de datos, cualquier análisis está limitado a analizar ciertas industrias (principalmente manufactura y servicios). En este sentido, la disertación está aún más motivada.

[2]El documento utiliza terminología como Economías de Bajos Ingresos y Economías de Altos Ingresos. Estas definiciones se basan en las clasificaciones de ingresos del Banco Mundial.

1.1 Motivación

Parte del problema de la falta de investigación en algunas industrias proviene de la dificultad de encontrar datos de suficiente calidad que puedan servir como una muestra representativa para el análisis. Los problemas de esto se agravan por el hecho de que se necesita disponer de datos para idealmente todas las empresas dentro de un mercado para que las conclusiones sean representativas. Esos datos generalmente están disponibles para los países desarrollados con sistemas avanzados de recopilación de datos.

El problema de la falta de datos disponibles restringe las posibilidades generales de investigación y no permite investigar la dinámica de los márgenes en los países de bajos ingresos. Las economías de los países de bajos ingresos dependen en gran medida del desarrollo de la industria agrícola.

Un margen alto en las economías de bajos ingresos podría utilizarse como una medida para denotar ineficiencias. El margen, o la diferencia entre el precio de venta de un bien o servicio y el costo marginal de producción, es un buen indicador para representar el poder de mercado cuando se analizan industrias con características similares, es decir, manufactura o servicios en economías de altos ingresos, con calidad institucional y sistemas políticos similares.

En las economías de bajos ingresos, sin embargo, el margen podría indicar que existen rigideces estructurales profundamente arraigadas dentro de la industria, o que hay un problema en la estructura de costos. Pueden existir otros factores en juego, además de los cambios en los precios o costos unitarios, cuando el margen está cambiando. En teoría, un cambio radical en el costo fijo puede causar alteraciones en el margen, lo cual podría ocurrir más fácilmente en las economías de bajos ingresos.

1.1.1 Midiendo el poder de mercado

Para visualizar esto más claramente, las ecuaciones que denotan los márgenes se elucidarán y su derivación se explicará con más detalle en el siguiente párrafo. Siguiendo el procedimiento descrito por De Loecker et al. (2020), la empresa produce output utilizando una función de producción Cobb-Douglas de la siguiente manera:

$$Q_{it} = \Omega_{it} V_{it}^{\alpha_{it}} K_{it}^{\beta_{it}} \tag{1.1}$$

donde Q_{it} representa las cantidades de producción total para la empresa i en el período de tiempo t, Ω la Productividad Total de los Factores, V_{it} los insumos variables que incluyen insumos intermedios y remuneraciones laborales, K_{it} las existencias de capital, y α_{it} y β_{it} las elasticidades correspondientes de los factores.

El modelo especifica que las empresas minimizan costos, resolviendo la siguiente función Lagrangiana:

$$\mathcal{L} = P_{it}^{V} V_{it} + P_{it}^{K} K_{it} - \lambda_{it}(\Omega_{it} V_{it}^{\alpha_{it}} K_{it}^{\beta_{it}} - \bar{Q}_{it}) - \mathbf{F_{it}} \tag{1.2}$$

Las variables P_{it}^K y P_{it}^V representan los precios de los factores de insumo K, las existencias de capital, y V, los insumos variables, mientras que λ_{it} es el multiplicador de Lagrange. Nótese aquí que F_{it} representa los costos fijos de las empresas. Se supone que las existencias de capital son fijas (inmutables) a corto plazo, por lo tanto, solo hay una condición de primer orden resultante:

$$P_{it}^V - \lambda_{it}\alpha_{it}\Omega_{it}V_{it}^{\alpha_{it}-1}K_{it}^{\beta_{it}} = 0 \tag{1.3}$$

En este punto, los costos fijos, aunque todavía influyen en la estructura de costos de la empresa, se eliminan de las partes posteriores de la ecuación. Esto expone un defecto al utilizar el margen, ya que pueden surgir situaciones en las que los costos fijos estén aumentando, con los costos marginales aumentando lentamente (o no aumentando en absoluto), y las empresas se vean obligadas a aumentar los precios para compensar. En tal situación, los márgenes parecerían estar aumentando, pero no indicarían que las empresas están ejerciendo poder de mercado.

La ecuación 1.3 puede luego reorganizarse multiplicándola por $P_{it}V_{it}$. Sustituyendo la ecuación resultante 1.1 se obtiene la expresión para el margen:

$$\mu_{it} = \frac{P_{it}}{\lambda_{it}} = \alpha_{it}\frac{P_{it}Q_{it}}{P_{it}^V V_{it}} \tag{1.4}$$

con $P_{it}Q_{it}$ representando el valor de la producción total, $P_{it}^V V_{it}$ el valor de los insumos variables, y α_{it} la elasticidad de los insumos variables respecto al output de una función de producción Cobb-Douglas.

El enfoque tradicional es estimar la elasticidad α_{it} econométricamente, utilizando datos de panel. La ecuación representada en la Ecuación 1.1 se estima (usando logaritmos) como:

$$q_{it} = \alpha_{it}v_{it} + \beta_{it}k_{it} + \omega_{it} \tag{1.5}$$

El coeficiente es la elasticidad estimada necesaria para el cálculo posterior del markup. Sin embargo, el enfoque microeconómico no es sencillo y es propenso a tener problemas de endogeneidad. En particular, el término de error tiene dos componentes ($\omega_{it} = \epsilon_{it} + \eta_{it}$). Un componente es conocido por la empresa (pero no por el econometrista) e influye en la elección de los factores de producción. Este componente puede definirse como ϵ_{it} y representa la productividad de la empresa. Puede estar influenciado por, por ejemplo, la capacidad de los empleados, las habilidades del gerente, y más. El segundo término η_{it} son choques repentinos desconocidos para la empresa. Es precisamente el componente ϵ_{it} el que causa la endogeneidad y los posibles sesgos de la estimación directa.

Los microeconomistas han encontrado formas de sortear los problemas causados por la endogeneidad, como se observa en los trabajos de Olley and Pakes (1996), Levinsohn and Petrin (2003) y Ackerberg et al. (2015). Estos enfoques generalmente utilizan un enfoque de mínimos cuadrados en dos o tres etapas para aislar el componente endógeno de manera no paramétrica. Sin embargo, la principal desventaja es que los coeficientes se asumen estáticos cuando se utiliza un enfoque de datos de panel.

La tesis utiliza datos macroeconómicos y se desvía de la estimación del markup utilizando enfoques econométricos tradicionales. Dado que nuestro tamaño de muestra es generalmente más pequeño en relación con el tamaño de los datos microeconómicos, se emplea un enfoque alternativo de estimación basado en la Entropía Máxima Generalizada. El método estima el markup de manera transversal para cada año, garantizando una elasticidad dinámica. Las ventajas adicionales de confiar en este método se discuten con más detalle en un capítulo posterior 3.

Además, al utilizar datos macroeconómicos contenidos en las tablas input-output, es posible obtener estimaciones del poder de mercado para una amplia cobertura de industrias y países. La cobertura es más extensa que la disponible al utilizar datos microeconómicos. Aunque las estimaciones derivadas de datos a nivel de empresa se consideran el estándar de precisión, el Capítulo 3 proporcionará evidencia de que el procedimiento es utilizable para sacar conclusiones.

La tesis utiliza esta característica para obtener estimaciones del markup para industrias donde no hay datos microeconómicos disponibles: la Industria de Alimentos Primarios. Este sector está compuesto por la agricultura, la caza, la pesca y la explotación forestal, y se considera clave para el desarrollo de economías de bajos ingresos.

1.2 Objetivos de la investigación

Los objetivos de investigación de esta tesis son los siguientes:

1. Probar la viabilidad de estimar markups utilizando datos agregados en forma de tablas input-output (Sección 3).

2. Usar la metodología para estimar los markups para industrias donde no hay datos disponibles. En el caso de esta disertación, la industria de Alimentos Primarios (Sección 4).

3. Determinar la relación causal entre los markups y las Cadenas Globales de Valor (Secciones 3 y 5).

4. Analizar los markups de la Industria de Alimentos Primarios (Secciones 4 y 5).

1.3 Estructura de la tesis

El resto de la tesis presentará cada artículo en orden de importancia. Cada capítulo introductorio será seguido por el artículo en su formato publicado. Las publicaciones no se presentan en orden de publicación, sino más bien ordenadas de manera que se mejore el flujo de información.

El Capítulo 3 introducirá la metodología de estimación de márgenes a partir de las Tablas Input-output y contrastará los resultados con un conjunto de datos basados en microdatos. El artículo estima los márgenes para los países europeos en los años 2000 y 2014. Luego se estiman las medidas de globalización y se mide su relación con respecto a los márgenes. Este capítulo sirve como base para los artículos posteriores y da legitimidad a la metodología. El Capítulo 4 aplica la metodología mencionada para estimar los márgenes de la industria de Alimentos Primarios (compuesta por agricultura, caza, pesca y explotación forestal) para 170 países del mundo entre los años 1995 y 2015, siendo los primeros en hacerlo. El Capítulo 5 luego utiliza un subconjunto del conjunto de datos explorado en el Capítulo 4 para investigar los márgenes de la industria de Alimentos Primarios en Asia, explorando cómo los niveles de ingresos, los sistemas políticos y la globalización en forma de Cadenas Globales de Valor impactan los márgenes.

La disertación luego concluye y resume los hallazgos en el Capítulo 6, mencionando las limitaciones de la metodología y explorando otras posibles vías de investigación.

Chapter 2

Introduction (English)

Market (monopolistic-) power is an integral part of economic reality. It is often a natural result of firm profit-maximizing strategies and is considered a reward for entrepreneurs' risk being taken by building and running the firm.[1] Entrepreneurs seek to increase their market power to lessen their risk while operating in markets, thereby increasing the chance of economic survival.

In well-functioning markets, the profit maximization strategy is additionally beneficial to society due to the spillover effects it derives from those efforts. The beneficial effects include, among other things, higher employment rates, more technological innovation (a key driver of economic growth), and increased societal income.

Nevertheless, market power also has the potential to cause harm to society and generate market inefficiencies. Too much market power distorts market incentives and reverts every beneficial effect given to society. At higher levels of market power, additional profit achieved is at the expense of society as a whole and to the benefit of owners. While in normal-functioning markets, profit-seeking activities increase societies' "size of the pie" that benefits everyone, in distorted markets, profit-seeking activities increase the "slice of the pie" to those monopolists while keeping the overall size equal.

However, the degree of monopolistic power in which such reversion from beneficial to detrimental effects occurs is, to date, unknown to science. The analysis of market power has been present in economic research for around 100 years, with examples including the prominent papers by Lerner (1934). Yet despite this longevity and strong presence in research, many unknowns remain due to the difficulty of collecting the required data to conduct a comprehensive, economy-wide analysis.

Throughout most of the past century, market power was assumed to be constant by academics and policymakers. Even though scholars were conducting analyses under less-than-ideal conditions by not possessing data of sufficient coverage and using methodologies based on strong assumptions, evidence indeed suggested that market power was more or less unchanging for most of the 20th

[1] In other words, higher firm market power implies more profits to firm owners.

century. Nevertheless, the last 40 years have seen a few profound economic "revolutions" that have substantially altered the landscape within markets. Among the most important changes have been the surge of Global Value Chains since the 1980s, the digitization of the economy since the late 1990s, and the move by High-income economies[2] towards service industries and away from manufacturing.

The term "Global Value Chains" or GVCs for short, refers to the international fragmentation of the production process by firms. Before the 1980s, most production took place within the same country and even the region where firms were located. The trend started changing due to technological innovations and the introduction of policies supporting free trade.

It is precisely during this time, that scholars have found a shift in the evolution of firms' market power. De Loecker et al. (2020), and other papers have found that since the 1980s, market power has been increasing continuously within the US, with the trend remaining strong throughout the 2020s (the end of their sample) except during the financial crises in 2008-2009. Many subsequent papers have corroborated these findings using other datasets for other countries.

The evolution of increasing market power has sparked interest among academics and policymakers due to the detrimental societal effects. Papers have found a link between rising market power and increasing income inequality (Diez et al., 2018), decreasing labor share of income (Autor et al., 2020), and miss-allocation of the factors market (Baqaee and Farhi, 2017), among others.

Despite the seriousness of the trend, the exact causes of rising market power are not well understood. As both the surge of Global Value Chains and rising market power occurred in the 1980s, this then may be seen as a prime cause. Nevertheless, market power is typically studied by microeconomists who rely on micro-data. This type of data constrains the analysis and cannot effectively research the relationship between globalization and market power. Furthermore, due to the unavailability of data, any analysis is constrained to analyzing certain industries (mostly manufacturing and service). On this note, the dissertation is further motivated.

2.1 Motivation

Part of the problem from the lack of investigation in some industries stems from the difficulty of finding data of sufficient quality that can serve as a representative sample for analysis. These problems are compounded by the fact that data for ideally every firm within a market needs to be available to make the conclusions representative. That data is generally available for developed countries with advanced data collection systems.

[2]The paper makes use of terminology such as "Low Income" and "High Income" Economies. These definitions are based on the World Bank income classifications.

The problem of the lack of available data restricts the overall research possibilities and does not allow the investigation of the dynamics of markups in Low-Income Countries. The economies of Low-Income Countries are strongly reliant on the development of the agriculture industry.

A high markup in Low-Income economies might be used as a measure to denote inefficiencies. The markup, or the wedge between the selling price of a good or service and the marginal cost of production, is a good proxy for representing market power when analyzing industries with similar characteristics, i.e. manufacturing or services in High-Income economies with similar institutional quality and political systems.

In Low-Income Economies, however, the markup might indicate that deep-seated structural rigidities are present within the industry or that there is a problem within the cost structure. There may be other factors than changes in pricing or unit costs influencing the markup. In theory, a radical change in the fixed cost may cause alterations in the markup, which might occur more easily in Low-Income Economies.

2.1.1 Measuring Market Power

To visualize this more clearly, the equations denoting the markup will be elucidated, and its mathematical derivation explained in more detail in the following paragraph. Following the procedure outlined by De Loecker et al. (2020), the firm produces output using a Cobb-Douglas Production Function as follows:

$$Q_{it} = \Omega_{it} V_{it}^{\alpha_{it}} K_{it}^{\beta_{it}} \tag{2.1}$$

with Q_{it} representing quantities of total output for firm i at time period t, Ω the Total Factor Productivity, V_{it} the variables inputs including intermediate inputs and labor remunerations, K_{it} the stocks of capital, and α_{it} and β_{it} the corresponding factor elasticities.

The model specifies that firms minimize costs, solving the following Lagrangian Function:

$$\mathcal{L} = P_{it}^{V} V_{it} + P_{it}^{K} K_{it} - \lambda_{it}(\Omega_{it} V_{it}^{\alpha_{it}} K_{it}^{\beta_{it}} - \bar{Q_{it}}) - \mathbf{F_{it}} \tag{2.2}$$

The variables P_{it}^{K} and P_{it}^{V} represent the prices for the input factors K, the stocks of capital and V, the variables inputs, whereas λ_{it} is the Lagrange Multiplier. Note here that F_{it} represents the firms' fixed costs. The stocks of capital are assumed to be fixed (unchangeable) in the short-run, therefore there is only one resulting First Order Condition:

$$P_{it}^{V} - \lambda_{it} \alpha_{it} \Omega_{it} V_{it}^{\alpha_{it}-1} K_{it}^{\beta_{it}} = 0 \tag{2.3}$$

At this point, the fixed costs, although still influencing the cost structure of the firm, are removed from further parts of the equation. This exposes a flaw when utilizing the markup, as situations might arise where fixed costs are increasing, with marginal costs also increasing slowly (or not at all), and firms being forced to increase prices to compensate. In such a situation, the markups would appear to be increasing, yet would not be indicative of firms exercising market power.

Equation 2.3 can then be rearranged by multiplying it with $P_{it}V_{it}$. Substituting the resulting Equation 2.1 then gives the expression for the markup:

$$\mu_{it} = \frac{P_{it}}{\lambda_{it}} = \alpha_{it}\frac{P_{it}Q_{it}}{P_{it}^{V}V_{it}} \tag{2.4}$$

with $P_{it}Q_{it}$ representing the value of total output, $P_{it}^{V}V_{it}$ the value of variable inputs, and α_{it} the variable inputs to outputs elasticity of a Cobb-Douglas Production Function.

The traditional approach is to estimate elasticity α_{it} econometrically, using panel data. The equation represented in Equation 2.1 is estimated (using logs) as:

$$q_{it} = \alpha_{it}v_{it} + \beta_{it}k_{it} + \omega_{it} \tag{2.5}$$

The coefficient is the estimated elasticity required for further calculation of the markup. The microeconomic approach is, however, not straightforward and is prone to having problems of endogeneity. In particular, the error term has two components ($\omega_{it} = \epsilon_{it} + \eta_{it}$). One component is known by the firm (but not the econometrician) and influences the choice of input factors. The component can be defined as ϵ_{it} and represents firm productivity. It may be influenced by, for example, the ability of employees, manager skills, and more. The second term η_{it} are sudden shocks unknown to the firm. It is precisely component ϵ_{it} that is the cause of endogeneity and potential biases from direct estimation.

Microeconomists have found ways to circumvent the problems caused by endogeneity, as seen in the papers by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015). These approaches generally use a two- or three-stage least squares approach to isolate the endogenous component non-parametrically. The main drawback, however, is that the coefficients are assumed to be static when using a panel-data approach.

The thesis uses macroeconomic data and deviates from estimating the markup using traditional econometric approaches. As our sample size is generally smaller relative to the size of using micro-data, an alternate estimation approach based on Generalized Maximum Entropy is employed. The method estimates the markup cross-sectionally for each year, guaranteeing a dynamic elasticity. Additional advantages of relying on this method are discussed in more detail in a subsequent Chapter 3.

Furthermore, by utilizing macroeconomic data contained within input-output tables, it is possible to derive estimates of market power for a broad coverage of industries and countries. The coverage is more extensive than would be available when using micro-economic data. Even though the estimates derived from firm-level data are considered the benchmark in terms of precision, Chapter 3 will provide evidence that the procedure is usable to draw conclusions.

The thesis uses this feature to derive estimates of the markup for industries where no micro-data is available – the Primary Foods Industry. The sector is comprised of agriculture, hunting, fishing, and logging and is considered key for the development of Low-Income economies.

2.2 Research objectives

The research objectives for this thesis are as follows:

1. Prove the feasibility of estimating markups using aggregate data in the form of input-output tables (Section 3).

2. Use the methodology to estimate the markups for industries where no data is available. In the case of this dissertation, the Primary Foods industry (Section 4).

3. Determine the causal relationship between markups and Global Value Chains (Sections 3 and 5).

4. Analyze the markups of the Primary Foods Industry (Sections 4 and 5).

2.3 Thesis structure

The remainder of the thesis will introduce each article in order of importance. Each introductory chapter is followed by an article in its published format. The publications are not presented by order of publication but rather ordered in a way to enhance the flow of information.

Chapter 3 will introduce the methodology of estimating markups from Input-output Tables and contrast the results from a micro-based data set. The paper estimates markups for European countries for the years 2000 and 2014. Measures of globalization are then estimated, and its relationship with regard to markups is measured. This chapter serves as the foundation for subsequent papers and gives legitimacy to the methodology. Chapter 4 applies the aforementioned methodology to estimate markups for the Primary Foods Industry (comprised of agriculture, hunting, fishing, and logging) for 170 countries in the world between the years 1995 to 2015, being the first ones in doing so. Chapter 5 then uses a subset of the data set explored in Chapter 4, to investigate markups of the Primary Foods Industry in Asia, exploring how income levels, political systems, and globalization in the form of Global Value Chains impacts markups.

The dissertation then concludes and summarizes the findings in Chapter 6, mentioning the limitations of the methodology and exploring further potential avenues of research.

Chapter 3

On the possibility of using Input-output Tables to estimate market power

As mentioned in the previous section, micro-economists face problems because of the lack of high-quality data to conduct adequate research. The first step to achieve the objectives outlined in Section 2.2 is to explore the possibility of using input-output tables to calculate the markup. The purpose of this section is to propose a methodology to calculate markups and compare the results with those obtained using firm-level data. The paper Rodríguez del Valle and Fernández-Vázquez (2023), shown in this section, will set out to do precisely this.

Even though Input-output Tables contain information at the industry or sector level, they carry assumptions compatible with microeconomic theory. Figure 3 shows an example of a national input-output table. The tables divide the total economic activity into a group of industries or economic sectors (used interchangeably). The cells represent the values of goods or services produced in one industry and used in the same or another. These tables are comprised of a series of components that are interconnected, including vectors denoting value added, a transaction matrix including values of intermediate inputs, a vector with total outputs, and a matrix with final demand.

The rows illustrate how final goods and services are produced and used across industries as intermediate inputs or final demand. In contrast, the columns represent the intermediate inputs required to produce output. In essence, the columns represent production functions, concretely Leontief Production Functions. In other words, it is assumed in input-output theory, that each column is one "firm" that produces using a Leontief Production Functions. This assumption gives concordance and legitimacy to applying microeconomic theory, concretely the calculation of the Equation 2.4 shown in Chapter 2.1.1.

A notable feature of the approach presented in the following as well as subsequent papers, is the use of alternative econometric techniques to estimate the markup. The markup is traditionally estimated using firm-level, micro-data using a panel approach. The thesis uses an estimation procedure based on Generalized Maximum Entropy (GME). The reasoning is that input-output tables used do not contain information for many years (either 15 or 21 years). The GME approach will produce more reliable results when the sample size is small, such as the case here. Furthermore, the GME approach offers additional advantages:

- constraint may be used to set the minimum values of the markup to 1. The use of microeconomic data often produces estimates of markups less than 1. This does not make economic sense.
- the variable input factor elasticity (α_{it}) may be estimated dynamically, therefore increasing the sources of variation when computing the markup μ_{it} from Equation 2.1.

The subsequent paper in Section 3.1 proposes to calculate the markups using input-output tables with a procedure based on the GME approach and comparing the results with an external database called CompNet. The CompNet Database provides markup estimates by calculating the markup for each firm operating in a market and then aggregating the results.

Figure 3.1: An illustrative example of an input-output table

	Industry 1	...	Industry N	Final demand (y)	Total output (x)
Industry 1	z_{11}	...	z_{1N}	y_1	x_1
Industry 2	z_{21}	...	z_{2N}	y_2	x_2
...	...	...	...	...	...
Industry N	z_{N1}	...	z_{NN}	y_N	x_N
Labour compensation (lc)	lc_1	...	lc_N		
Other value added (w)	w_1	...	w_N		
Imports + taxes (m)	m_1	...	m_N		
Total output (x)	x_1	...	x_N		

3.1 Article 1) Estimating market power for the European manufacturing industry between 2000 and 2014

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ORIGINAL PAPER

Estimating market power for the European manufacturing industry between 2000 and 2014

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Abstract

The study of market power has gained a lot of attention by scholars and policy-makers since De Loecker and Eeckhout (Global market power. Working paper 24768, National Bureau of Economic Research, 2018). In their work, they show the temporal evolution of market power worldwide using detailed data from the financial statements of thousands of firms. In this paper, we propose an alternative way of estimating market power using sectoral-based data. By utilizing the aggregates observable in a series of input–output tables and by applying an estimation procedure based on entropy; indicators of market power can be derived without requiring the use of micro-data. We document a heterogeneous evolution of market power across 28 European countries and 14 manufacturing sectors between 2000 and 2014. Market power is found to be rising for several central- and East-European countries, while decreasing in multiple South- and West-European nations. Globalisation and value chain positioning are both seen to have a significantly decreasing impact on markups.

Keywords Market power · Input–output tables · Generalized maximum entropy · Global value chains

1 Introduction

The study of market power has gained a lot of attention since De Loecker and Eeckhout (2018) and De Loecker et al. (2020). Using firm-based data, their papers have shown that market power has continually increased since the 1980's (except for a brief decrease during the 2007–2008 Financial Crisis) for the US and the world as a whole, mostly driven by the largest firms within markets. Although a too low market

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power could indicate a loss of competitiveness, an increase in aggregated market power is often associated, at least in theory, with a range of negative economic developments such as: decreasing total factor productivity and output (Baqaee and Farhi 2017), a decrease in the labour share of income (Autor et al. 2020), decreases in investments (Gutiérrez and Philippon 2017), loss of innovation after reaching a threshold (an inverted U-shape relationship), as seen in, for example, Diez et al. (2018) and Mulkay (2019). Furthermore, rising market power also has societal implications due to its contribution to rising income-inequality, see Ennis et al. (2019).

This development has sparked interest globally among policy-makers, scholars and members of industry who are interested in understanding the cause of these changes, as well as obtaining a deeper understanding to measure market power. Central Banks are amongst the most important of these entities investigating this phenomenon due to the impact it has on pricing (see for example Koujianou Goldberg and Hellerstein (2012)), with examples including the recent speeches made by Praet (2019) at the European Central Bank, and the Economic Policy Symposium of 2018 organized by the Federal Reserve at Jackson Hole. Moreover, the question of competition and market power is gradually seeping into the political arena with calls increasingly being made to make markets fairer for all of those involved and more efficient as evidenced, for example, by the warnings and reform proposals given by the books Eeckhout (2021) and Baker (2019). This can be seen in Europe not only at the EU level (EU commission), but also at the national level with member-states using various tools and policies to reduce monopolistic action.

The topic of market power has always been of crucial importance within the field of industrial organization, ever since Lerner (1934) first proposed an index measuring the markup of price over marginal cost. Subsequent literature adopted the Structural- Conduct-Performance (SCP) approach to study the market structure in detail to understand the causes of market power (Perloff et al. 2007). These papers did not rely on formal models of industry behaviour, rather were often case studies and inter-industry analysis mostly focused on one single year (Schmalensee 1987). The SCP approach was mostly interested in understanding market structures, and therefore limited itself to investigating one or two industries. Hall (1988) outlined a formal model and laid the framework through which markups estimation was generalized. The papers from Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2015) introduced novel ways to estimate production functions using a two- or three stages approach with control functions, solving the usually large problems of endogeneity caused by direct regressions. These papers paved the way to derive estimates for markups directly from production functions, for instance De Loecker et al. (2020). The markup, or the ratio between selling price of a final good and the marginal cost of production, is commonly used in the literature as a proxy for market power. Using De Loecker and Eeckhout (2018) terminology, the markup for firm i at year t is: $\mu_{it} = P_{it}/\lambda_{it}$. Assuming that firms are profit maximizers, a markup of 1 is indicative that the firm is setting prices in such a way that they are not able to move beyond the break-even point ($P_{it} = \lambda_{it}$), and not making profits. A markup larger than 1 is commonly associated with firms exercising market power ($P_{it} > \lambda_{it}$).

We propose using this same methodology of calculating markups based on production functions but using aggregated sector-level data instead of the firm-level data, which it was originally designed for in the paper by Hall (1988).[1] More specifically, in this paper we propose using a General Maximum Entropy (GME) approach with data from the World Input–Output Database (WIOD) as well as the WIOD Socio Economic Accounts (SEA) in order to estimate sector-level markups. Input–output tables such as the ones from WIOD, divides total global economic activity into sectors or industries (used interchangeably during the remainder of the paper). They provide information on the flows of goods or services encompassed within an industry, originating in one sector and ending up in another.

Even though markup estimation using micro-based data is considered to be the benchmark in terms of precision (being able to provide estimates by percentile of firm-size along the distribution and conduct granular research), it also has a few notable problems, including: potential sample selection bias due to firms entering bankruptcy during the years of observation (sample attrition), difficulty of classifying a firm into a sector if it produces several goods and the problems of extracting *volumes* of inputs and outputs, which the SEA conveniently does provide, thus avoiding potential estimation bias arising from pricing,[2] and difficulty of finding data that is accurately representative of total market activity. The largest databases containing firm activity, such as Worldscope, have information for 70000 firms (De Loecker et al. 2020). These firms are often publicly traded thereby potentially skewing results upwards i.e. successful firms with sound balance sheets will be overproportionately reported as they have better chances of selling stocks. Firm-level data has the further inconvenience of lacking information on certain sectors, thereby any analysis is constrained to a few, predominantly manufacturing sectors. This is a further advantage of using the SEA of the WIOD, as the data contained therein encompasses total market activity within countries, and represents at least 85% of world economic activity (Timmer et al. 2012). Finally, the WIOD and SEA are free and easily accessible to the general public. This runs in contrast to many databases offering firm-level information, as they generally require fees or are private and not accessible to the general public (for example, due to laws requiring confidentiality on handling firm data). Additionally, the use of micro-data is computationally very demanding, with programs having to process thousands (even hundreds of thousands) of firms thereby necessitating considerable amounts of time for estimates to be produced.

The use of macro-data circumvents all of these problems, and is potentially able to yield results for the whole world, yet sacrifices precision. Moreover, this approach allows to fully integrate the strengths of input–output analysis into market power research. Input–output tables are excellent in calculating a myriad of measures and indicators pertinent to the fields of international trade and industrial organisation.

[1] A recent paper by Puty (2018) also explores the evolution of markups using aggregate data between 1958 and 1996, finding that market power evolves pro-cyclical relative to the business cycle.

[2] It is not possible to take differences of prices in every firm into account when aggregating firm-level data therefore a bias may arise.

These measures may not be easily obtainable using pure firm-level data, thus other dimensions may be opened up for research. A simple example of this type of analysis is shown in Sect. 5.3, which estimates the relationship between the positioning of the production process and Global Value Chains (GVC's) i.e. the international fragmentation of the production process with markups. The results derived in that section corroborates theory and the empirical results of papers focusing on individual countries and industries.

The paper is organized as follows. Section 2 gives a summary of further relevant literature, Sect. 3 presents the basics of the methodology required to estimate market power indicators from IO data. Section 4 provides a general description of the estimation procedure proposed to derive these indicators from aggregate information. Section 5 presents an empirical application for manufacturing industries in the EU basing on data from the World IO database for the period 2000 to 2014. Section 6 closes the paper.

2 Related literature

Numerous recent papers have expanded the knowledge regarding the study of market power; not only fine-tuning methodological aspects of De Loecker et al. (2020), but also applying the existing technique using evermore detailed datasets and focusing on granularity. In the former category, papers such as Morlacco (2017) expand the existing methodology to include measures of buyer market power and apply this to firms in the French manufacturing industry, finding the significance of this as well as finding evidence for carrying distortionary effects throughout the value chain.

Even though Hall et al. (1986) is considered to have kick-started the research of market power at a macro-level, research using aggregate data was slow relative to the micro approach. This was due to macroeconomists' reliance on Kaldor's Stylised Facts that assumes a stable evolution of market power and labour share of income. Nevertheless, De Loecker and Eeckhout (2017) spurred renewed research interest using macro-data. Cavalleri et al. (2019) use both micro- and macro-data to estimate market power trends for four countries in the Eurozone, and find a stable (plateaud) evolution. More recently, Colonescu (2021a) and Colonescu (2021b) derived measures of market power using macro-data contained within IOT's and the methodology proposed by Olley and Pakes (1996). These recent papers make use of the advantages of using IOT's, namely the ability to conduct Global Value Chain Analysis (GVC) in conjunction with potential markup estimation, thereby opening-up a whole new potential avenue for research, not possible with with using micro-based data. The use of both micro- and macro-based data can therefore complement each other well.[3]

There has also been an increasing surge in interest on finding determinants of markups, and measuring the types of relationships between both of these. Papers investigating this question often fall into one of two complementary groups: those

[3] Note: drawbacks for using this methodology is discussed in subsequent chapters.

analysing structural changes and those assessing the impact of policy. Of these, the former has had a noteworthy increase in research activity, with papers increasingly focusing on investigating the role of globalisation (with emphasis on trade in intermediates) on markups, generally finding a pro-competitive relationship. Empirical examples include: De Loecker et al. (2016), Gradzewicz and Mućk (2019) and Choi et al. (2021). Nevertheless, these studies often focus almost exclusively on individual countries, therefore, a comprehensive analysis based on numerous countries is of great interest.

3 Methodology

We follow here the same approach as in De Loecker et al. (2020) to derive market power indicators following the cost-based method. One crucial difference is that they use firm-level data to implement their analysis, while we propose using aggregate data at sectoral level. One reason for doing this is that, even when micro-data analysis allows for a richer detail in the results, the appropriate data required to do this are not always at hand and they are not easily accessible.

Let us denote the production in industry i at time t by the Cobb–Douglas technology:

$$Q_{it} = \Omega_{it} V_{it}^{\alpha_{it}} K_{it}^{\beta_{it}} \tag{1}$$

where V_{it} denotes the variable inputs i.e., intermediate consumptions plus labor, K_{it} represents the capital stock and Ω_{it} is the total factor productivity. Defining the output and the variable inputs prices as P_{it} and P_{it}^{V}, De Loecker et al. (2020) estimate the markup of a firm i (industry i in our case) as:[4]

$$\mu_{it} = \alpha_{it} \frac{P_{it} Q_{it}}{P_{it}^{V} V_{it}} \tag{2}$$

They implement this approach by estimating first the output elasticity α_{it} in 1 and then, assuming that this estimate is common for all the firms in the same sector and year, is plugged into 2. The approach proposed here is different and is based on aggregate information by industry, which can be easily accessed from the data present in a standard IO table.

Our point of departure is an $(N \times N)$ industry-by-industry IO table for an open economy at time period t with the following basic structure:[5]

The elements z_{ij} indicate how much of the production of industry i is used as intermediate input on industry j. Industry j requires not only intermediate inputs to produce, but primary factors as well (payments to production factors other than intermediate inputs). The compensation paid for these primary factors is split in our

[4] They derive this equation by solving a cost minimisation problem using Lagrange functions.

[5] The notation is simplified here, and we eliminate the subscript t, although all the figures in the IO table refer to a specific time period.

	Industry 1	...	Industry N	Final demand (y)	Total output (x)
Industry 1	z_{11}	...	z_{1N}	y_1	x_1
Industry 2	z_{21}	...	z_{2N}	y_2	x_2
...	...	...	...	...	...
Industry N	z_{N1}	...	z_{NN}	y_N	x_N
Labour compensation (lc)	lc_1	...	lc_N		
Other value added (w)	w_1	...	w_N		
Imports + taxes (m)	m_1	...	m_N		
Total output (x)	x_1	...	x_N		

Fig. 1 An illustrative example of an input–output table

example in labour compensation (lc_j), plus other terms in the value added (capital compensation, for example) labelled as w_j. Summing up across columns equals the total input on industry j ($x_j = \sum_i z_{ij} + lc_j + w_j + m_j$) while the sum across rows adds up to the total production of industry i ($x_i = \sum_j z_{ij} + y_i$).[6]

All the terms in this IO table are given in monetary units, so it is relatively easy to find a correspondence between the IO table cells and the elements used by De Loecker and Eeckhout (2018) to estimate the markups. Note that the total output in industry i at time period t in an IO table (x_{it}) corresponds to $P_{it}Q_{it}$, while the sum $\sum_i z_{ijt} + lc_{jt}$ is equal to $P^V_{jt}V_{jt}$ in Eq. 2. This means that part of the terms required to quantify the market power for one industry as μ_{it} can be directly recovered from IO tables.[7]

Additionally, we would need to estimate the output elasticity α_{it} to finally get measures of μ_{it}. This step is comparatively more problematic, since only aggregated information is available in IO databases. Ideally, we would need to have data on physical output produced Q_{it}, units of the variable inputs employed (V_{it}) and stock of capital K_{it}. These variables are not normally observable in IO databases, because of two main problems: (i) IO are expressed in monetary and not physical units, and (ii) IO cells are flows and not stocks.

However, these two difficulties can be partially solved by using the information publicly available in the World IO database—the Socio-Economic Accounts, which complements the national and international IO tables with additional indicators of physical output and intermediate consumptions, number of hours worked by the employees and stocks of capital. This information is available for 43 different countries along the period 2000–2014 with a sectoral breakdown into 56 industries.[8]

[6] The terms y_j and m_j denote respectively the part of the production in industry j that satisfies its final demand and the part of the cost of this industry devoted to pay its imports and taxes.

[7] Figure 1 represents a national input–output table. In the case of a world input–output table, the imports contained within vector m_{ij} are included in z_{it} i.e. elements of column-sector that do not correspond to the rows of the same country.

[8] Timmer et al. (2015) provides a more in-depth explanation for the WIOD project, see http://www.wiod.org/database/seas16 for details.

Since the indicators on gross output and intermediate consumptions are given in the form of volume indices (with base at 2010), some modifications are necessary in the estimable forms of the production function. In particular, we will assume that for one specific industry i and a time period t, the output elasticities α_{itc} and β_{itc} as well as the factor productivity in Ω_{itc} are constant for all the countries studied. This transforms Eq. (1), which can be re-written as:

$$Q_{itc} = \Omega_{it} V_{itc}^{\alpha_{it}} K_{itc}^{\beta_{it}} \tag{3}$$

Then, Eq. (3) is linearised and expressed in differences with respect to the 2010 levels as:

$$ln\left(\frac{Q_{itc}}{Q_{i0c}}\right) = ln\left(\frac{\Omega_{it}}{\Omega_{i0}}\right) + \alpha_{it} ln\left(\frac{V_{itc}}{V_{i0c}}\right) + \beta_{it} ln\left(\frac{K_{itc}}{K_{i0c}}\right) \tag{4}$$

Where the subscript 0 refers to the base period 2010. By adding a noise term ϵ_{itc}, equations like the following can be estimated:

$$ln\left(\frac{Q_{itc}}{Q_{i0c}}\right) = \Omega_{it}^{*} + \alpha_{it} ln\left(\frac{V_{itc}}{V_{i0c}}\right) + \beta_{it} ln\left(\frac{K_{itc}}{K_{i0c}}\right) + u_{itc} \tag{5}$$

Being $\Omega_{it}^{*} = ln\left(\frac{\Omega_{it}}{\Omega_{i0}}\right)$. Equations like (5) will be estimated for each one of the 56 industries present in the WIOD tables. This implies that the estimates of α_{it} will based on a number of data points that correspond to the number of countries that we want to study (C), and for which we assume that the production technology is the same. This naturally generates a set-up where the sample size C is expected to be small, which prevents the use of traditional econometric techniques that rely on the central limit theorem due to the limited number of degrees of freedom. Note that we want to produce an estimate of the elasticity α_{ij} for each industry and year, and not imposing parameter homogeneity along time. This prevents the use of more traditional estimators based on a panel-data structure. Our proposal is to use estimators based on entropy econometrics, which have been previously used in contexts of limited information (see, among others, Golan and Vogel (2000); or Fernandez-Vazquez (2015); for applications within the field of IO tables).

4 GME estimation of market power for EU manufactures; 2000–2014

A GME estimator has been applied to equations like 5 for each year from 2000 to 2014 and for a set of 23 manufacturing industries.[9] The dataset comprises the EU-28 economy ($C = 28$), and the values of Q_{itc}, V_{itc} and K_{itc} have been taken from the WIOD database. The list of countries and industries studied are reported in Tables 3 and 4.

[9] Technical details of GME methodology can be found in appendix 2.

Applying the GME estimator, requires the specification of supporting vectors for the parameters and the error terms. The parameters in Eq. 5 are the output elasticities α_{it} and β_{it} and the factor productivities Ω_{it}. For the term Ω_{it} we set support vectors with $M = 3$ values ($b_{\Omega m}$) centered at 0 and with bounds at ± 10. For the output elasticities we define supporting vectors with $M = 3$ points ($b_{\alpha m}$ and $b_{\beta m}$ respectively) centered at the corresponding mean value of the shares of V_{itc} and K_{itc}, and the limits of these vectors set as these means ± 10 to assure having wide enough supports. Similarly, for the error term, the support vectors are based on the three-sigma rule, which specifies vectors centered at 0 and sets the limits as $\pm$ three times the standard deviation of the dependent variable. Note that this approach implies that, in absence of information, the GME estimator produces uniform probabilities and the point estimates of the parameters will be equal to the central value in the vectors. By setting these central values at the mean of V_{itc}, the uninformative GME solution makes the mean mark-up μ_{itc} equal to one by construction. In other words, our prior assumption is that there is no market power and only if data contains information that contradicts this initial assumption, the GME estimator will produce a different result.

The GME programs for the estimations on each industry $i = 1, \dots, 23$ and $t = 2000, \dots, 2014$ can be written as follows:

$$\max_{\boldsymbol{P},\boldsymbol{W}} E(\boldsymbol{P}, \boldsymbol{W}) = \sum_{m=1}^{M} p_{\Omega m} ln(p_{\Omega m}) + \sum_{m=1}^{M} p_{\alpha m} ln(p_{\alpha m}) + \sum_{m=1}^{M} p_{\beta m} ln(p_{\beta m}) + \sum_{c=1}^{C} \sum_{j=1}^{J} w_{cj} ln(w_{cj}) \tag{6}$$

subject to:

$$ln\left(\frac{Q_{itc}}{Q_{i0c}}\right) = \sum_{m=1}^{M} b_{\Omega m} p_{\Omega m} + \sum_{m=1}^{M} b_{\alpha m} p_{\alpha m} ln\left(\frac{V_{itc}}{V_{i0c}}\right) + \sum_{m=1}^{M} b_{\beta m} p_{\beta m} ln\left(\frac{K_{itc}}{K_{i0c}}\right) + \sum_{j=1}^{J} v_j W_{cj}; \qquad c = 1, \dots, C \tag{7}$$

$$1 = \sum_{m=1}^{M} p_{\Omega m} = \sum_{m=1}^{M} p_{\alpha m} = \sum_{m=1}^{M} p_{\beta m} \tag{8}$$

$$\sum_{j=1}^{J} w_{cj} = 1 \quad c = 1, \dots, C \tag{9}$$

$$\sum_{m=1}^{M} b_{\alpha m} p_{\alpha m} \frac{P_{itc} Q_{itc}}{P^V_{itc} V_{itc}} \geq 1 \tag{10}$$

One additional advantage of using the GME estimator in this context is that its flexibility allows us to accommodate additional constraints related to the theoretical characteristics of the phenomenon analyzed. In the case under study, theory tells us that the market power should not be lower than one, and this theoretical restriction is included into the GME program by means of Eq. 10. Note that this equation forces the estimates of μ_{itc} to be equal or larger than one, preventing to get solutions that do not fit with the basic assumptions used in the model from which the estimable equations have been derived.

By solving these programs, the GME estimator produces point estimates and estimated variances for the parameters of interest. In particular our estimates of α_{it} are calculated as $\sum_{m=1}^{M} b_{\alpha m} p_{\alpha m}$ and the estimates of μ_{itc} as $\sum_{m=1}^{M} b_{\alpha m} p_{\alpha m} \frac{P_{itc} Q_{itc}}{P_{itc}^{V} V_{itc}}$.[10] Next section shows the main results found and compares them with other alternative approaches.[11]

5 Results

We have estimated Eq. 5 by using GME based on the available data from WIOD. Furthermore, we got access to sector-level aggregated micro-data obtained from the database CompNet,[12] on which the original approach presented by De Loecker and Eeckhout (2018) and De Loecker et al. (2020) can be replicated. This comparison allows for testing to what extent the GME estimates are similar to those obtained from more detailed data.

The evolution of market power shows a large variation according to the method of aggregation. Appendix 1 gives detailed descriptive statistics of markups disaggregated by years and industries estimated using WIOD and micro-data. Table 6 illustrates the descriptives for markups disaggregated by industries derived from WIOD, with GME being capped at a minimum of one (due to the constraint depicted in Eq. 10), displaying low levels of variation relative to the evolution obtained from micro-data, as seen in Table 7.

Both the minimum and maximum values are largely heterogeneous across sectors, and have a large standard deviation. The highest maximum values from the GME method is seen to be in the aggregate sector corresponding to coke and petroleum manufacture, the lowest related to textile, rubber and non-metalic mineral products. Table 5 shows individual country—sectors with the five highest markup values for 2000 and 2014. Sectors corresponding to the manufacturing of petroleum and chemical products appear frequently, especially for 2014. Tables 8 and 9 further illustrate these summary statistics disaggregated by years, showing stronger minimum values during 2009 for GME estimates.

[10] Details of estimates of α_{it} can be found on the appendix 4.

[11] A separate file with the dataset containing all the results presented here, is also provided.

[12] see di Mauro and Lopez-Garcia, 2015 for more informarion.

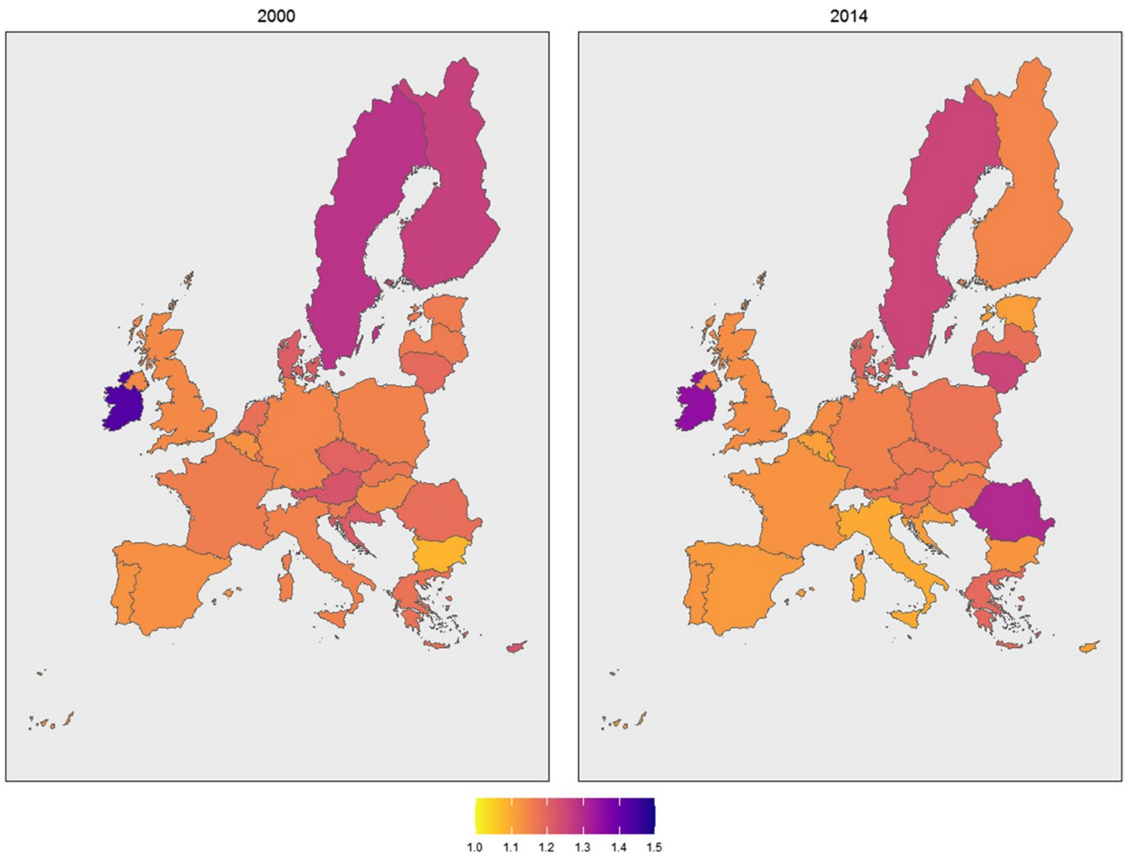

Fig. 2 Markups during 2000 and 2014

5.1 Results using the world input–output database

Figure 7 details the evolution of markups in its highest form of aggregation. The markups were found to be highest during 2003 and lowest in 2008. Up until 2008, market power was seen to be having a decreasing trend. Thereafter, market power was increasing nearly continuously for subsequent periods. Estimates for market power were higher at the end of the sample period in 2014 than they were at the start in 2000. Figure 9 further shows how the output elasticity of labour evolved throughout the sample period.

Figure 2 shows the country-aggregate market power for the years 2000 and 2014, for the manufacturing industries illustrated in Table 4. The map indicates persistent variations of market power by levels across geographic regions. Scandinavian and Baltic countries (with the exception of Estonia and Finland in 2014), South-Eastern countries such as Romania, Greece, and finally Ireland consistently reported relatively higher markups compared to other countries. By 2014 many South-European countries had relatively low-levels of market power, especially Italy and Croatia. Additionally, Belgium, Luxembourg and Estonia had low markups relative to the other countries.

Figure 3 further shows percentage changes for markups between 2000 and 2014. The colouring of the map indicates a remarkable geographic pattern; countries whose markup have increased or decreased tend to be in proximity with each other (with the exception of Ireland and Portugal and Finland). Central European

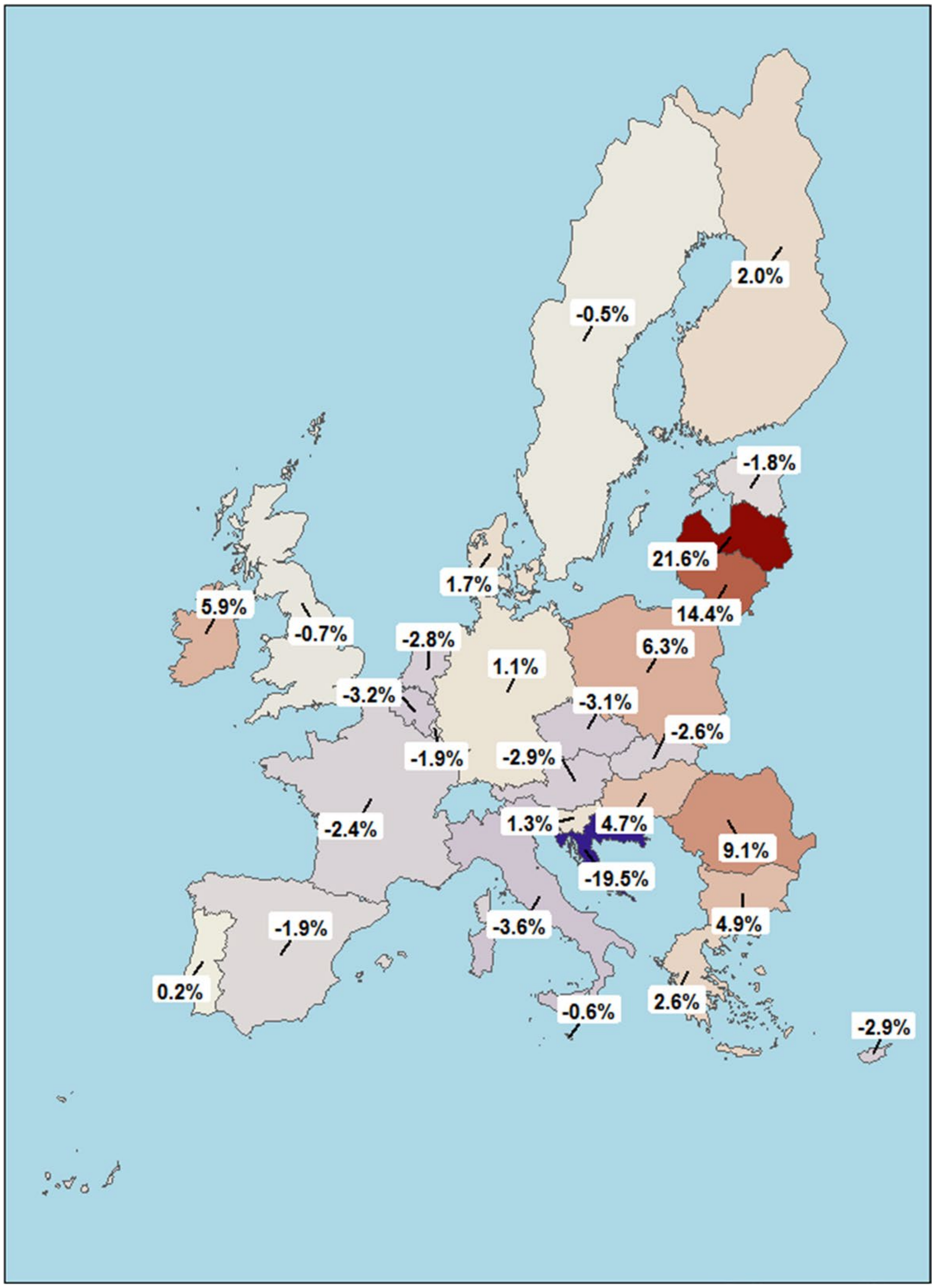

Fig. 3 Percentage change GME markups 2000 to 2014 for each country

countries such as Germany and Poland saw an increase in market power. Southern Baltic countries, Denmark, Finland, Ireland and the South-eastern region also had increasing markups. In contrast, most South- and West-European countries saw decreasing markups. The manufacturing sectors from a total of 13 countries had increasing markups between 2000 and 2014. A total of 7 of these countries with increasing markups joined the European Union somewhere during the sample period; either in 2004 as in the case of: Hungary, Lithuania, Latvia, Poland and Slovenia, or in 2007 such as Bulgaria and Romania. The remaining countries with increasing markups were: Germany, Denmark, Finland, Greece, Ireland and Portugal.

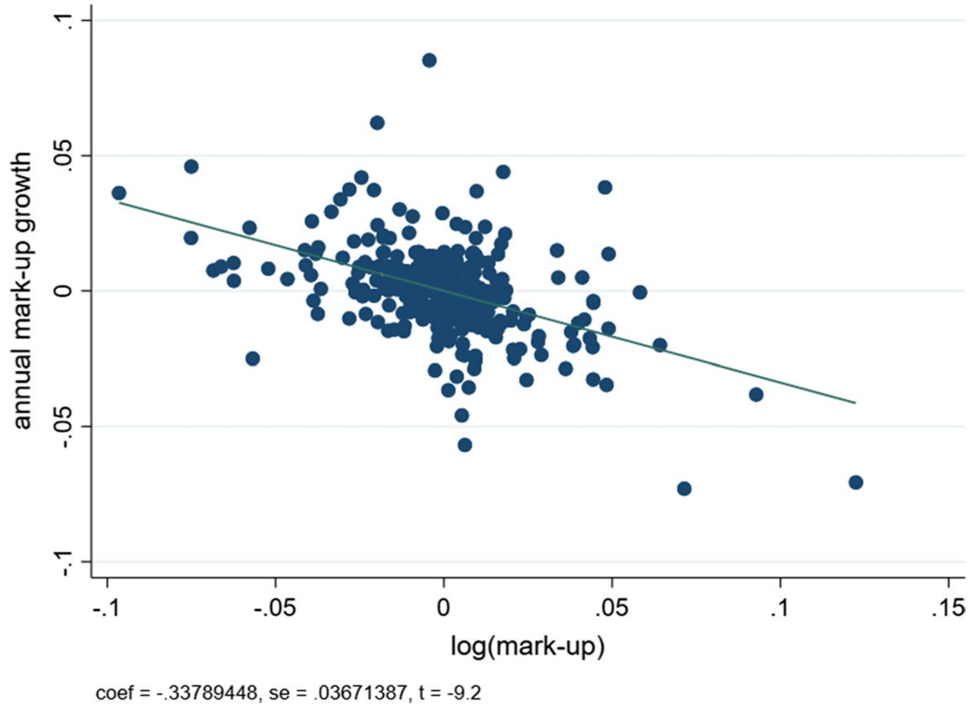

Fig. 4 Beta convergence of markups aggregated by country using a two-way fixed effects model

Nevertheless, our estimates suggest that the mean value of aggregate market power along these countries have been converging slowly between 2000 and 2014. A country-wise absolute beta-convergence analysis using a fixed effects regression, where market power growth rates between 2000 and 2014 was regressed on its lagged values, produces an estimate of the beta coefficient of −0.338 (significant at 0.1%). The results of which is shown as a scatter-plot in Fig. 4. This result indicates that overall the dispersion of aggregated market power decreased during the sample period.

5.2 Comparisons to firm-level data

A possible concern revolves around the actual precision of these results, given the assumption in an input–output table that each sector is produced by one representative firm. The WIOD Markup sample was compared with the 7*th* Vintage CompNet database that provides estimates for market power using firm-level micro data. The evolution of these measures of market power were then plotted across time. Even though the WIOD and the SEA contain information for 56 sectors and 43 countries for the years 2000–2014 (except 2010 due to it being the base year), the markup data within CompNet is unbalanced. The is because different European countries have unequal systems for collecting firm data. Some countries report data for every firm, while others require a firm fulfilling certain thresholds, such as a minimum number of workers being employed at a firm. Due to the aggregated nature of WIOD, only CompNet countries with full firm samples were used. In total, 14 sectors were compared for five European countries—each country having data for differing spans of

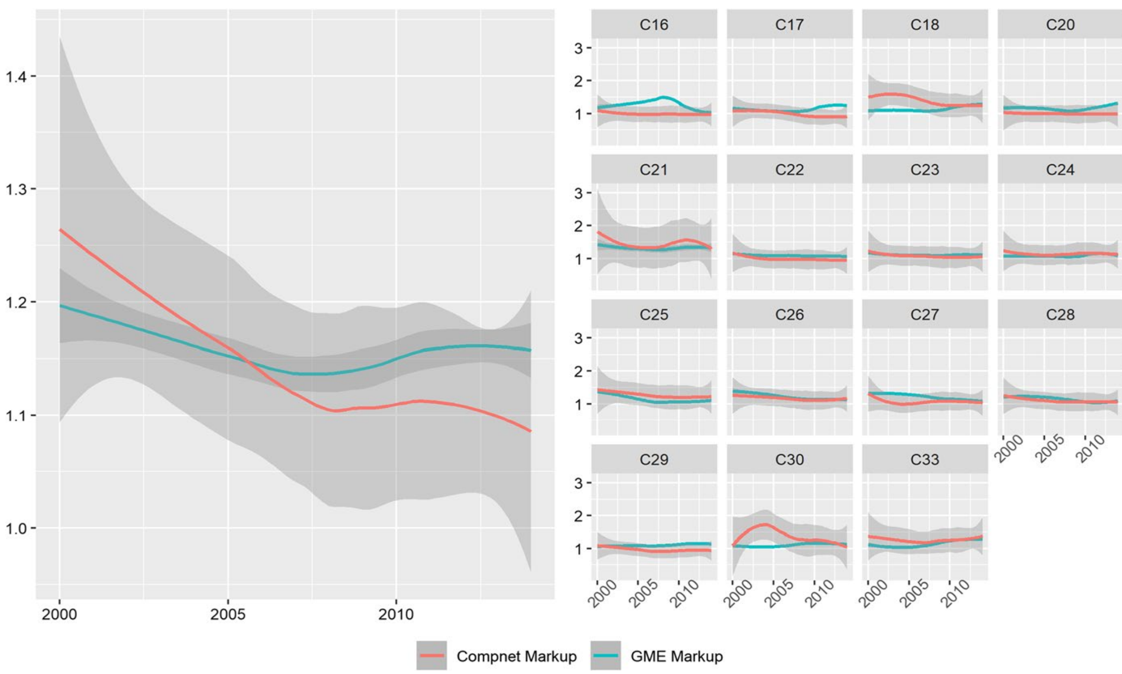

Fig. 5 Evolution aggregate and per sector markups using loess smoothing estimated using WIOD and firm-level data from CompNet

time.[13] Data from WIOD that did not find a match were removed from the sample, making the comparison as homogeneous as possible. Tables 7 and 9 describe the CompNet variable in more detail.

The markup from the micro data was estimated by using a Cobb–Douglas production function with the firm's revenue being used as a proxy for output, and the elasticity for intermediates used for the markup computation, see Eq. (2). This form was chosen as it is the most similar to the approach presented here.

Figure 5 shows the evolution of all the markup estimates with confidence intervals at the 95% level. These aggregates are calculated by averaging markups for each country, years and industry using industry volumes of output in the WIOD as weights. A function was fitted through the scatter-plot using the Loess smoothing technique, thereby revealing the evolution. GME markup is seen to generally have overlapping confidence intervals with the estimates derived from micro-data. Nevertheless, disaggregating the data at a sector level shows divergence for some industries; most notably for sectors manufacturing wood, media, pharmaceutical products and other transport equipment not included in the manufacture of cars (notably airplanes, ships, locomotives and spacecraft).

Estimates corresponding to industries C16, C18, C21 and C30, and are seen to deviate significantly from each other. This can highlight how the use of macro-based data for markup estimation has a few unique potential pitfalls that can bias results. These have to do with the uniformity of the distribution within the market being considered. Macro-data assumes that each sector is produced

[13] The following countries are represented in the sample: Belgium, Denmark, Spain, Croatia and Italy.

Fig. 6 Evolution market power for four selected industries

by one representative firm, and considers averages. If the sector is comprised of very few firms, or the distribution is very fat-tailed, bias may ensure. Macro-data cannot disentangle what is happening to top percentile-size within the firm-size distribution, which may be problematic as most market power is seen to be generated by this fragment of the market.

Both measures indicate that markups declined until 2008. GME markups reached their lowest point by that year, with a reversal of this declining trend occurring thereafter during the 2009–2014 period. The CompNet markups reportedly remained stable after the 2008 period, not reaching the levels of pre-2007. Both measures show that market power never fully recovered the initial values seen in the 2000 period. Noteworthy is that the estimates derived from CompNet often have a minima under 1, which would seemingly indicate that goods were being sold at a price under its marginal cost of production. This is something which frequently occurs when handling firm-level data. These values contradict theory, since firms will not operate when profits cannot be achieved. This is more relevant with aggregated sector-level values, as this would indicate a substantial number of firms setting prices under marginal costs.

A larger year-to-year variation can be seen in Fig. 6, showing the sector-aggregated development for four selected manufacturing industries (Sect. 1 within the appendix shows the evolution for all the sectors in the combined sample). The sectors corresponding to the manufacture of fabricated metal products and the manufacture of computer and electronics, show a relative larger variation, whereas those sectors related to the manufacture of machinery and motor vehicles were more stable.

5.3 Markups and global value chains

As can be seen in the descriptive tables in Sect. 1, a large heterogeneity exists across countries and sectors when examining these markups. This section investigates potential causes of this disparity by using two exogenous determinants of markups—making use of WIOT's capacity to compute measures of inter-industrial linkages. One of these measure indicates how globalised, or internationalised, the factors used to produce an output are within each industry whilst the other indicates the relative positioning with regards to tasks being produced. This section serves as a simple exercise to further give credence to the results derived via the GME approach, but, by no means is this a complete analysis of the full determinants of markups. Other characteristics could theoretically impact markups, such as a country's institutional quality (including corruption), and ease of access to credit by larger firms, among other things.

In order to understand how these measurements are computed, a few concepts are explained in the following paragraphs. Using the notations in matrix form from Fig. 1 (representing a Leontief Demand Model); X represents a vector with total output for industry i, Y be a vector containing values of final demand, VA be a vector with value added (which includes labour compensation and capital rents) and Z a matrix containing the monetary value of the intermediate inputs coefficients. The technical inputs coefficients A may be obtained by multiplying $Z\hat{X}^{-1}$, with $\hat{X}^{-1}$ representing the inverse of the diagonal matrix containing values of total output along the diagonal.

Total output produced can be decomposed into intermediate or final consumption, as seen in: $X = AX + Y$. This can be re-written as: $X = (I - A)^{-1}Y$, with I representing an identity matrix. The expression $(I - A)^{-1}$ is known as the Leontief Inverse Matrix and represents the value of output produced across all stages of production required to produce one unit of Y (sometimes called direct and indirect effects by input–output economists). The intuition behind this can be seen more clearly with the following geometric sequence: $I + A + A^2 + A^3 + \cdots + A^N = (I - A)^{-1}$, with N approaching infinity.

Estimates on the degree of an industry's degree of globalisation is obtained by calculating the foreign share of value added (factor content) used in producing output in a respective industry. This methodology was first proposed by Johnson and Noguera (2012) and applied with slight modifications by Timmer et al. (2015). The equation of total value added is given by:

$$TVA = \widehat{VAS}(I - A)^{-1}\hat{Y} \tag{11}$$

$\widehat{VAS}$ here represents a diagonal matrix with shares of value added with respect to total output along its diagonal ($\widehat{VAS} = VA\hat{X}^{-1}$) and $\hat{Y}$ another diagonal matrix with values of final demand along its diagonal. This equation yields another matrix with each element representing direct and indirect value added generated in industry i and used in industry j. Summing along the columns gives the total value added used for production by industry j. This then can be used to calculate the shares of value added of a country's industry used by origin—being able to separate domestic and

Table 1 Two-way fixed effects results. Dummies are used for each year and combination of country-sector

	GME markup		
	(1)	(2)	(3)
Foreign VA	−0.991***	−2.100***	−2.113***
	(0.037)	(0.103)	(0.103)
I(Foreign VAˆ2)		1.196***	1.197***
		(0.104)	(0.104)
Upstreamness	−0.0001	−0.005***	−0.007***
	(0.001)	(0.002)	(0.003)
I(Upstreamnessˆ2)		0.00003***	0.00004***
		(0.00001)	(0.00001)
I(Upstreamness * Foreign VA)			0.005
			(0.004)
N	7,226	7,226	7,226
R^2	0.098	0.117	0.117
Adjusted R^2	0.025	0.044	0.044
F statistic	363.938*** (df = 2; 6680)	220.266*** (df = 4; 6678)	176.426*** (df = 5; 6677)

***Significant at the 1 percent level.

foreign value added by doing so. Table 10 summarises these shares of foreign value added for each country in the sample.

The Leontief Demand Model assumes that outputs leave the system at the end of the process (Miller and Blair 2009). An alternative approach proposed by Ghosh measures the unit values entering the system. This is done by transposing the model, giving the following equation: $X = XB + VA$, with B represent the allocation coefficients, computed by $B = \hat{X}^{-1}Z$. Re-arranging the former equation gives: $X = VA(I - B)^{-1}$.[14] The matrix $(I - B)^{-1}$ is known as the Ghosh Inverse Matrix, and counts the monetary value of value added across all stages of production. Summing across each row of this matrix gives a measure of how strong forward linkages are within an industry. Concurrently, Antràs et al. (2012) finds, that summing across each of these rows gives a measure of upstreamness—concretely it gives the average number of times an output is processed before reaching consumers (see also Johnson (2018)). The larger values this measure takes, the more upstream the industry will be positioned.

[14] Note: the value added represented in this calculation is the difference between total intermediate inputs and total output. It includes, among other things, taxes, subsidies and transport margins and is therefore different than the value added used in Eq. 11.

Table 2 Marginal effects by country. For the sake of a better understanding of these marginal effects, this table shows the marginal effects of increasing the foreign value added by 1% or increasing by 100 units the upstreamness indicator

Country	Foreign VA	Upstreamness
AUT	− 0.0123***	− 0.4802***
BEL	− 0.0105***	− 0.4802***
BGR	− 0.0107***	− 0.4822***
CYP	− 0.0112***	− 0.4789***
CZE	− 0.0115***	− 0.4793***
DEU	− 0.0144***	− 0.4807***
DNK	− 0.0125***	− 0.4809***
ESP	− 0.0142***	− 0.4797***
EST	− 0.0099***	− 0.4796***
FIN	− 0.0134***	− 0.4791***
FRA	− 0.0139***	− 0.481***
GBR	− 0.015***	− 0.4806***
GRC	− 0.016***	− 0.4833***
HRV	− 0.0132***	− 0.4824***
HUN	− 0.0094***	− 0.4803***
IRL	− 0.0104***	− 0.4803***
ITA	− 0.0148***	− 0.4803***
LTU	− 0.0134***	− 0.4798***
LUX	− 0.0077***	− 0.4796***
LVA	− 0.0121***	− 0.4723***
MLT	− 0.009***	− 0.4813***
NLD	− 0.0118***	− 0.4804***
POL	− 0.0131***	− 0.4808***
PRT	− 0.0124***	− 0.4807***
ROU	− 0.014***	− 0.4815***
SVK	− 0.0106***	− 0.4805***
SVN	− 0.0121***	− 0.4774***
SWE	− 0.0134***	− 0.4798***

***Significant at the 1 percent level

In order to test the impact of these two variables, a two-way fixed effects model is used:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \alpha_i + \delta_t + \epsilon_{it} \tag{12}$$

with β_0 representing the constant, $\beta_1 X_{1it}$ the set of independent variables mentioned previously, α_i representing entity dummies (in this case for every pair of country-sector), δ_t the time dummies and ϵ_{it} the error term.

Table 1 shows the regression results of both measures of percentage share of foreign value added and upstreamness. Both variables were also interacted with itself and each other in order to test for possible non-linear relationships. Model 1 clearly shows that foreign value added significantly reduces markups, with upstreamness showing a negative, albeit non-significant, negative coefficient sign. Furthermore, the results in model 2 suggest that both globalisation and upstreamness significantly reduce markups, but at a decreasing rate for higher levels of values. This can be seen more clearly in Table 2, which shows the negative mean marginal effects by countries of both variables on the markups.

It should be noted, that WIOTs are capable of computing measures for both forward linkages (value added and intermediate inputs originating from the country-sector being analysed and ending up somewhere in the world) and backward linkages (value added and intermediate inputs originating somewhere in the world and ending up in the country-sector being analysed). The share of Domestic Value Added used here is one that measures backward linkages, whereas the Upstreamness index measures forward linkages. Result might change depending on what kind of linkages are being considered.[15] These results could therefore still be consistent with papers such as De Loecker and Warzynski (2012), who find a positive effect of trade liberalisation on markups when analysing exporter firms in Slovenia.

6 Concluding remarks

Estimates of market power were given using the methodology of De Loecker et al. (2020) and data provided by the Socio-Economic Accounts of the World Input–Output Database. Using these datasets circumvent several problems when utilizing micro-data. A GME estimator was used to estimate markups, and found that the evolution of market power was heterogeneous when analysing geographic clusters and specific industries. The findings suggest that, all in all, market power for manufacturing sectors in Europe did not increase substantially during the period 2000–2014. In fact, the aggregated markup of several countries saw a decreasing market power. This contradicts the findings from De Loecker and Eeckhout (2018), who found a generalized increase in market power for a substantial number of countries in the world, and are more in line with the results found by Weche and Wambach (2018). These authors also finds a heterogeneous evolution of market power for European manufacturing sectors, with markups decreasing on aggregate until 2009, and seeing a generalised increase after 2013.

Furthermore, two significantly contributing factors were found that impacted markups: a measure of globalisation and an industry's relative positioning with regards to its production process. It has been found, that both reduce markups as expected by theory, although these effects are progressively smaller at higher levels. These results also confirm the many other papers that have focused on analysing this relationship within specific countries and industries.

[15] Note: A substantial number of papers use VAX or related measures that measure forward linkages. There is still an active debate going on, whether all of these measures using forward linkages are completely accurate and free from double counting and other measurement errors, see, for example, Arto et al. (2019) and other papers from the EU for an overview of these measures with their potential drawbacks.

The use of aggregate data has notable advantages, as it avoids problems stemming from the use of micro-data. The results derived by this method also ensures that they are economically sound, due to them not being able to take values below 1. Additionally, the method may be applied to any type of dataset containing aggregate information with the relevant variables; the WIOD is not the only possible source of information. In fact, datasets with larger spans of time will make estimations using the entropy method even more robust. Furthermore, IOT's homogeneous sector classification for total economic activity allows for an efficient inter-sectoral and international analysis. It is therefore possible to extend this analysis to any other country or industry that are of high interest to policy-makers or scholars.

Future research might improve these results and methodology further by estimating each industry's firm-size distribution. This could be achieved by applying GME to reverse-engineer these distribution by using, for example, measures of concentration ratios and/or the Hirschman-Herfindahl Index. This has been already successfully achieved in Golan et al. (1996), albeit with more narrowly defined industrial classifications.

Summary statistics

See Tables 3, 4, 5, 6, 7, 8, 9 and 10.

Table 3 Country code and description

Country code	Country	Country code	Country
AUT	Austria	HUN	Hungary
BEL	Belgium	IRL	Ireland
BGR	Bulgaria	ITA	Italy
CYP	Cyprus	LTU	Lithuania
CZE	Czech Republic	LUX	Luxembourg
DEU	Germany	LVA	Latvia
DNK	Denmark	MLT	Malta
ESP	Spain	NLD	Netherlands
EST	Estonia	POL	Poland
FIN	Finland	PRT	Portugal
FRA	France	ROU	Romania
GBR	United Kingdom	SVK	Slovakia
GRC	Greece	SVN	Slovenia
HRV	Croatia	SWE	Sweden

Table 4 Industry code and description

Industry	Description
C10–C12	Manufacture of food products, beverages and tobacco products
C13–C15	Manufacture of textiles, wearing apparel and leather products
C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
C17	Manufacture of paper and paper products
C18	Printing and reproduction of recorded media
C19	Manufacture of coke and refined petroleum products
C20	Manufacture of chemicals and chemical products
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22	Manufacture of rubber and plastic products
C23	Manufacture of other non-metallic mineral products
C24	Manufacture of basic metals
C25	Manufacture of fabricated metal products, except machinery and equipment
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment n.e.c
C29	Manufacture of motor vehicles, trailers and semi-trailers
C30	Manufacture of other transport equipment
C31-C32	Manufacture of furniture; other manufacturing
C33	Repair and installation of machinery and equipment

Table 5 Five sectors with the highest GME markup values for 2000 and 2014

2000			2014		
Sector	Country	GME markup	Sector	Country	GME markup
C19	HRV	3.51	C33	GRC	2.86
C26	GRC	2.11	C21	LTU	2.50
C21	IRL	2.05	C20	SWE	2.27
C33	MLT	1.95	C21	FIN	2.14
C20	SWE	1.82	C20	IRL	2.11

Table 6 Descriptive statistics for markups estimates using input–output tables

Variable	Industry	N	Min	Max	Mean	SD
Markup (GME)	Manufacture of basic metals	372	1.0	3.4	1.1	0.2
	Manufacture of basic pharmaceutical products and pharmaceutical preparations	387	1.0	2.5	1.3	0.2
	Manufacture of chemicals and chemical products	392	1.0	2.3	1.2	0.2
	Manufacture of coke and refined petroleum products	343	1.0	3.5	1.1	0.2
	Manufacture of computer, electronic and optical products	387	1.0	2.1	1.2	0.2
	Manufacture of electrical equipment	391	1.0	1.6	1.3	0.1
	Manufacture of fabricated metal products, except machinery and equipment	384	1.0	1.5	1.2	0.1
	Manufacture of food products, beverages and tobacco products	392	1.0	1.5	1.1	0.1
	Manufacture of furniture; other manufacturing	376	1.0	1.9	1.3	0.2
	Manufacture of machinery and equipment n.e.c.	389	1.0	1.5	1.2	0.1
	Manufacture of motor vehicles, trailers and semi-trailers	384	1.0	1.7	1.2	0.1
	Manufacture of other non-metallic mineral products	388	1.0	1.4	1.1	0.1
	Manufacture of other transport equipment	359	1.0	2.0	1.2	0.1
	Manufacture of paper and paper products	386	1.0	1.6	1.2	0.1
	Manufacture of rubber and plastic products	389	1.0	1.4	1.1	0.1
	Manufacture of textiles, wearing apparel and leather products	374	1.0	1.4	1.1	0.1
	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	371	1.0	2.0	1.3	0.2
	Printing and reproduction of recorded media	391	1.0	2.2	1.2	0.1
	Repair and installation of machinery and equipment	371	1.0	2.9	1.2	0.2
	All	7226	1.0	3.5	1.2	0.2

Table 7 Descriptive statistics for markups estimates using micro-data

Variable	Industry	N	Min	Max	Mean	SD
Markup (Compnet)	Manufacture of basic metals	51	0.5	2.5	1.1	0.6
	Manufacture of basic pharmaceutical products and pharmaceutical preparations	54	0.5	4.8	1.4	1.2
	Manufacture of chemicals and chemical products	54	0.5	1.9	1.0	0.5
	Manufacture of computer, electronic and optical products	54	0.6	2.1	1.2	0.5
	Manufacture of electrical equipment	54	0.6	2.4	1.1	0.5
	Manufacture of fabricated metal products, except machinery and equipment	54	0.6	2.6	1.3	0.7
	Manufacture of machinery and equipment n.e.c	54	0.6	2.2	1.1	0.5
	Manufacture of motor vehicles, trailers and semi-trailers	54	0.5	1.8	1.0	0.4
	Manufacture of other non-metallic mineral products	54	0.6	2.2	1.1	0.6
	Manufacture of other transport equipment	48	0.5	3.3	1.4	0.8
	Manufacture of paper and paper products	54	0.5	1.8	1.0	0.4
	Manufacture of rubber and plastic products	54	0.5	2.0	1.0	0.5
	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	54	0.6	1.9	1.0	0.4
	Printing and reproduction of recorded media	54	0.6	2.6	1.4	0.7
	Repair and installation of machinery and equipment	47	0.6	3.0	1.3	0.6
	All	794	0.5	4.8	1.1	0.6

Table 8 Summary statistics for WIOD markups by year

Variable	Year	N	Min	Max	Mean	SD
Markup (GME)	2000	510	1.000	3.510	1.199	0.175
	2001	517	1.000	2.030	1.198	0.138
	2002	523	1.000	1.960	1.184	0.141
	2003	519	1.000	1.890	1.199	0.134
	2004	519	1.000	1.670	1.172	0.121
	2005	517	1.000	2.050	1.162	0.132
	2006	520	1.000	1.930	1.154	0.125
	2007	522	1.000	1.890	1.158	0.126
	2008	518	1.000	1.960	1.141	0.137
	2009	506	1.000	3.410	1.175	0.197
	2011	517	1.000	2.960	1.207	0.214
	2012	518	1.000	2.670	1.223	0.191
	2013	509	1.000	2.760	1.197	0.180
	2014	511	1.000	2.860	1.192	0.182
	All	7226	1.000	3.510	1.183	0.161

Table 9 Summary statistics for CompNet markups by year

Variable	Year	N	Min	Max	Mean	SD
Markup (Compnet)	2000	30	0.508	3.242	1.291	0.767
	2001	30	0.532	2.631	1.222	0.687
	2002	43	0.549	3.262	1.194	0.678
	2003	44	0.561	3.181	1.168	0.673
	2004	43	0.568	2.936	1.266	0.746
	2005	43	0.557	2.783	1.132	0.644
	2006	59	0.544	2.997	1.137	0.596
	2007	60	0.553	3.045	1.141	0.599
	2008	74	0.532	3.721	1.070	0.550
	2009	73	0.462	3.636	1.121	0.604
	2011	74	0.500	4.820	1.129	0.696
	2012	74	0.493	4.713	1.099	0.640
	2013	74	0.497	3.537	1.097	0.579
	2014	73	0.509	3.333	1.087	0.578
	All	794	0.462	4.820	1.138	0.632

Table 10 Average share of foreign value added by country. The averages are computed using simple means

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2011	2012	2013	2014
AUT	31.8	32.5	32.8	33.5	33.9	36.0	36.7	36.9	38.6	36.5	41.9	42.1	39.6	39.3
BEL	41.6	41.2	40.1	39.5	40.1	39.9	40.7	41.6	43.9	41.4	49.9	50.5	50.1	51.1
BGR	40.0	38.8	36.4	38.1	43.5	43.9	46.3	47.6	48.1	39.1	43.4	45.1	47.2	44.9
CYP	37.9	39.7	40.2	40.2	40.9	40.3	42.7	43.2	46.1	44.4	39.0	42.2	40.7	40.7
CZE	34.4	34.7	34.5	34.6	37.7	39.1	40.2	41.0	40.7	39.5	42.9	45.9	46.0	46.1
DEU	24.6	24.1	22.5	23.6	24.5	25.9	27.8	28.7	29.6	27.9	32.0	31.8	31.1	31.0
DNK	32.3	32.6	32.6	32.3	33.8	35.6	36.7	37.6	38.1	34.3	38.4	37.9	38.0	38.3
ESP	29.1	26.8	25.7	25.1	26.0	27.0	28.4	28.6	27.8	25.0	32.0	32.0	31.9	32.6
EST	43.8	44.2	43.0	42.9	45.6	46.7	47.5	46.2	46.1	43.5	49.0	50.9	51.0	50.3
FIN	28.1	26.4	26.5	27.0	28.2	30.2	31.5	32.4	33.9	31.7	36.9	37.6	36.8	36.1
FRA	26.9	26.5	25.9	25.4	27.3	28.7	29.8	29.9	30.7	29.3	34.3	34.2	33.6	33.7
GBR	20.8	21.3	21.5	20.4	21.6	22.5	24.3	24.5	24.8	25.5	32.6	32.2	28.4	27.7
GRC	21.5	21.0	19.6	19.3	19.6	19.5	21.0	22.9	22.2	20.1	22.8	21.8	21.2	22.6
HRV	29.3	31.3	33.3	32.9	32.9	32.5	34.8	35.2	32.0	27.6	31.2	34.1	34.4	35.8
HUN	47.5	45.5	43.6	44.4	44.5	45.4	49.0	48.8	49.1	47.2	53.2	53.2	53.1	53.3
IRL	42.7	42.7	41.2	40.8	41.0	41.8	43.4	44.8	46.3	45.9	47.7	48.9	47.4	48.9
ITA	23.6	23.2	22.6	22.2	23.0	24.4	26.3	26.5	26.3	25.9	31.0	30.2	27.8	27.7
LTU	25.7	27.5	27.7	28.6	29.3	31.3	33.7	33.9	33.8	31.4	35.3	35.7	36.1	35.5
LUX	50.2	51.6	49.7	51.2	55.5	55.5	58.3	57.1	60.8	58.6	57.9	57.9	56.7	56.9
LVA	33.8	35.1	34.7	34.0	37.0	37.6	40.3	39.5	36.3	33.9	39.3	40.9	39.1	39.0
MLT	45.6	46.0	45.3	47.7	50.0	51.4	52.0	51.8	52.5	48.3	50.9	52.9	53.3	52.2
NLD	33.1	34.1	34.5	34.0	34.6	34.9	36.2	35.2	37.5	37.1	46.4	46.8	46.6	46.2
POL	28.9	28.0	28.8	31.0	31.1	31.2	33.2	33.6	33.9	31.8	38.2	37.6	36.8	37.0
PRT	34.3	33.8	33.3	33.0	34.2	34.5	36.1	36.6	37.9	34.5	39.4	38.7	38.9	39.9
ROU	28.6	29.0	28.5	30.2	30.9	29.6	29.7	29.0	27.0	25.3	30.2	31.2	29.8	29.7
SVK	35.9	38.9	39.4	39.1	42.0	43.8	45.9	45.8	44.7	43.6	46.1	47.8	49.4	48.8
SVN	32.7	32.5	32.1	32.6	34.8	36.8	37.9	38.9	39.6	36.3	41.9	41.7	41.1	40.3
SWE	30.7	30.7	30.0	29.7	30.2	31.6	32.6	32.8	34.5	32.5	33.2	32.9	32.1	32.3

An overview of entropy econometrics

The point of departure is a linear model where the variable of interest y depends on H explanatory variables x_h with C observations:

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{u} \tag{13}$$

where $\boldsymbol{y}$ is a $(C \times 1)$ vector of observations, $\boldsymbol{X}$ is a $(C \times H)$ matrix of observations for the x_h variables, $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_H)$ is the $(H \times 1)$ vector of unknown parameters to be estimated, and $\boldsymbol{u}$ is a $(C \times 1)$ vector containing the realizations of the random disturbance of the linear model.

The GME estimator re-parametrizes Eq. 13 in terms of probability distributions. First, each element β_h of the vector of parameters $\boldsymbol{\beta}$ is assumed to be a discrete random variable with $M \geq 2$ possible realizations. These potential values of the unknown parameter are included in a support vector $\boldsymbol{b'_h} = \{b_{h1}, \ldots, b_{hM}\}$ with corresponding unknown probabilities $\boldsymbol{p'_h} = (p_{h1}, \ldots, p_{hM})$. The values in $\boldsymbol{b_h}$ are chosen based on priors on the values of β_h. Finally, each parameter β_h is specified as follows:

$$\beta_h = \boldsymbol{b'_h p_h} = \sum_{m=1}^{M} b_{hm} p_{hm}; \qquad h = 1, \ldots, H \tag{14}$$

In turn, the vector $\boldsymbol{\beta}$ can be written as:

$$\boldsymbol{\beta} = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_H \end{pmatrix} = \boldsymbol{BP} = \begin{pmatrix} \boldsymbol{b'_1} & 0 & \cdots & 0 \\ 0 & \boldsymbol{b'_2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \boldsymbol{b'_H} \end{pmatrix} \begin{pmatrix} \boldsymbol{p_1} \\ \boldsymbol{p_2} \\ \vdots \\ \boldsymbol{p_H} \end{pmatrix} \tag{15}$$

where $\boldsymbol{B}$ and $\boldsymbol{P}$ are matrices with dimensions $(H \times HM)$ and $(HM \times 1)$ respectively.

A similar approach is followed for the random disturbances. Although, GME does not require specific assumptions about the probability distribution function of $\boldsymbol{u}$, some assumptions are necessary. First, the uncertainty about the realizations of vector $\boldsymbol{u}$ is addressed by treating each element u_t as a discrete random variable with $J \geq 2$ possible outcomes contained in a convex set $v' = v_1, \ldots, v_J$ which, for the sake of simplicity, will be common for all the realizations of the random disturbance u_t. Second, we also assume that these possible outcomes of the random disturbance are symmetric and centered on zero $(v_1 = v_J)$. As a result, $\boldsymbol{u}$ has mean $E[u] = 0$ and a finite covariance matrix $\sum$. Additionally, it is common practice to establish the upper and lower limits of the vector v applying the three-sigma rule (Pukelsheim 1994).[16] Under these conditions, the value of the random term for an observation t equals:

[16] This rule takes as bounds for the support vector three times the positive and negative values of the sample standard deviation of the dependent variable.

$$u_c = v' w_c = \sum_{j=1}^{J} v_j w_{cj}; \qquad c = 1, \dots, C \tag{16}$$

Or, in matrix terms:

$$\boldsymbol{u} = \begin{pmatrix} u_1 \\ \vdots \\ u_H \end{pmatrix} = \boldsymbol{VW} = \begin{pmatrix} \boldsymbol{v'} & 0 & \cdots & 0 \\ 0 & \boldsymbol{v'} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \boldsymbol{v'} \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_H \end{pmatrix} \tag{17}$$

Therefore, using 15 and 17 Eq. 13 can be rewritten as:

$$\boldsymbol{y} = \boldsymbol{XBp} + \boldsymbol{VW} \tag{18}$$

This specification of the original model transforms the estimation of the coefficients of the regression Eq. 13 into the estimation of $H + C$ probability distributions. At this point, the principle of Maximum Entropy (ME) is used to recover unknown probability distributions of discrete random variables that can take M different values. Specifically, ME estimates $\hat{\boldsymbol{p}}$ by maximizing the Shannon Entropy measure (Shannon 1948) $E(\boldsymbol{p})$:

$$\max_{\boldsymbol{p}} = E(\boldsymbol{p}) = \sum_{m=1}^{M} p_m ln(p_m) \tag{19}$$

$E(\boldsymbol{p})$ achieves a maximum when all the M values are equally probable i.e., $\boldsymbol{p}$ is uniform. However, if some additional data are available, this will lead to a Bayesian update of the uniform solution to $\boldsymbol{p}$. The intuition is that the uniform distribution provides the best estimation when there are no data. In this case, equal probabilities are assigned to all possible outcomes of the discrete random variable. However, the uniform distribution could not be a reasonable estimate if it fails to generate the observed data. Therefore, a reasonable approach is to use as an estimate the probability distribution closer to the uniform able to generate the observed data. In other words, the probability distribution that maximizes the Entropy measure subject to being able to generate the observed data.

The underlying idea of the ME methodology can be applied for recovering the parameters of the re-parametrized Eq. 18, defining the GME estimator. Matrices $\boldsymbol{P}$ and $\boldsymbol{W}$ are estimated by maximizing the entropy function $E(\boldsymbol{P}, \boldsymbol{W})$, subject to: (i) being consistent with the sample and (ii) some normalization constraints. The GME estimator can be written as follows:

$$\max_{\boldsymbol{P},\boldsymbol{W}} E(\boldsymbol{P}, \boldsymbol{W}) = \sum_{h=1}^{H} \sum_{m=1}^{M} p_{hm} ln(p_{hm}) + \sum_{c=1}^{C} \sum_{j=1}^{J} w_{cj} ln(w_{cj}) \tag{20}$$

subject to:

$$y_c = \sum_{h=1}^{H} \sum_{m=1}^{M} b_{hm} p_{hm} x_{hc} + \sum_{j=1}^{J} v_j w_{cj}; \qquad c = 1, \dots, C \tag{21}$$

$$\sum_{m=1}^{M} p_{hm} = 1; \qquad h = 1, \dots, H \tag{22}$$

$$\sum_{j=1}^{J} w_{cj} = 1; \qquad c = 1, \dots, C \tag{23}$$

The restrictions in 21 ensure that the estimates can generate the sample data contained on $\boldsymbol{y}$ and $\boldsymbol{X}$ while Eqs. 22 and 23 are normalization constraints. By solving this constrained optimization problem, solutions for $\boldsymbol{P}$ and $\boldsymbol{W}$ are found and point estimates $\hat{\beta}_h$ and $\hat{u}_c$ are derived.

Additionally, the following basic assumptions guarantee consistency and asymptotically normality :

- The support for the errors v' is symmetric around zero.
- The support space b' bounds the true value of each one of the unknown parameters and it has a finite lower and upper bounds b_1 and b_M, respectively.
- The errors are i.i.d.
- $\lim_{C\to\infty} C^{-1}\boldsymbol{X}'\boldsymbol{X}$ exists and is non-singular.

Under these assumptions, GME estimates distribute as $\hat{\boldsymbol{\beta}} \to N[\boldsymbol{\beta}, \hat{\boldsymbol{\sigma}}^2(\boldsymbol{X}'\boldsymbol{X})^{-1}]$ and it is possible to obtain their approximate variance matrix as $\hat{\boldsymbol{\sigma}}^2(\boldsymbol{X}'\boldsymbol{X})^{-1}$. $\hat{\boldsymbol{\sigma}}$ is a diagonal matrix, where a typical element $\hat{\sigma}_h$ is defined as:

$$\hat{\sigma}_h^2 = \hat{\sigma}_e^2\left(\frac{\sigma_{bh}^2}{\sigma_{bh}^2 + \sigma_v^2}\right), \qquad h = 1, \dots, H \tag{24}$$

Where $\hat{\sigma}_e^2 = \left[\frac{1}{C-H}\right] \sum_{c=1}^{C} \hat{e}_c^2$; being $\hat{e}_c = \sum_{j=1}^{J} v_j \tilde{w}_{cj}$ and:

$$\sigma_{bh}^2 = \sum_{m=1}^{M} b_{hm}^2 \tilde{p}_{km} - \left(\sum_{m=1}^{M} b_{hm}\tilde{p}_{km}\right)^2 \tag{25}$$

$$\sigma_v^2 = \sum_{c=1}^{C}\sum_{j=1}^{J} v_j^2 \tilde{w}_{cj} - \sum_{c=1}^{C}\left(\sum_{j=1}^{J} v_j \tilde{w}_{cj}\right)^2 \tag{26}$$

Markup estimates evolution

See Fig. 7.

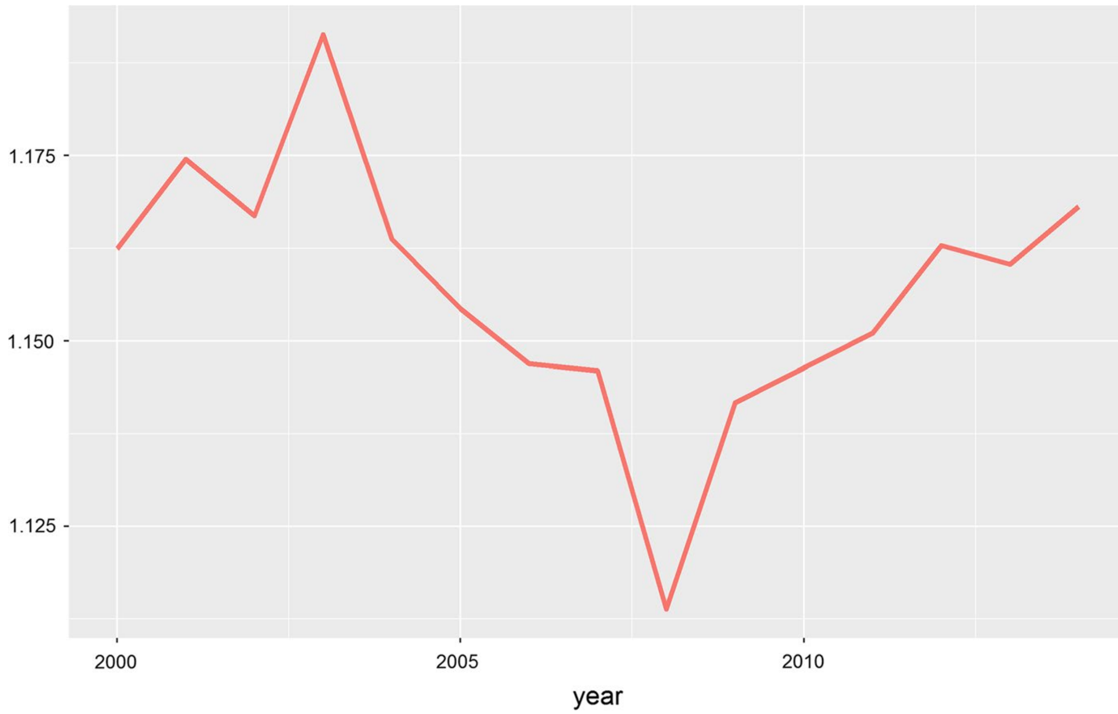

Fig. 7 Evolution GME weighted average markups, using the WIOD full sample. The sector's volume of output is used as weights

By sector using WIOD and CompNet

See Fig. 8.

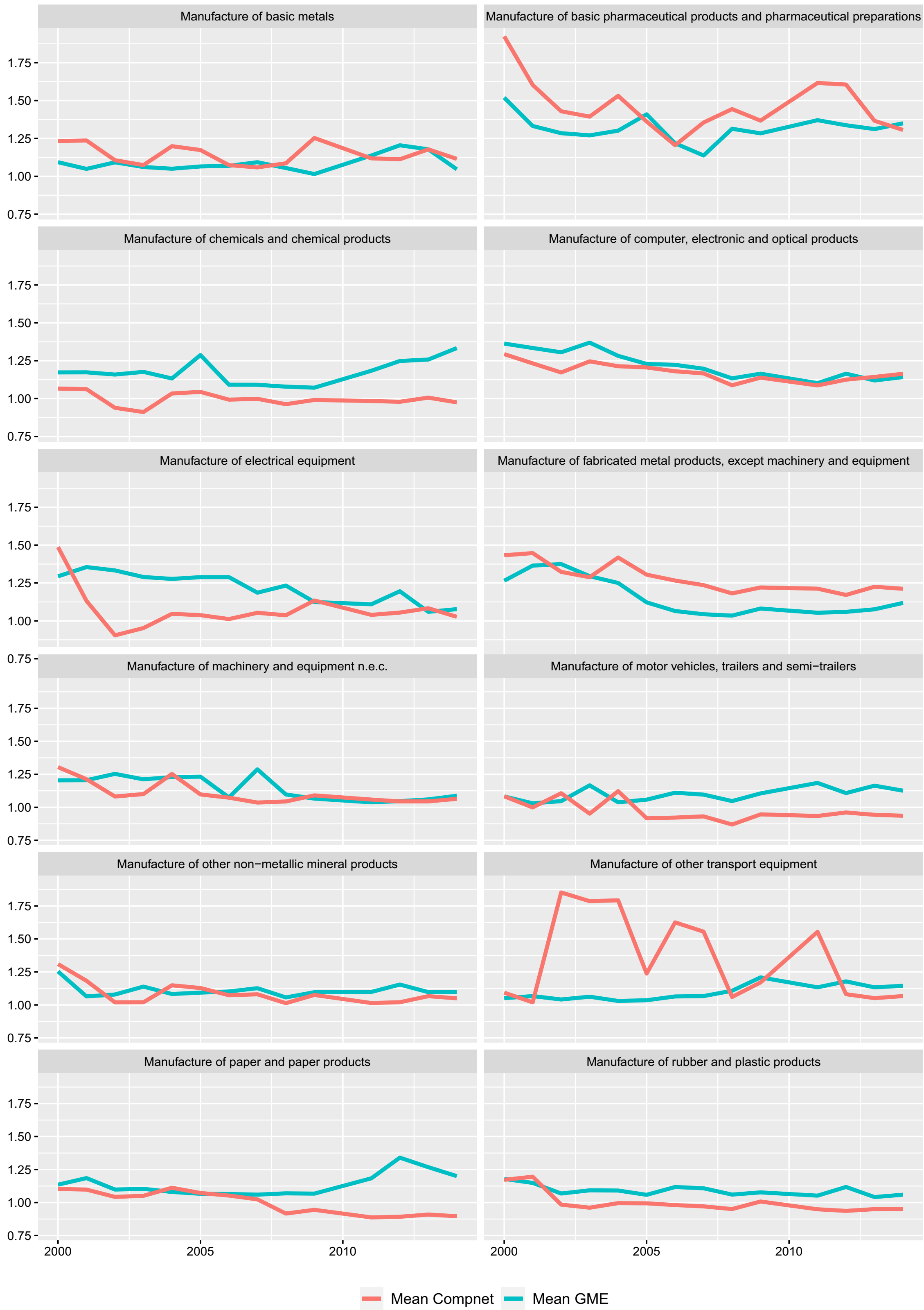

Fig. 8 Evolution of GME and Compnet markups aggregated by sector

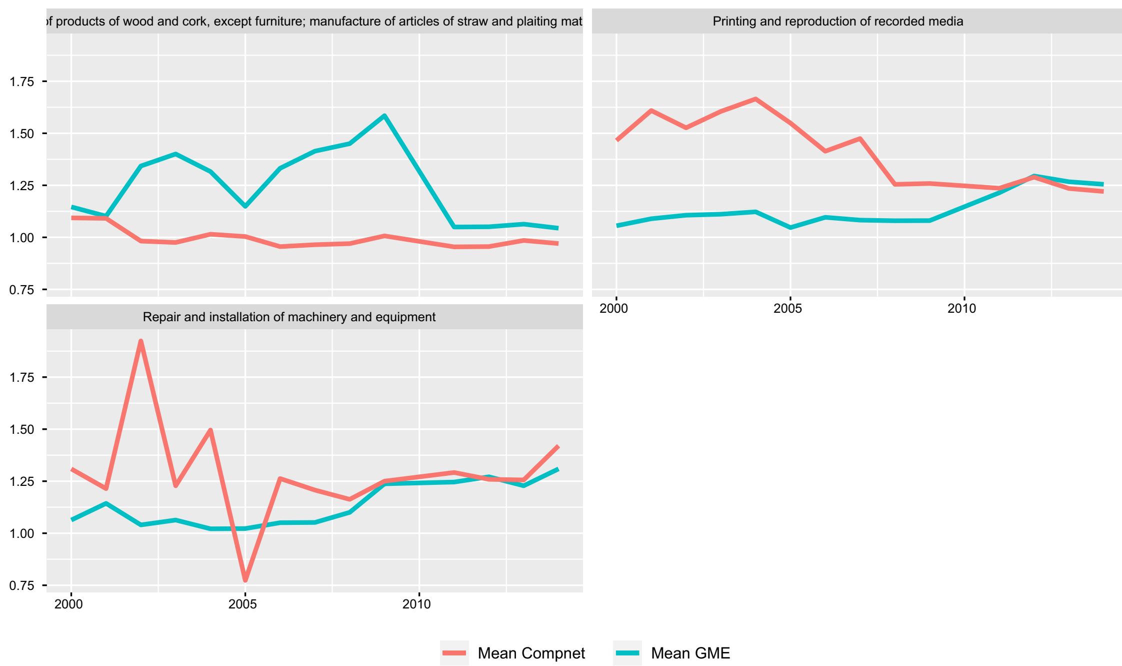

Fig. 8 (continued)

Evolution output elasticity of variable inputs

This section shows the evolution of the output elasticity of variable inputs (α_{it}). The full WIOD sample was used for the aggregation (Fig. 9).

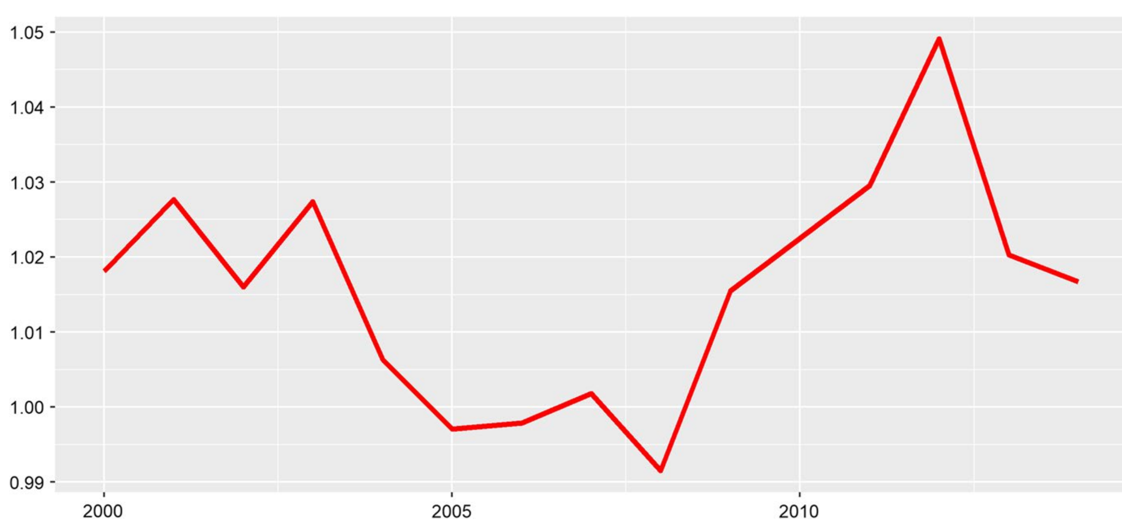

Fig. 9 Evolution of variable inputs elasticity. Volumes of output were used as weights

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References

Ackerberg DA, Caves K, Frazer G (2015) Identification properties of recent production function estimators. Econometrica 83:2411–2451

Antràs P, Chor D, Fally T, Hillberry R (2012) Measuring the upstreamness of production and trade flows. Am Econ Rev 102(3):412–16

Arto I, Dietzenbacher E, Rueda Cantuche J (2019) Measuring bilateral trade in terms of value added (KJ-NA-29751-EN-N (online),KJ-NA-29751-EN-C (print))

Autor D, Dorn D, Katz LF, Patterson C, Reenen JV (2020) The fall of the labor share and the rise of superstar firms. Q J Econ 135(2):645–709

Baker JB (2019) The antitrust paradigm: restoring a competitive economy. Harvard University Press, Harvard

Baqaee DR, Farhi E (2017) Productivity and misallocation in general equilibrium. Working paper 24007, National Bureau of Economic Research

Cavalleri MC, Eliet A, McAdam P, Petroulakis F, Soares A, Vansteenkiste I (2019) Concentration, market power and dynamism in the euro area. Working paper series 2253, European Central Bank

Choi J, Fukase E, Zeufack AG (2021) Global value chain participation, competition, and markups: evidence from Ethiopian manufacturing firms. J Econ Integr 36(3):491–517

Colonescu C (2021a) Compounded markups in complex market structures. Athens J Bus Econ 8:1–14

Colonescu C (2021b) Price markups and upstreamness in world input–output data. Acta Universitatis Sapientiae Econ Bus 9:71–85

De Loecker J, Eeckhout J (2017) The rise of market power and the macroeconomic implications. NBER working papers 23687, National Bureau of Economic Research, Inc

De Loecker J, Eeckhout J (2018) Global market power. Working paper 24768, National Bureau of Economic Research

De Loecker J, Warzynski F (2012) Markups and firm-level export status. Am Econ Rev 102(6):2437–71

De Loecker J, Goldberg PK, Khandelwal AK, Pavcnik N (2016) Prices, markups, and trade reform. Econometrica 84(2):445–510

De Loecker J, Eeckhout J, Unger G (2020) The rise of market power and the macroeconomic implications. Q J Econ 135(2):561–644

di Mauro F, Lopez-Garcia P (2015) Assessing European competitiveness: the new CompNet microbased database. Working paper series 1764, European Central Bank

Diez FJ, Leigh D, Tambunlertchai S (2018) Global market power and its macroeconomic implications. IMF working papers 18/137, International Monetary Fund

Eeckhout J (2021) The profit paradox: how thriving firms threaten the future of work. Princeton University Press, Princeton

Ennis SF, Gonzaga P, Pike C (2019) Inequality: a hidden cost of market power. Oxf Rev Econ Policy 35(3):518–549

Fernandez-Vazquez E (2015) Empirical estimation of non-linear input–output models: an entropy econometrics approach. Econ Syst Res 27(4):508–524
Golan A, Vogel SJ (2000) Estimation of non-stationary social accounting matrix coefficients with supply-side information. Econ Syst Res 12(4):447–471
Golan A, Judge G, Perloff JM (1996) Estimating the size distribution of firms using government summary statistics. J Ind Econ 44(1):69–80
Gradzewicz M, Mućk J (2019) Globalization and the fall of markups. Technical report
Gutiérrez G, Philippon T (2017) Declining competition and investment in the U.S. Working paper 23583, National Bureau of Economic Research
Hall R (1988) The relation between price and marginal cost in U.S. industry. J Polit Econ 96(5):921–47
Hall RE, Blanchard OJ, Hubbard RG (1986) Market structure and macroeconomic fluctuations. Brook Pap Econ Act 1986(2):285–338
Johnson RC (2018) Measuring global value chains. Annu Rev Econ 10(1):207–236
Johnson RC, Noguera G (2012) Accounting for intermediates: production sharing and trade in value added. J Int Econ 86(2):224–236
Koujianou Goldberg P, Hellerstein R (2012) A structural approach to identifying the sources of local currency price stability. Rev Econ Stud 80(1):175–210
Lerner AP (1934) The concept of monopoly and the measurement of monopoly power. Rev Econ Stud 1(3):157–175
Levinsohn J, Petrin A (2003) Estimating production functions using inputs to control for unobservables. Working paper 7819, National Bureau of Economic Research
Miller RE, Blair PD (2009) Input–output analysis: foundations and extensions, 2nd edn. Cambridge University Press, Cambridge
Morlacco M (2017) Market power in input markets: theory and evidence from French manufacturing
Mulkay B (2019) How does competition affect innovation behaviour in French firms? Struct Chang Econ Dyn 51(C):237–251
Olley GS, Pakes A (1996) The dynamics of productivity in the telecommunications equipment industry. Econometrica 64(6):1263–97
Perloff JM, Karp LS, Golan A (2007) Estimating market power and strategies. Number 9780521804400 in Cambridge books. Cambridge University Press, Cambridge
Praet P (2019) Market power: a complex reality. Speech retrieved from https://www.ecb.europa.eu/press/key/date/2019/html/ecb.sp190318_1~8d608350ab.en.html
Pukelsheim F (1994) The three sigma rule. Am Stat 48(2):88–91
Puty CACB (2018) Sectoral mark-ups in U.S. manufacturing. Struct Chang Econ Dyn 46(C):107–125
Schmalensee R (1987) Collusion versus differential efficiency: testing alternative hypotheses. J Ind Econ 35(4):399–425
Shannon CE (1948) A mathematical theory of communication. Bell Syst Tech J 27(3):379–423
Timmer M, Erumban AA, Gouma R, Los B, Temurshoev U, de Vries GJ, Arto I, Genty VAA, Neuwahl F, Rueda-Cantuche JM, Joseph (2012) The world input–output database (WIOD): contents, sources and methods. IIDE discussion papers 20120401, Institute for International and Development Economics
Timmer MP, Dietzenbacher E, Los B, Stehrer R, de Vries GJ (2015) An illustrated user guide to the world input–output database: the case of global automotive production. Rev Int Econ 23(3):575–605
Weche JP, Wambach A (2018) The fall and rise of market power in Europe. Working paper series in economics 379, University of Lüneburg, Institute of Economics

Chapter 4

Extending the analysis to estimate market power globally for the Primary Foods Industry

The methodology from Section 3.1 can be used to obtain estimates of the markups from potentially any source containing macroeconomic data, provided it contains information on all the relevant variables explained in Section 2.1.1.

The novel approach paves the way to open up new avenues of research by allowing the estimation of markups for virtually every country and industry in the world, thereby circumventing problems when handling microeconomic data. One key industry that has not been explored adequately in the literature is agriculture.

The following paper provides estimates of markups for the agriculture industry for 1995 - 2015 using the EORA Input-output Database and information on stocks of capital from the UN FAOSTAT Database. The paper provides evidence that markups have evolved differently across regions, with Africa and Asia having increasing markups, Europe and North America a stable evolution, and South America decreasing markups across time.

The approach and results derived thereof are novel and unique. Traditional approaches seeking to estimate market power utilize micro-data for specific segments within the value chain and certain goods. It is not possible to analyze markups at an industry level in a systematic way using micro-data. Using input-output data is advantageous as the industry classification is harmonious and comparable with each other.

4.1 Article 2) Global Markup Estimates for the Primary Foods Industry

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Data Article

Global market power dataset of the primary foods industry

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ABSTRACT

The study of market power has garnered interest from academia, policymakers, and industry in recent times since the publication of de Loecker et al. (2020). This paper introduced a novel methodology to estimate the markup, a proxy commonly used to denote market power. Using said methodology, they found that the markup has been increasing nearly continuously since the 1980′s. Rising markups have been connected to a myriad number of negative economic developments, yet most papers are constrained to study these effects on specific industries related to manufacturing and service. Furthermore, even though data exists for a considerable number of countries globally, the quality and reliability is reduced when examining low-income economies.[1]
To circumvent these problems, the authors have devised an alternate approach to calculate the markup, not by using firm-level data but by using macroeconomic data and an estimation procedure based on Generalised Maximum Entropy (GME). The methodology permits the estimation of markups for virtually every country in the world and a substantial number of industries.
The dataset provides estimates of the markups for 170 countries in the world for the so-called Primary Foods industry (comprising agriculture, hunting, fishing, and logging). It was calculated by aggregating two datasets: the EORA input-output tables and the UN FAO-Stat database. The merged

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[1] Note: this paper makes references to “high-income” and “low-income” countries. The income groups mentioned are based on the four-income classification system proposed by the World Bank and is explained in more detail here

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dataset produced a panel from which the markup estimates were then calculated.

The publication potential of this dataset is very high, as no other source exists that captures this detail of information across countries with different income levels. The Primary Foods industry is also crucial for the development of poorer countries, as it often accounts for a large portion of their economy. This dataset opens up avenues of research finding ways to reduce the markup, thereby making economies more efficient and potentially improving the welfare of agents within the economy.

The usage of macro-data opens up additional avenues of research not available to micro-data, including measuring the impact of Global Value Chains (a form of globalization), institutional quality, and more on markups.

Specifications Table

Subject	Economics, Econometrics and Finance/Macroeconomics
Specific subject area	The data falls within the field of industrial organisation and provides measures of market power, concretely the markup, of the Primary Foods Industry for 170 countries of the world.
Data format	Filtered data, displaying only the relevant variables required for analysis
Type of data	Table
Data collection	The data was collected by first merging two auxiliary datasets. The first one is the EORA input-output tables, or more concretely, the EORA26 Tables in basic prices. These tables fulfilled most of the requirements to calculate the markup, including measures of total output, labor remunerations, and intermediate inputs. EORA has information on 190 countries and regions for the years 1990 to 2015, with values being denoted in US dollars at current prices The second dataset is from the United Nations Food and Agriculture Organization Database (FAO-Stat). In particular, the stocks of capital were used in conjunction with the aforementioned variables from EORA. This dataset contains information on 188 territories or countries for 1995 to 2015, although it contains missing information for several years. The stocks of capital are also valued in US Dollars at current prices. Both sources of data are accessible for free; the former requires only registering to the site. As the industrial classification between sectors differs between both datasets, two industries within EORA were merged using an identity matrix. This procedure and the estimation of the markup self, is explained in more detail in the paper by [6].
Data source location	The EORA input-output database can be accessed here: https://worldmrio.com/, requiring registration to verify the users' academic credentials. The latter can be accessed through this link for free: https://www.fao.org/faostat/en/#data/CS
Data accessibility	Repository name: Mendeley Data Data identification number: 10.17632/879zmf9tzh.1 Direct URL to data: https://data.mendeley.com/datasets/879zmf9tzh/1
Related research article	Rodriguez del Valle and Fernández-Vázquez (2024)

1. Value of the Data

- This topic is of high political relevance. Unfortunately, there are severe constraints in calculating the markup because of the unavailability of firm-level micro-data. Most studies focus on developed countries with more advanced data collection systems. We circumvent this problem by calculating the markup using specialized, industry-level macro data, being the first to do so. Whereas firm-level (micro) studies link the markups with firm-level characteristics to derive correlations and causal relationships, macro-data opens up other channels that explain the markups.

- The authors have already found a significant relationship between globalization and markup, concluding that opening up to trade might be beneficial to the economy by reducing markups. However, there are considerable further avenues that are available. For example, evidence exists that institutional quality, or how efficient the Government is at creating sound policies and implementing them, can impact markups and economic efficiency. No exhaustive study has been done on this to date, however the dataset might allow us to do so.

2. Background

Evidence exists that market power has been increasing since the 1980′s. The development is concerning since rising market power is connected with detrimental economic developments such as rising prices, decreasing output, decreasing innovation, and higher costs of entry into the market. These inefficiencies are particularly problematic for poorer countries, as the Primary Foods industry comprises a large part of their total economy. The dependency of low-income economies on the Primary Foods industry is visualized more clearly in Fig. 1, with higher income levels having progressively a lower share of value added for this industry.

The majority of studies to date analyzing the impact of market power do so using micro-level (firm-level) data, that is available for only high-income countries. The authors were motivated to propose an alternate way of deriving estimates of the markup to study this phenomenon for countries all over the world.

High-income countries often share similar characteristics, such as having similar institutions, geographic areas, political systems, history, climate, and access to trade, to name a few. Current research, therefore, cannot easily discern the impact of these factors on markups. The data proposed here provides a wide enough coverage of countries so that research into many new topics is feasible, thereby potentially opening up newer avenues of research. Fig. 2 further reinforces this idea, as the evolution of markups for the Primary Foods Industry is relatively stable for Europe and North America, regions having predominantly high-income economies but more volatile for Africa and Asia. Noteworthy is that Africa is found to have a near-continuously

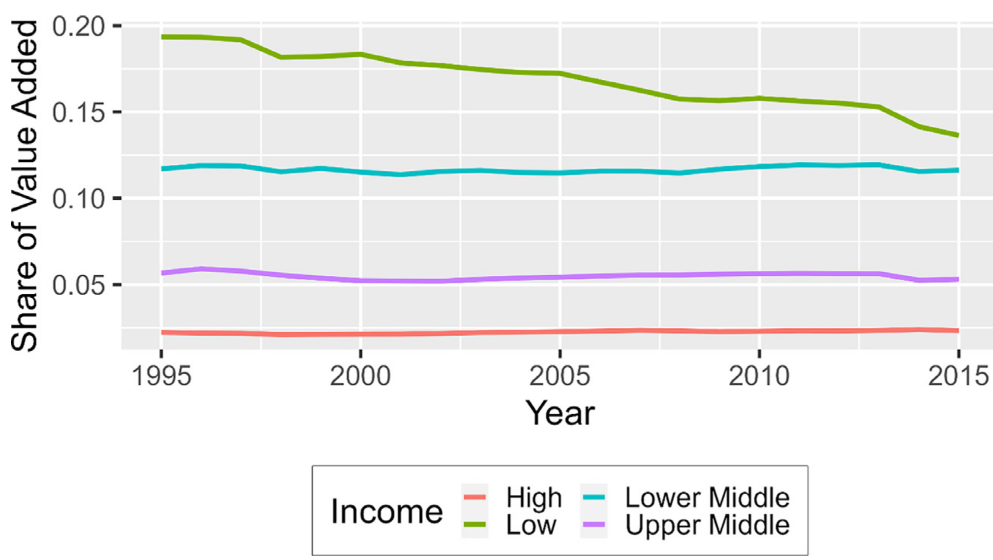

Fig. 1. Share of value added of the primary foods industry relative to total value added, divided by income groups.
Note: Aggregated using weighted averages based on value added. For ease of interpretation, only the income level classification for of 1995 was used for all countries. The calculations are based on the authors using data from the EORA Input-output Data.

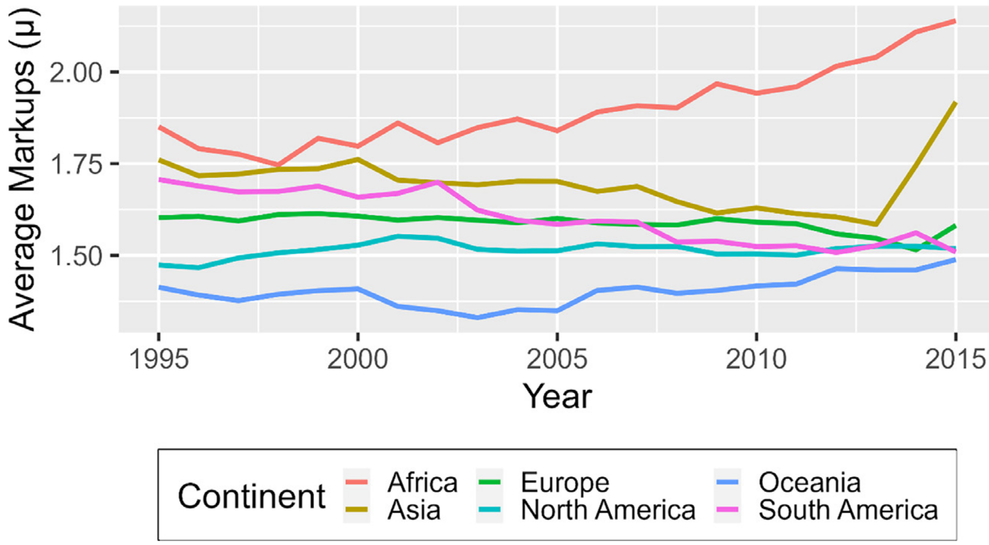

Fig. 2. Evolution of Average Markups of the Primary Foods Industry, divided by Continent
Note: Aggregated using weighted averages based on value added. The calculations are based authors using the database described in this paper.

increasing markup throughout the sample period between 1995 and 2015. The motivation to understand this discrepancy is therefore significant.

3. Data Description

The data is comprised of one single Excel file called "Global Markups Primary Food". The file has several variables, including year, country, country code in ISO3 format, continent, and a subregion defined as "Region 1". The variable "income" represents the World Bank's income classification for each country, categorized into four labels: "L" for low income, "LM" for lower medium income, "UM" for upper medium income and "H" for high income. The classification is dependent on the estimated Gross National Index per capita of each country using predefined ranges set by the World Bank for a specific year.

The database is constructed using two external datasets: the EORA input-output tables and the UN FAO-stat Database. A considerable number of variables present in the database were obtained using the EORA26 tables. These tables are simplified versions that contain information for only 26 industries, in contrast to the EORA full tables. The database makes use of the simplified prices, denoting values in current US Dollars. The authors extracted variable "L" directly from vector "Labor Remunerations" that is present in the EORA26 "bp_VA" files, the value-added matrix. The intermediate inputs vector "II" was calculated by summing the columns of the transaction matrix "bp_T". Total output "Q", was calculated by adding the sum of columns contained within the transaction matrix and the value added matrix. The variable VA represents the value-added vector and was calculated by subtracting Q (total output) from II (intermediate inputs). Variable K represents the value in current US Dollars of the stocks of capital for agriculture, hunting, logging, and fishing (defined here as the Primary Foods Industry). The industrial coverage from the FAO-stat is broader than the one from EORA, as it includes industries within ISIC Rev. 3 sectors A and B. Because of this, two industries from EORA were aggregated using an aggregation matrix. Concretely, industry "agriculture" comprising of agriculture, hunting, and logging (ISIC Rev. 3 sector 1 and 2, or A) was aggregated with industry "fishing" (ISIC Rev. 3 sector 5, or B) to make both datasets harmonious.

The aforementioned variables were then used to calculate the main highlights of the dataset: (i) the variable "markup" describes the markup (μ) calculated using the GME method; (ii) the variable "rts" contains the estimated returns to scale calculated as the sum of the elasticities of

Table 1
Summary statistics markup by year.

Variable	Year	n	Min	Max	x	s
Markup	1995	146	0.89	4.69	1.95	0.69
	1996	146	0.92	4.17	1.90	0.60
	1997	146	0.86	3.60	1.83	0.51
	1998	146	0.88	3.67	1.80	0.48
	1999	146	0.78	4.21	1.83	0.49
	2000	169	0.86	3.72	1.73	0.40
	2001	170	0.96	4.04	1.80	0.47
	2002	169	0.96	3.42	1.77	0.44
	2003	170	0.95	4.62	1.83	0.54
	2004	170	0.97	3.93	1.86	0.57
	2005	169	0.96	3.81	1.85	0.54
	2006	170	0.95	4.05	1.89	0.59
	2007	170	0.96	4.20	1.90	0.60
	2008	169	0.95	4.05	1.89	0.59
	2009	169	0.92	4.38	1.92	0.64
	2010	169	0.89	4.37	1.92	0.64
	2011	167	1.03	4.35	1.93	0.65
	2012	168	0.90	5.24	2.00	0.75
	2013	168	0.89	6.06	2.04	0.82
	2014	169	0.89	6.94	2.07	0.90
	2015	167	0.92	6.01	2.05	0.82
	all	3433	0.78	6.94	1.89	0.63

Table 2
Summary statistics markup by continent.

Variable	Continent	n	Min	Max	x	s
Markup (μ)	Africa	988	0.78	6.94	2.11	0.74
	Asia	862	0.89	4.62	1.77	0.55
	Europe	792	0.89	4.98	1.61	0.35
	North America	421	0.99	5.07	1.99	0.67
	Oceania	147	1.57	4.60	2.33	0.77
	South America	223	1.07	3.19	1.92	0.34
	all	3433	0.78	6.94	1.89	0.63

output to variable inputs and output to capital (α and β respectively in the production function); and (iii) the variable "profit rate" describes the aggregate profits in relative terms to the gross revenues, based in the relationship $rts = \mu \times \ (1 - profit\ rate)$. The remaining variables are derived directly from the input-output tables. By order of appearance; Q represents total output, II are the intermediate inputs, VA is the value added, LAB is the total labor remunerations, and K is the stocks of capital. Subsidies are the subsidies given to the Primary Foods industry, and Taxes are the taxes obtained from the Primary Foods industry (Tables 1 and 2).

The data contains 82 missing values, stemming from the lack of information on the stocks of capital for some countries.

4. Experimental Design, Materials and Methods

The point of departure for deriving markups is based on the works by De Loecker and Eeckhout [2] and De Loecker et al. [3]. The authors exploit rich databases at firm level to estimate Cobb-Douglas production functions with variable (intermediate consumptions and labour) and fixed inputs (capital stock) as:

$$Y_i \ = \Omega \, V_i^{\alpha} K_i^{\beta} \tag{1}$$

Where Y_i stands for the output, V_i and K_i represent the variable inputs and the stock of capital respectively, and Ω is a measure of the factor productivity for a company i. Let us denote the mark-up of company (μ_i) It can be proved that, after some manipulations, μ_i can be calculated as follows:

$$\mu_i = \alpha \frac{Y_i}{V_i} \tag{2}$$

The application of this expression simplifies the estimation of mark-ups, since the elasticities α can be retrieved from the estimates of econometric regressions of the production functions like (1), while Y_i and V_i can be observed directly in some datasets. Actually, De Loecker and Eeckhout [2] follow this approach to study the evolution of market power approximated by the evolution of mark-ups from a database containing detailed information at company level. While this strategy is appealing when dealing with specific industries (manufactures and services) and countries (i.e., western economies) covered in these datasets, it cannot be directly applied to the study of market power for agricultural activities in non-western countries.

There have been recent attempts to overcome these difficulties by, following the idea of Hall [4] of studying market power with aggregated data, apply a similar strategy to macro-indicators present in global input-output (IO) databases. Colonescu [1] and Rodriguez del Valle and Fernandez-Vazquez [5], take advantage of the information contained in the World Input-Output database (WIOD) to estimate nark-ups for European manufacturing industries in recent years. Similarly, the strategy followed in this paper is to use data comprised in global IO database and other global datasets with a similar purpose for the agricultural activities of a set of 43 Asian countries. More specifically, we use the information on output (Y_i) and variable inputs (V_i) observable on a yearly basis in the EORA database for the agricultural sector between 1995 and 2015 for the countries under study. Additionally, we will complement our required variables with data of capital stocks (K_i) for the agricultural industries in these countries coming from the FAO database.[2]

With these data at hand, we estimate equations like (1) for each year between 1995 and 2015. In our analysis, i does not refer to a company, but it stands for the agricultural sector in one country. We assume that elasticities are common within continents but evolving along time. This implies that we need to estimate a production function for each continent and year. Our approach requires, in consequence, estimating a total of 21 years $\times$ 6 continents regressions. We follow this approach to accommodate the larger flexibility possible by allowing time-varying coefficient in the production functions. The cost for this flexibility is the reduction in the number of data points on each regression, and the GME estimator is particularly attractive in such ill-conditioned samples where traditional estimation techniques relying on larger sample sizes can be problematic. We follow the same strategy as in Rodriguez del Valle and Fernandez-Vazquez (2023) and apply a Generalized Maximum Entropy (GME) estimator. This estimator has the advantage of producing robust estimates with limited data by means of a reparametrization of the elasticities of interest and the error term.

The GME estimator reparametrizes the element of a typical linear regression $y = X\beta + u$ in terms of probability distributions. Each element of the vector of parameters β is assumed to be a discrete random variable with $M \geq 2$ possible realizations. These potential values of the unknown parameter are included in a support vector $\mathbf{b_h'} = b_{h1}, ..., b_{hM}$ with corresponding –unknown– probabilities $\mathbf{p_h'} = (p_{h1}, ..., p_{hM})$. A similar approach is followed for the random disturbances. Although GME does not require specific assumptions about the probability distribution function of the noise term, some assumptions are necessary. First, the uncertainty about the realizations of this element is addressed by treating each element u_i as a discrete random variable with $J \geq 2$ possible outcomes contained in a convex set $v' = v_1, ..., v_J$ which, for the sake of simplicity, will be common for all the realizations of the random disturbance u_t. Second, we also assume that these possible outcomes of the random disturbance are symmetric and centered on zero ($-v_1 = v_J$). As a result, $\mathbf{u}$ has mean $E[\mathbf{u}] = 0$ and a finite covariance matrix $\mathbf{\Sigma}$. Additionally, it is common practice to establish the upper and lower limits of the vector v applying the three-sigma rule (± 3 times the standard deviations of the dependent variable in the sample). Under

[2] Details on the datasets employed are presented in the section with the data description.

these conditions and some mild assumptions, GME estimates distribute as $\hat{\beta} \rightarrow N[\beta, \hat{\sigma}^2(\mathbf{X}'\mathbf{X})^{-1}]$ and it is possible to obtain their approximate variance matrix as $\hat{\sigma}^2(\mathbf{X}'\mathbf{X})^{-1}$.

Our application of the GME estimator requires the specification of supporting vectors for the parameters and the error terms. The parameters be estimated are the output elasticities α_{it} and β_{it} and the factor productivities Ω_{it}. For the term Ω_{it} we set support vectors with $M = 3$ values ($b_{\Omega m}$) centered at 0 and with bounds at ± 2. For the output elasticities we define supporting vectors with $M = 3$ points ($b_{\alpha m}$ and $b_{\beta m}$ respectively) centered at the corresponding mean value of the shares of variable inputs and the stock of capital, being the limits of these vectors set as these means plus and minus 2 again, in order to assure having wide enough supports. This approach implies that, in absence of information, the GME estimator produces uniform probabilities, and the point estimates of the parameters will be equal to the central value in the vectors. Consequently, the uninformative GME solution makes the mean markup μ_{itc} equal to one by construction. In other words, our prior assumption is that there is no market power and only if data contains information that contradicts this initial assumption, the GME estimator will produce a different result

Limitations

One limitation of the dataset is the assumption the authors had to take for the values to be computable. The assumption is that each industry is produced by one representative firm, as explained in more detail in Rodriguez del Valle and Fernández Vázquez (2023; 2024). The assumption is most likely not critical in countries having farms of similar size, as this assumption would represent the markup of an average farm. However, the assumption might be more critical when the industry is comprised of a few large firms that dominate the market. In such cases, the results might be biased. In contrast, relying on aggregate data instead of exploiting individual firm observations allows us to limit the "transmission bias" problem, which frequently appears when firm-specific productivity shocks impact the use of inputs, biasing the estimates of elasticities by traditional econometric techniques. However, aggregated, industry-level, shocks might still be a concern.

Large farm sizes appear in high-income countries and are nearly non-existent in low-income countries. As such, caution is needed when examining this industry for high-income countries. Furthermore, the macrodata contained within the EORA input-output tables will occasionally estimate values for the industries of certain countries when no data is present. In these cases, a certain bias might also arise. Similarly, for some continents and years the datapoints used to conduct the estimates are reduced, and our estimates are based in these small datasets. Additionally, the estimates presented in the database are naturally limited by the validity of the assumptions made to model the production technology, in particular the assumption of a common production function for each continent and year.

Ethics Statement

The authors confirm having read Data in Brief's ethical requirements. The authors have followed these requirements closely while producing the dataset to ensure that ethical standards were upheld. Furthermore, the creation of the dataset did not involve human subjects, animal experiments and the use of social media.

Data Availability

Global Markup Estimates for the Primary Foods Industry (Original data) (Mendeley Data).

CRediT Author Statement

Adrian Rodriguez del Valle: Conceptualization, Data curation, Validation, Writing – original draft; **Esteban Fernández-Vázquez:** Methodology, Software, Writing – review & editing.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] C. Colonescu, Price markups and upstreamness in world input-output data, Acta Univ. Sap. Econ. Bus. 9 (2021) 71–85, doi:10.2478/auseb-2021-0004.
[2] J. De Loecker, J. Eeckhout, Global market power. NBER Working Paper 24768, Natl. Bur. Econ. Res. (2018), doi:10.3386/w24768.
[3] J. De Loecker, J. Eeckhout, G. Unger, The rise of market power and the macroeconomic implications, Q. J. Econ. 135 (2) (2020) 561–644, doi:10.1093/qje/qjz041.
[4] R. Hall, The relation between price and marginal cost in U.S. industry, J. Polit. Econ. 96 (5) (1988) 921–947, doi:10.1086/261570.
[5] A. Rodriguez del Valle, E. Fernández-Vázquez, Estimating market power for the European manufacturing industry between 2000 and 2014, Empirica 50 (2023) 141–172, doi:10.1007/s10663-022-09559-4.
[6] A. Rodríguez del Valle, E. Fernández-Vázquez, Analyzing market power of the agricultural industry in Asia, Econ. Anal. Policy 81 (2024) 652–669, doi:10.1016/j.eap.2023.12.010.

Chapter 5

The role of income levels, political systems and Global Value Chains on markups

The paper described in Section 4 is analyzed more carefully, and attempts are made to understand the macroeconomic determinants of the markup.[1] In particular, a sub-sample based on the Asian continent is used for this analysis. The reason is that Asia has countries of all income groups (high, low, upper middle, and lower middle), as well as political systems.[2]

By using this sub-sample, we can examine the role that income levels, political systems, and Global Value Chains have on the markup for the Primary Foods Industry. The paper presented in Section 5 motivates this idea further, and presents the results from this analysis in more detail.

5.1 Article 3) Analyzing market power of the agricultural industry in Asia

[1]Note: The paper mentioned in Section 4 was published prior to the paper introduced in this Section. The ordering was changed to enhance the flow of information.

[2]Noteworthy is that there are three communist countries in the sample (China, Vietnam, and Laos).

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Full length article

Analyzing market power of the agricultural industry in Asia☆

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A R T I C L E I N F O

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A B S T R A C T

The study of market power in the primary foods industry is of high interest to policymakers seeking to help develop low-income countries, due to its potential source to create market inefficiencies and hamper economic development. Recent studies have provided ample empirical evidence, that market power has been increasing nearly continuously since the 1980s. Nevertheless, due to the (un)availability of firm-level data, most research is constrained to analyzing firms within industries of a few high-income with a particular focus on manufacturing and service sectors. This paper proposes to remedy this gap in the literature by using aggregate data contained within the Eora Input-Output Tables and a procedure based on Generalized Maximum Entropy to provide estimates of the markup for the primary foods industry (defined as the agriculture, hunting, logging and fishing industries) for 43 countries in Asia. We document a large heterogeneity based on a country's income level classification. Furthermore, measures of globalization are seen to significantly reduce markups. Opening up to trade might therefore be an attractive option to policymakers seeking to stimulate economic efficiency.

1. Introduction

The study of the industrial structure within the agriculture industry is a topic of significant political interest, particularly for understanding and helping develop the economies of underprivileged countries. International organizations such as the World Bank and the Food and Agriculture Organization, place yearly objectives for the reduction of extreme poverty by helping develop the agriculture industry of low-income countries to become more productive.[1]

The development of the agriculture industry is considered to be key for achieving these objectives, as can be seen by numerous economic papers starting from (Johnston and Mellor 1961). The agriculture industry of low-income countries constitutes on average around 12 – 22% of total value added as can be seen in Fig. 1. Increases in productivity in agriculture (Zepeda, Food, and United Nations. 2001), livestock (Food and United Nations. 2002), and fishery are key for low-income countries to escape the poverty trap, by raising income levels. The focus on increasing productivity is also compounded by the fact that many developing countries cannot expand the amount of arable land they can cultivate on (because of the climate). A more productive agriculture industry also eases the transition of subsistence-level farming to agricultural commercialization i.e., the actual selling of foodstuffs to an external market

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[1] This paper makes use of the World Bank's income classification, which is comprised of four groups. Here, "low-income" refers to a country, whose GNI per capita for the years 1995 and 2015 is lower than \$765 and \$1045 US Dollars respectively.

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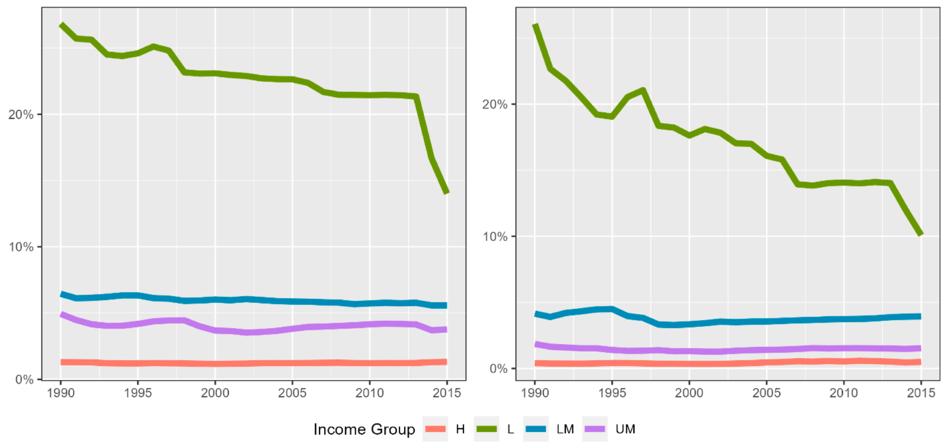

Fig. 1. Weighted Average Percentage Share of Value Added in the Primary Foods Industry with respect to the country-wide total for countries in Asia.
Note: the left figure denotes value added produced whereas the right figure includes direct and indirect value added required to produce output (based on the methodology from (Timmer et al., 2015)). Data derived from the Eora Input-Output Database. *Note:* Former Soviet countries are excluded from this calculation.

rather than self-consumption. Evidence exists that agriculture commercialization is one key to increase farmer income and reduce poverty (Zheng and Ma, 2023).

Moreover, as consumers with low income spend large amounts of their disposable income on foods, it is imperative that the prices of these remain low to solve problems of hunger, thereby making development more conducive. The implementation of technological innovations in the agricultural industry is further linked to developments to the economy as a whole, as previous labor used in farming is freed up to work in other industries located within urban areas. The beneficial effect of increasing productivity on economic and societal development is multiplicative due to the general inelastic nature of food. As consumers with low income spend large amounts of their disposable income on foods, it is therefore imperative that the prices of these either decrease or remain low to solve problems of hunger, thereby making development more conducive. Improvements in productivity can reduce the pricing agricultural foodstuffs (Barrett et al., 2022).

Additionally, a more efficient agriculture sector increases potential revenue for the Government by increasing the available sources of taxation (Irz et al., 2001). Apart from the aforementioned direct effects that the development of the agriculture industry has on employment and pricing, any further development of the agriculture industry also has indirect effects with the development of linkages between producers (creating potential multiplicative effects). This includes stimulating upstream linkages through, for example, the inputs market (seeds and fertilizers), and downstream linkages through storage (Dethier and Effenberger, 2012).

However, it is unclear how market power can help or hamper the development within the economies of low-income nations, as few studies exist that tackle this question directly. Existing empirical studies suggest that market power of manufacturing and service sectors has been rising not only for high-income countries (De Loecker, Eeckhout, and Unger 2020), but also globally, including low-income countries (De Loecker and Eeckhout 2018). They do so by applying a novel methodology to estimate the markup, a commonly used proxy to represent market power. The markup, defined as the wedge between the selling price of a good or service with the marginal cost of production, is notoriously challenging to calculate due to requiring data that is difficult to obtain. The De Loecker, Eeckhout, and Unger (2020) simplifies this process by requiring estimating only production functions at a firm-level, which are then aggregated at an industry-level.

Rising market power is connected with numerous detrimental economic developments, including: decreasing investment rates (Diez et al., 2018), increasing miss-allocation in the factors market (Baqaee and Farhi 2017), decreasing labor share of income (Diez et al., 2018), and increasing unemployment rates for low-skilled labor. Fundamental economic theory additionally suggests that increasing market power results in rising prices and decreasing output. These structural rigidities could further obstruct development efforts in a given country. Market power is a factor that influences growth and productivity[2] and is also intrinsically linked to globalization, being affected by impediments to trade. Furthermore, constraints to market participation can also negatively impact farmers subjective feelings of wellbeing (Li et al., 2023). A general bleak outlook of life can, in turn, have negative implications to farmer productivity and income, as well as welfare.

Despite the profound implications, market power studies are often inconclusive due to substantial data limitations. These constraints stem from both data scarcity and inconsistencies in sector harmonization across countries – for example, with some countries including information on the self-employed and others not. Most extant studies either research market power in certain value chain fragments (Sexton et al., 2007), or prioritize developed countries (Deconinck 2021). However, some research has found significant welfare decline attributable to market power –such as, Creedy and Dixon (1998) and Urzúa (2013).

[2] The relationship between market power and productivity can be seen in, for example, (Liu, Mian, and Sufi 2022)

This paper estimates market power for the primary sectors related to farming, hunting, fishing, and logging using aggregate data contained within input-output tables. These activities are defined throughout the paper as the primary food industries, indicating that these food products are directly extracted from nature in one form or another, and contrast them with food-producing activities tied to the manufacturing industry. We estimate and show the evolution of market power for 43 countries in Asia. To the best of our knowledge, this is the first study that (i) systematically measures markups of agricultural activities in Asia, and (ii) relates these estimated markups with indicators of participation in global markets. The results of the paper's two primary research objectives are the derivation of markup estimates for the primary foods industry and linking them with measures of globalization, and they are analyzed in more detail in Section 4.2. This sample is comprised of countries with wide range of socio-economic and political characteristics, making the analysis richer – with the potential to unearth further determinants of markups. Among these are differing income groups that might be correlated with markups.

This paper proposes using the same methodology of calculating markups based on production functions but using aggregated sector-level data instead of firm-level data. Market power in the scientific literature has been conventionally studied using micro (firm-level) data. Nevertheless, recent papers (see Colonescu, 2021; Rodriguez del Valle and Fernandez-Vazquez, 2023) have utilized macro (aggregate, industry-level) data to estimate markups. This approach helps circumvent some problems connected to the handling of micro-data. In the first place, macro data has the advantage of providing information for a very substantial number of countries in the world (depending on the input-output table being used), opening up new avenues of research on analyzing market power for countries in different geographical regions and along multiple income groups. Furthermore, input-output tables contain information on all economic activity carried out by a country in a given year. This makes it ideally suited to fulfill the data requirements needed to carry out estimating the markups, which would not be possible had micro data been used.

Moreover, input-output tables employ a standardized industrial classification, which is consistent across all the countries included in the data. This uniformity allows for efficient international analysis and mitigates potential problems arising from countries using different classification systems.[3] Nevertheless, the use of macro data comes with a few methodological problems. The most prominent drawback is the inability to measure markups for each decile within the firms' size distribution. At least for the manufacturing- and service sectors, the firms driving the markups higher on average tend to be larger firms (De Loecker, Eeckhout, and Unger 2020). Depending on the distribution of the firms operating in an industry, the use of macro data might provide significantly biased results, thereby favoring estimates using firm-level data. Nevertheless, empirical evidence exists that a substantial number of farms globally are relatively small, particularly within developing countries (Lowder et al., 2016). A more in-depth discussion about the global farm distribution size is given in Section 6. Therefore, the results derived should still be representative of the actual industry-specific characteristics.

In this paper, a General Maximum Entropy (GME) approach is employed using data from the Eora World Input-Output Database (Eora) as well as the FAO-Stat to estimate sector-level markups. Input-Output tables such as the ones from Eora divide the total global economic activity into sectors or industries (used interchangeably during the remainder of the paper). They provide information on the flows of goods or services encompassed within an industry, originating in one sector and ending up in another. These two data-sets have the notable advantage of providing informational coverage for a wide range of countries, which is essential to accomplish the two primary research objectives. Nevertheless, a potential limitation might be the accuracy of the information contained within, particularly for developing countries. The producers of these data-sets often have to estimate values through imputation techniques to cover missing values. The estimates might or might not deviate from the real results, with no way of knowing with certainty. Nevertheless, to the author's knowledge, no other sources with this type of coverage exist (either at a micro- or a macro-level). This approach further opens up other unique avenues of research that is usually not possible when using micro data; including measuring the impact of Global Value Chains (GVC's) i.e., the international fragmentation of the production process., on markup estimates. This analysis is shown more in detail in Section 4.2.

This paper contributes to the literature studying market power in the Primary Foods industry, that includes agriculture. It advances this literature by elucidating a methodology that allows to derive estimates of markups for potentially the whole world, and then uses said methodology to provide estimates for markups (for Asia). This paper further contributes to the more general industrial organization literature, by providing evidence of the beneficial effects of Global Value Chains to the economy, through the reduction of markups. The literature studying the evolution of markups in the Primary Foods industry is relatively scarce, and tends to fall into one of several camps, or a combination of these: literature providing a purely theoretical analysis on the effects of market power on society, case studies studying market power of specific countries and articles focusing on specific segments within the value chain.

The paper is structured as follows: Section 2 describes the related literature, Section 3 presents the methodology, Section 4 illustrates the results derived, Section 5 discusses the results, and finally, Section 6 concludes the paper.

2. Related literature

A substantial body of literature is concerned with understanding the market power dynamics between entities along the value chain, particularly between farmers, downstream food processors and retailers. This particular value chain is visualized as being akin to an hourglass, with there being many farmers and retailers, but relatively fewer processors. There are therefore concerns, that processors could hold both buying and selling power i.e., the ability to reduce upstream input prices and increase output selling prices.

[3] Other papers estimating markups using input-output tables include (Colonescu 2021) and (Rodriguez del Valle and Fernández-Vázquez 2023). The latter also includes a comprehensive list of advantages of using macro-data with regards to micro data.

	Industry 1	…	Industry N	Final demand (y)	Total output (x)
Industry 1	z_{11}	…	z_{1N}	y_1	x_1
Industry 2	z_{21}	…	z_{2N}	y_2	x_2
…	…	…	…	…	…
Industry N	z_{N1}	…	z_{NN}	y_N	x_N
Labour compensation (lc)	lc_1	…	lc_N		
Other value added (w)	w_1	…	w_N		
Imports + taxes (m)	m_1	…	m_N		
Total output (x)	x_1	…	x_N		

Fig. 2. An illustrative example of an input-output table.

The existence of such market power could theoretically create considerable distortions to the detriment of both farmers and consumers simultaneously. As such, the topic has a high degree of interest with policymakers.

Those scientific articles focusing on analyzing market power within segments of the value chain, generally fall into two camps. The first uses the Structure-Conduct-Performance framework (SCP), that relies on measures of market concentration to proxy over buyer and seller market power. It is assumed that higher levels of market concentration translate to higher market power. The second utilizes is the New Economic Industrial Organization (NEIO) approach, that estimates structural models.

The former camp has focused mostly on seller power affecting consumers. For instance, Saitone and Sexton (2017) finds that between the years 2007 and 2012, the Hirschman-Herfindahl Index (HHI) representing sellers' market power, increased by 13.2 % for 36 NAICS-6 industries in the US. Amongst these were manufacturing of coffee and tea (68 %), Retail bakeries (66 %) and Frozen Specialty Food Manufacturing (52 %). Research papers using the SCP framework face notable challenges with both the collection of relevant data, as well as the interpretation of the index itself. Most data that is available is constrained to the US and European countries, with few exceptions (Deconinck, 2021). Furthermore, measures of concentration might not accurately reflect market power (Syverson, 2019). Finally, concentration ratios might have difficulties in disentangling both buyer and seller power.

The NEIO approach uses econometric estimation techniques to estimate conjectural variation parameters, or the strategic response of firms given the strategy of other firms within a timespan (Bonanno et al., 2017). Perekhozhuk et al. (2016) includes a literature review of 38 studies on the NEIO literature, particularly for 6 high-income countries. They generally find no deviations from perfect competition for the beef and packing industry in the US. Deconinck (2021) further provides a literature review and finds mixed evidence, mentioning papers that do find distortionary effects from buyer power in Greece and China. Downstream stages are seen to be more concentrated, yet no overwhelming evidence exists showing misuse in bargaining power. Perekhozhuk et al. provides a list of potential drawbacks from using this methodology.

Further papers seek to measure the impact globalization on market power in the agriculture value chain. These papers tackle this question from dimensions. Firstly, papers such as Harilal (2021) raise concerns about the impact "laissez faire" globalization will have on farmers in Asia, particularly by strengthening the power of downstream firms. Whereas Sexton et al. (2007) is concerned about the economic impact that protectionist policies by high-income countries might have in impeding the development of lower income countries.

3. Methodologies

The analysis of this research primarily involves utilizing input-output tables, not only extract all the required data for markups estimation, as presented in Section3., but also to explain how input-output can be employed to compute industry-level measures of internationalization, as discussed in Section3.3.

3.1. Input-output analysis

A brief explanation is first provided about what an input-output table is, and how the results it contains can be interpreted. Fig. 2 shows an example of an Input-Output Table. It is precisely these types that are used throughout the paper.

The elements z_{ij} indicate the amount of industry i's production that is used as intermediate input in industry j. Industry j requires not only intermediate inputs to produce, but primary factors as well (payments to production factors other than intermediate inputs). The example shown here divides the compensation paid for these primary factors into labor compensation (lc_j), plus other terms in the value added (capital compensation, for example) labeled as w_j. Note that the total value added for industry j (v_j) can be defined as $v_j = lc_j + w_j$. Summing up across columns equals the total input on industry j ($x_j = \sum_i z_{ij} + lc_j + w_j + m_j$), while the sum across rows adds up to the total production of industry i ($x_i = \sum_j z_{ij} + y_i$).[4]

3.2. Measuring market power

Estimates of market power traditionally falls into two groups. The first are measures of concentration that, roughly show how much output is concentrated in the hands of the largest firms (in terms of output or revenue) within a market. Two measures include the Hirschmann-Herfindahl Index and concentration ratios. The second category includes a measure that calculates market power directly; by estimating the markup. The markup is defined as the wedge between the selling price of a good or service with its marginal cost of production. Using the terminology of (De Loecker and Eeckhout 2018), the markup can be defined as $\frac{P}{\lambda}$.

Our point of departure is a Cobb-Douglas production function for a firm i (in this paper i represents the primary foods industry) at year t using the technology expressed in the function: $Q_{it} = \Omega V_{it}^{\alpha_{it}} K_{it}^{\beta_{it}}$

With Y_{it} representing output, V_{it} and K_{it} representing the variable inputs and the stock of capital respectively, and Ω is a measure of the factor productivity. Both α_{it} and β_{it} represent the elasticities for the respective inputs. The equation to calculate the markup is based on the procedure derived by (De Loecker and Eeckhout 2018). The representative firm solves a cost minimization problem: $P_{it}^{V} V_{it} + P_{it}^{K} K_{it} - \lambda_{it}(\Omega_{it} V_{it}^{\alpha_{it}} K_{it}^{\beta_{it}} - \overline{Q_{it}})$, where P_{it} and λ_{it} refers to price and marginal costs respectively. The resulting First Order Condition gives: $P_{it}^{V} - \lambda_{it}\alpha_{it}\Omega_{it} V_{it}^{\alpha_{it}-1} K_{it}^{\beta_{it}} = 0$. Multiplying the previous expression with $P_{it} V_{it}$, substituting Q_{it} and re-writing gives:

$$\mu_{it} = \frac{P_{it}}{\lambda_{it}} = \alpha_{it} \frac{P_{it} Y_{it}}{P_{it}^{V} V_{it}} \tag{1}$$

This expression simplifies the estimation of markups, since it is not necessary to estimate a cost function, which is highly difficult due to the information that is needed. Furthermore, the data required to calculate the Right-Hand Side of this equation can be obtained relatively easily; the elasticities α_{it} can be retrieved from the estimates of econometric regressions of the production functions, while Y_i and V_i can be observed directly in some datasets. Originally, (De Loecker and Eeckhout 2018) follow this approach to study the evolution of market power approximated by the evolution of markups from a database containing detailed information at the company level. While this strategy is appealing when dealing with specific industries (manufactures and services) and countries (i.e., western economies) covered in these datasets, it cannot be directly applied to the study of market power for agricultural activities in non-western countries.

There have been recent attempts to overcome these difficulties by, following the idea of (Hall et al., 1986) of analyzing market power with aggregated data, and applying a similar strategy to macro-indicators present in global input-output (IO) databases. These tables usually contain most, although not all, of the data requirements needed to compute markups. Auxiliary datasets are needed to provide additional information on the stocks of capital, which input-output tables usually do not have. For example, (Colonescu 2021) and (Rodriguez del Valle and Fernández-Vázquez 2023), take advantage of the information contained in the World Input-Output Database (WIOD) to estimate markups for European manufacturing industries in recent years. Similarly, the strategy followed in this paper is to use data comprised in the global IO database and other global datasets with a similar purpose for the agricultural activities of a set of 43 Asian countries. More specifically, we use the information on output (Y_{it}) and variable inputs (V_{it}) observable on a yearly basis in the Eora database for the agricultural sector between 1995 and 2015 for the countries under study. Additionally, we will complement our required variables with data of capital stocks (K_{it}) for the agricultural industries in these countries coming from the FAO database. The maximum timespan available from the academic, non-commercial, version of the Eora tables is 1990 to 2015. However, the FAO-Stat provides information on the stocks of capital only after 1995. Therefore, the useable sample for this analysis has only 21 years.

The production functions are estimated from the sample created for each year between 1995 and 2015. In our analysis, i does not refer to a company, but it stands for the primary foods industry in one country. This leaves us with only 43 data points to estimate the production functions, being this size a problem for traditional econometric strategies that rely on large samples. As a consequence, we follow the same strategy as in (Rodriguez del Valle and Fernández-Vázquez 2023) and apply a Generalized Maximum Entropy (GME) estimator. This estimator has the advantage of producing robust estimates with limited data using a reparameterization of the elasticities of interest and the error term. More details on the general characteristics of the estimator are presented in the appendix. The choice of this estimator is justified by the reduced sample size available: since the production function is estimated independently for each year, the number of observations reduces to the number of Asian countries studied, which prevents the use of traditional estimators relying on central limit theorems. For its implementation, we have made use of the *gmentropylinear* Stata command (see Corral et al., 2017, for details). Measuring markups is only half of the analysis presented here. The next subsection describes the methodology for calculating the second stage of the analysis presented here; the measurement of Global Value Chains using input-output tables.

3.3. Measuring global value chains

The independent variable used to represent economic globalization, in the form of Global Value Chains, is calculated directly from

[4] The terms y_j and m_j denote respectively the part of the production in industry j that satisfies its final demand and the part of the cost of this industry devoted to paying its imports and taxes.

the Eora input-output tables using the methodologies from (Antràs et al., 2012) and (Timmer et al., 2015). Both of these measures capture globalization regarding the means of production. The former measures the relative positioning within the value chain, measuring the average number of stages the industry requires for a good or service to reach consumers. The latter measures the amount of value added originating from abroad required to produce output. An important feature of calculating measures of inter-industrial linkages using input-output tables, is that measures can either be calculated either as forward or backward linkages. A difference between the two aforementioned measures is that "upstreamness", describing the positioning within the value chain, is a measure of backward linkages whereas the variable "Foreign Value Added", describing the direct and indirect value added originating from abroad, is a measure of backward linkages.

As can be observed from Fig. 2, each Input-Output Table is comprised of several components – all relevant for this paper here as shown later. Using matrix notations, Z represents a matrix with values of intermediate goods and services, that shows the flow of goods and services used as intermediate inputs for production. Vector Y represents goods and services used for final consumption, vector X total gross output, and V, the value added vector. The rows represent values of goods and services that have been produced at a certain year, while the columns represent the values of goods and services that have been used as inputs. The sum of rows and columns should, ceteris paribus, yield the same values of gross outputs: $X = Z + Y$. A critical feature of input-output tables is the ability to calculate the technical coefficients matrix A, detailing the ratio of inputs required to produce a unit of output. This matrix can be calculated by multiplying the intermediate goods matrix with the inverse of a matrix containing the values of total output along the diagonal: $A = Z\widehat{X}^{-1}$. The latter equation can be plugged into the former giving expression: $X = A\widehat{X} + Y$, which can be rewritten as: $X = (I - A)^{-1}Y$. The expression $(I - A)^{-1}$ is known as the Leontief Inverse Matrix and describes the value of inputs required along every stage of production (see Miller and Blair, 2009, for details).

The share of foreign value added is calculated using the following expression:

$$FVA = \widehat{VO}(I - A)^{-1}\widehat{Y} \tag{2}$$

With $\widehat{VO}$ denoting a matrix with value added per output (calculated by $VO = V\widehat{X}^{-1}$) along the diagonal, matrix A calculated by multiplying the intermediate inputs matrix with the inverse of the total output matrix along the diagonal $A = ZX^{-1}$. FVA yields a matrix whose elements describe the direct and indirect value added generated in industry i and consumed in industry j. Summing across all the columns gives the total value added, which can be then used to derive the shares of foreign and domestic value added.

The previous model represents a Leontief Demand Model. Transposing the system gives a Ghosh system. The sum of rows under this system gives $X = VA + AX$. Rearranging this gives $(I - B)^{-1}$, representing the Ghosh Inverse Matrix. Here, B denotes the coefficients of allocation. The measure of upstreamness is calculated by summing the rows of a Ghosh Inverse Matrix, taking the form:

$$U = \sum (I - B)^{-1} \tag{3}$$

This measure of foreign value added has a notable advantage regarding the usage of traditional trade data. Using raw trade data for measuring the flow of intermediate inputs has the notable disadvantage of suffering from problems of double counting, resulting in potential measurement errors when using the data. The value added approach to measuring GVC's circumvents these problems, being able to produce more reliable estimates of the degree of inter-industrial linkages.[5]

3.4. Data

Two main datasets were used for constructing the panel structure used to derive estimates for markups presented in this paper: the Eora Input-Output Tables and the FAO-Stat data-set containing information on stocks of capital for the agriculture, hunting, fishing, and logging sectors (categorized as sectors A, B, C from NACE rev.4).

The first main datasets used were the EORA Input-Output tables, which contains, among other things, aggregate data on the flow of goods and services originating from one sector and being used as inputs in another. This data set is balanced i.e., including information on every country and for every year, and contains information on 189 countries for the years 1990 to 2015. More information on the Eora Input-Output Tables can be found at (Lenzen et al., 2012) and (Lenzen et al., 2013).

The second data-set main was obtained from FAO-Stat, which includes information on measures of net stocks for capital for up to 190 countries between the years 1995 to 2020.[6] To make the values compatible between datasets, only current prices in US Dollars were used. The FAO-Stat data-base only has aggregate information on agriculture, hunting, fishing and logging. To make both datasets compatible for merging, two industries within the Eora Input-Output Tables were aggregated. The procedure was done to limit the potential bias in the merged data-set, generated from the over-representation of the more broadly defined stocks of capital. In particular, the industry "Agriculture" (containing information on agriculture, logging, and hunting activities) was aggregated with another industry "fishing" for each Input-Output table at a given year. This was achieved by following the approach from (Miller and Blair 2009); that requires the creation of an $m \times n$ dimensional aggregation matrix S, with n representing the original number of industries and m the dimensions with both sectors aggregated (in this case $i - 1$). This matrix might be understood as being similar to

[5] More information on problems of double counting when using trade data can be found in (Koopman, Wang, and Wei 2014) and (Miroudot and Ye 2022).

[6] More information on these estimates is elucidated in (Van der Donckt, Chan, and Silvestrini 2021).

Table 1
Countries contained within the Sample with their respective Income Classification.

Country	UN Sub-region	Income Classification (2015)
Afghanistan	Southern Asia	L
Armenia	Western Asia	LM
Azerbaijan	Western Asia	UM
Bahrain	Western Asia	H
Bangladesh	Southern Asia	LM
Bhutan	Southern Asia	LM
Brunei	South-Eastern Asia	H
Cambodia	South-Eastern Asia	LM
China	Eastern Asia	UM
Cyprus	Western Asia	H
Georgia	Western Asia	UM
India	Southern Asia	LM
Indonesia	South-Eastern Asia	LM
Iran	Southern Asia	UM
Iraq	Western Asia	UM
Israel	Western Asia	H
Japan	Eastern Asia	H
Jordan	Western Asia	UM
Kazakhstan	Central Asia	UM
Kuwait	Western Asia	H
Kyrgyzstan	Central Asia	LM
Laos	South-Eastern Asia	LM
Lebanon	Western Asia	UM
Malaysia	South-Eastern Asia	UM
Maldives	Southern Asia	UM
Mongolia	Eastern Asia	LM
Myanmar	South-Eastern Asia	LM
Nepal	Southern Asia	L
Oman	Western Asia	H
Pakistan	Southern Asia	LM
Philippines	South-Eastern Asia	LM
Saudi Arabia	Western Asia	H
South Korea	Eastern Asia	H
Sri Lanka	Southern Asia	LM
Syria	Western Asia	LM
Tajikistan	Central Asia	LM
Thailand	South-Eastern Asia	UM
Turkey	Western Asia	UM
Turkmenistan	Central Asia	UM
United Arab Emirates	Western Asia	H
Uzbekistan	Central Asia	LM
Vietnam	South Eastern Asia	LM
Yemen	Western Asia	LM

an identity matrix, in that it has 1 s along the diagonal. Nevertheless, the 1 s in the aggregation matrix corresponds to the industries that are to be united in the input-output tables. In our case, this aggregation matrix has 4725 $\times$ 4914 dimensions, taking the form:

$$S_{[4725\ \times\ 4914]} = \begin{pmatrix} 1 & 1 & 0 & 0 & \dots & 0 \\ 0 & 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & 0 & \dots & 1 \end{pmatrix}$$

Matrix S was used to aggregate each of the components within the input-output table, i.e., $V^* = SV$, $Y^* = SY$, $X^* = SX$ and $Z^* = SZS'$, with S' indicating the transposed of matrix S. The use of this matrix therefore ensures that the correct dimensions and aggregation is used. These calculations then produce the new modified matrices with aggregate industries used in the remaining sections of this paper.

These two files were merged generating an unbalanced panel data set for the years 1995 to 2015. Finally, a subset of the general sample was created that included 43 countries located in Asia. The selection criterion for these countries is based on the UN geoscheme for Asia, and the sample includes countries within all subregions. The exact country composition within the sample can be observed in Table 1. The income classification is based on the World Bank's definition and includes four groups: low income (L), lower middle income (LM), upper middle income (UM) and high income (H). These classifications are determined for each country by their Gross National Income per capita. In 2015, this corresponds to less than \$1025 for low income, between \$1026 and \$4035 for low middle income, between \$4036 and \$12,475 for upper middle income, and more than \$12,475 for high income countries.

The summary statistics of the results from this merged data-set is shown in the appendix. The unbalanced structure within the

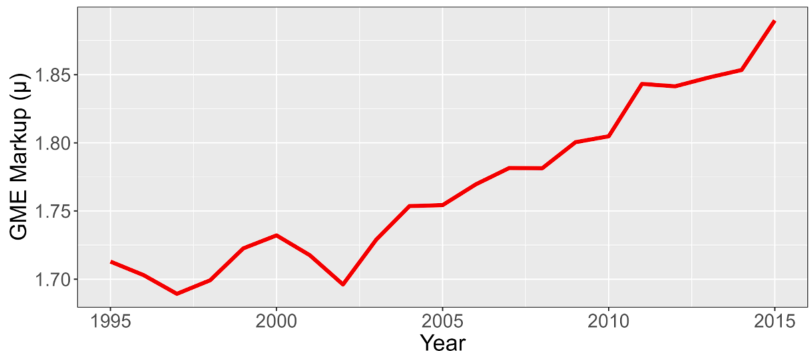

Fig. 3. Evolution Average Markups in Asia *Note:* based on the authors own calculations.

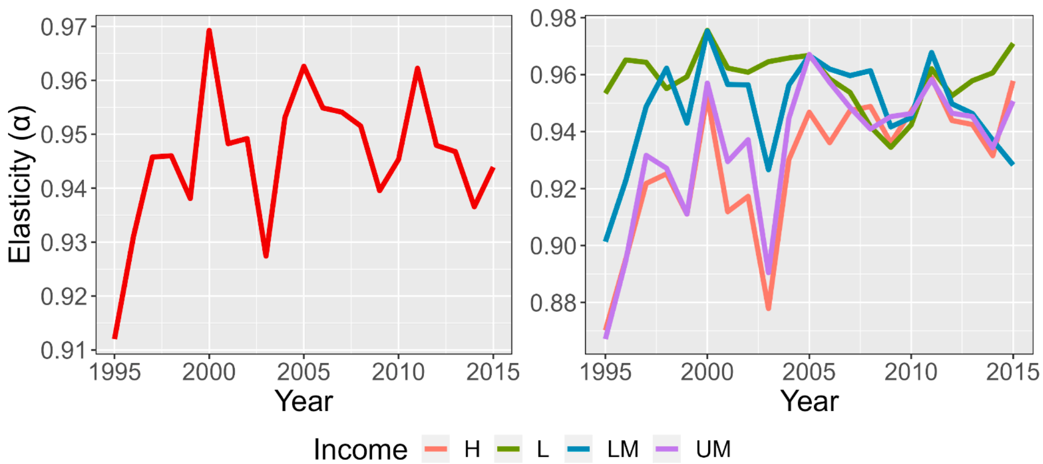

Fig. 4. Estimates for the Variable Inputs Elasticity derived from the Cobb-Douglas Production Function *Note:* results derived from the authors own estimation.

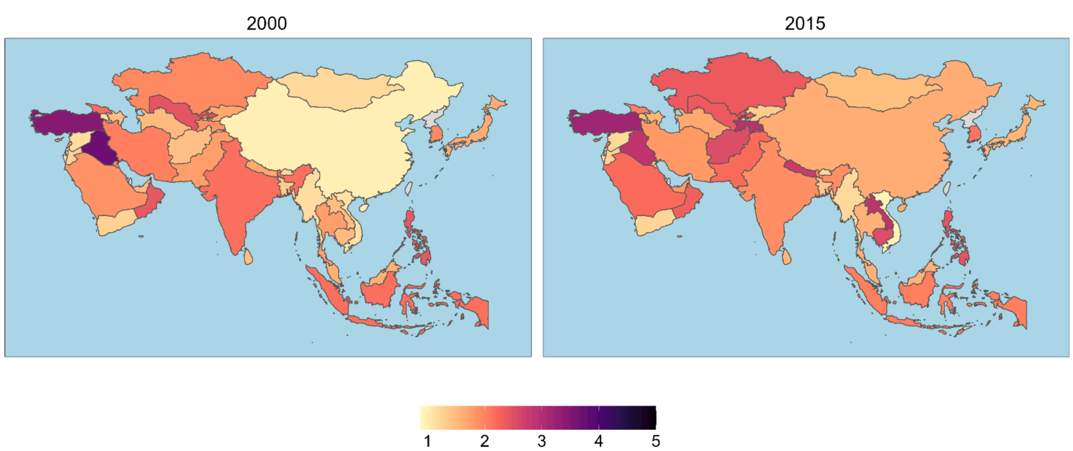

Fig. 5. Markup levels for 2000 (left) and 2015 (right) *Note:* data derived from the authors calculations based on the methodology and sample described in Section 3.

sample stems from the numerous missing values for several countries pre 2000s caused by the FAO-Stat database. Because of this, the paper mostly focuses on analyzing on the results between 2000 and 2015. Table 6 further shows the general equal distribution of the four income groups, although "UM" has relatively fewer observations.

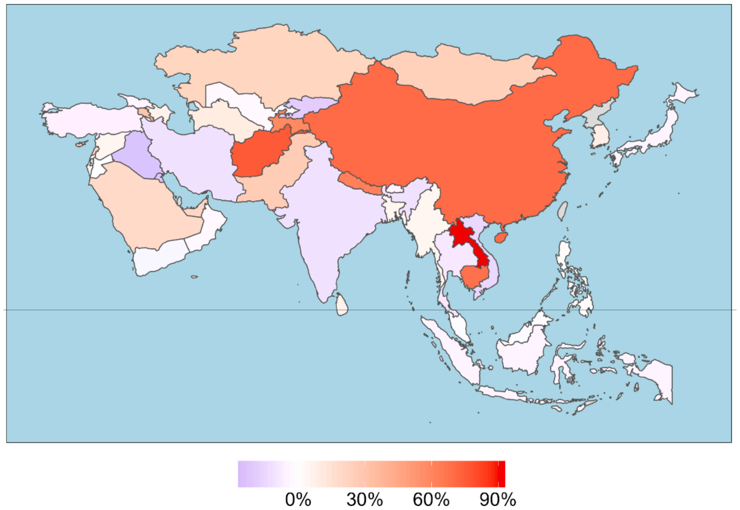

Fig. 6. Percentage change markups between 2000 and 2015 *Note:* data derived from the authors calculations based on the methodology and the sample explained in Section 3.

4. Results

4.1. Evolution markups

The markup estimates derived from the methodology proposed in Section 3.2 is described in more detail throughout the following paragraphs, detailing the evolution at both a country-, income-, and aggregate level. As can be seen from Fig. 3, the average markups increased on aggregate between 2000 and 2015 by around 9.1 %. Most of this increase is seen to be occurring post-2000s, with slight fluctuations dips observed in 2002, 2005, and 2007. Nevertheless, great heterogeneity exists when examining the markups at a geographic level. This can be seen in Figs. 5 and 6. Table 7 in the appendix shows this in more depth, with the region of Western Asia showing a wide range of values for the markup, with the region of “Eastern Asia” showing the lowest range.

Further analysis shows countries with persistently high markup levels relative to other countries. This is seen to be the case in 2015 for Turkey, Iraq, Laos, Kazakhstan, Tajikistan, Nepal, and Afghanistan. Other countries are seen to have persistent lower levels of markups, including among others: Myanmar, Vietnam, Bhutan, Syria, Jordan, and Israel. The 5 five countries with the highest increases in markups between 2000 and 2015 were Laos (93.21 %), Afghanistan (74.72 %), China (69.72 %), Cambodia (68.37 %), and Nepal (62.42 %). Both Afghanistan and Nepal were classified as "Low Income" by the World Bank. Noteworthy also, is that two countries with a socialist economic organization (China and Laos), are among the countries with the strongest increases in markups. In contrast, a few countries were found to have successfully decreased their markups – the most notable of which are: Bahrain (−27.19 %), Iraq (−23.53 %), Kuwait (−22.94 %), Kyrgyzstan (−20.24 %) and Vietnam (−15.84 %). These countries have a variety of income group classifications.

Fig. 4 further shows the evolution of the elasticity derived from the production function. The left figure shows that on aggregate, the elasticity has had an increasing trend throughout time. The right figure shows the same evolution disaggregated by income groups. It has been found that low-income countries have a generally higher elasticity that high-income countries.

Although the paper focuses on measuring the role that Global Value Chains have on markups, as explored in the next Section, additional macroeconomic and political events that have a tentative causal relationship are described briefly. Firstly, countries in Asia introduced anti-monopolistic policies at differing timeframes. Consequently, some countries left monopolistic actions unregulated for longer than others. For instance, according to Balisacan (2022), Japan, South Korea, and Indonesia introduced relevant legislation in 1947, 1980, and 1999 respectively. Other countries implemented them at a later date, including China (2007), Malaysia (2010), Philippines (2015) and Thailand (2017). Some of these countries also include exemptions within the law for cooperatives to strengthen the relatively weak bargaining position of farmers, whereas others have not done so directly. How effective these policies are at reducing aggregate markups is probably specific to each country and possibly their institutional quality. The institutional quality of a nation is tied to its income level; therefore, low-income countries might be additionally burdened by the problems caused by market power.

A second important event relevant to the phenomenon of globalization is the so-called “China Shock”. China entered acceded to the World Trade Organization in 2001. Even though the event created an overall net benefit globally, in the short run, there were significant disruptive changes in output across countries globally. How and if this event has caused changes in markups is, nevertheless, unknown.

Finally, a country’s political and economic system might also influence markups. The sample contains information on three out of five communist countries in the world: China, Laos, and Vietnam. It is expected that these countries have relatively low levels of markups. These results are partially confirmed due to the sample mean of the markup for each country being 1.04, 2.3, and 1

Table 2
Average marginal effects of the percentage of foreign value added (FVA) and upstreamness on agricultural market power.

	Estimate	Standard deviations
FVA	− 0.0309**	0.0140
Upstreamness	− 0.1702***	0.0646

Note: (**) and (***) stand for estimates significantly different from zero at 5% and 1% respectively.
Note: (**) and (***) stand for estimates significantly different from zero at 5% and 1% respectively.

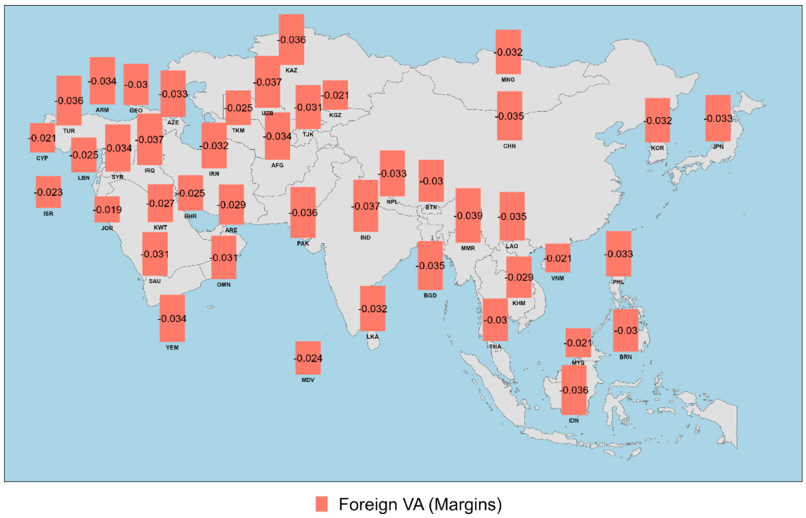

Fig. 7. Margins of foreign value added *Note:* the variable was aggregated for each country using simple means for 1995 to 2015.

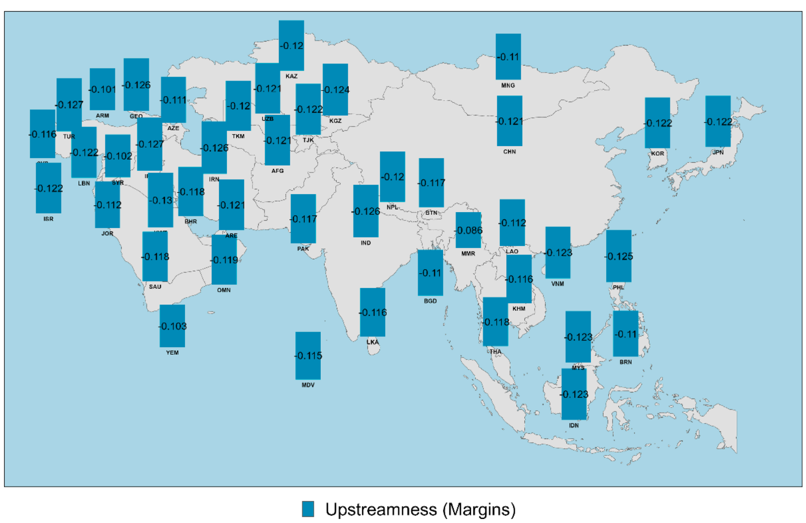

Fig. 8. Margins of Upstreamness *Note:* the variable was aggregated for each country using simple means for 1995 to 2015.

respectively, with the total mean being 1.77. With these political and macroeconomic considerations having been deliberated, the next chapter examines a relationship that does affect every country – Global Value Chains. 4.2. Markups and Global Value Chains

This section explores the exogenous determinants of markups using a two-way fixed effects panel model. All independent variables are calculated by employing the Eora input-output tables, and include several well-known exogenous determinants of markups, such as the percentage share of factor content originating from abroad and value chain positioning, as shown previously in Section 3.3.

These two measures are ideal to measure econometrically, as they are strictly causal determinants of markups and therefore completely exogenous. The measure of foreign value added shown in Eq. (2), is a measure of backward linkages, describing value

Table 3
Average marginal effects of the percentage of foreign value added (FVA) and upstreamness on agricultural market power by income category. The values in brackets are the standard deviations.

	Number of observations (countries × years)	FVA	Upstreamness
High	180	−0.0294***	−0.5029***
Upper-medium	144	−0.0218	−0.0327
Low-medium	293	−0.0336	−0.0965
Low	245	−0.0340	−0.0948

Note: (**) and (***) stand for estimates significantly different from zero at 5 % and 1 % respectively.

added originating from somewhere in the world and ending up in the industry being examined. The measure of upstreamness shown in Eq. (3), is an approximate indicator of value chain positioning. Tables 8 and 9 in the Appendix show detailed data by country on the measures of foreign value added (Table 8) and upstreamness (Table 9). Tables 10 and 11 display summary statistics of both variables by income group and year, respectively.

The equation for the regression model takes the following form:

$$y_{it} = f(GVC_{it}) + \delta_i + \rho_t + \epsilon_{it} \tag{4}$$

In Eq. (4), y_{it} represents estimated markups for country i at time t, $f(GVC_{it})$ denoting the independent variables mentioned previously. The element GVC_{it} reflects the effect that the two factors measuring integration in global value chains, namely the percentage of foreign value added (FVA) and the indicator of upstreamness, on the markups estimated. Since the effects of these two variables can have a non-linear nature, we have considered both variables in levels, in quadratic terms, and interacting between themselves utilizing cross-products. Additionally,δ_i describes dummies for each country; ρ_t denotes the dummies for each year and ϵ_{it} the error term. Table 4 in the Annex display the estimates of a fixed-effects regression. Given that countries might have some idiosyncratic unobservable conditions affecting the markups, we opted for a fixed-effects estimator strategy to capture this country heterogeneity. More interestingly, our estimates allow for quantifying the marginal effects of the two variables of interest (percentage of foreign value added and the indicator of upstreamness) on the market power of the agricultural sector in each one of the countries and years studied. Table 2 below presents a summary of the mean marginal effects estimated, and Figs. 7 and 8 map these mean effects for the Asian countries studied in our dataset:

The estimates of these average marginal effects indicate that, as expected, the integration of the agricultural industries in the global value chains has, generally, a negative impact on the markups present in this sector. Larger shares of foreign value added or higher values for the indicator of upstreamness impact on reducing the market power of the agricultural activities. These results are predicted by the theory and are in line with those obtained by (Colonescu 2021) and (Rodríguez del Valle and Fernández-Vázquez 2023) for the case of European manufacturing industries.[7]

Interestingly, one can detect some heterogeneity in these marginal effects depending on the classification of the country into income categories: while the indicators of a larger integration in global value chains of high-income countries seem to decrease the markups on agricultural products, these effects are not so clear for other income categories. Bigger percentages of foreign value added reduce market power for the agricultural sector for low and low-medium-income countries, but not for those countries classified as having a low income. Moreover, a higher upstreamness of the industry is only relevant for high-income countries but not significant for other categories of income. Table 3 summarizes these results:

A more detailed description of this heterogeneity can be found in the average estimates of both effects for each one of the countries in our data set, as shown in Table 5 in the appendix and it is displayed visually in Figs. 7 and 8 below:

5. Discussion

This section discusses factors that might bias the markup estimates derived via the GME approach, as well as potential shortcomings of the econometrics results seen in Section 4.

The procedure described utilizes input-output tables to meet the majority of the data requirements to conduct the GME estimates. Each industry within this framework is assumed to be produced by one representative firm, according to input-output theory. A certain bias to these results might arise, if the distribution size of agriculture firms, or holdings is very fat-tailed. This could be problematic, as the averages used here might not be able to disentangle what is happening to the largest farm plantations. There is evidence for the year 2000, that a vast majority of global farm-holdings (over 80%) are relatively small with less than 2 hectares in size (Lowder et al., 2016).[8] The previous result is also corroborated for Asia explicitly in Otsuka et al. (2016). These distributions are more uniform if the countries are categorized as low income.[9] Assuming that these distributions were maintained throughout time, the estimates derived

[7] (Deconinck 2021) also finds evidence of higher concentration in the final stages of production, corroborating results found here.

[8] Note: agriculture, logging, and hunting comprised a global average of 59,9 % of value added within the primary foods industry in the year 2000, and is dependent on country-specific characteristics not related to income.

[9] (Lowder, Skoet, and Raney 2016) also finds that between 1990 – 2000, the average farm size has been decreasing everywhere in the world apart from more high-income countries and a few South American countries.

Table 4
Regression results using White robust standard errors.

	Dependent variable: μ GME		
	(1)	(2)	(3)
Income Group L	0.047	0.058	0.045
	(0.040)	(0.041)	(0.042)
Income Group LM	0.031	0.031	0.025
	(0.034)	(0.034)	(0.034)
Income Group H	0.079**	0.073**	0.065*
	(0.038)	(0.034)	(0.036)
Foreign Value Added	−0.028***	−0.039***	−0.060***
	(0.003)	(0.008)	(0.012)
(Foreign Value Added)2		0.0004**	0.001***
		(0.0002)	(0.0002)
Upstreamness	−0.015**	−0.141***	−0.228***
	(0.006)	(0.035)	(0.070)
(Upstreamness)2		0.004***	0.007***
		(0.001)	(0.002)
Foreign Value Added x Upstreamness			0.007**
			(0.003)
Observations	862	862	862
R2	0.110	0.139	0.147
Adjusted R2	0.034	0.064	0.071
F Statistic	19.540***(df = 5; 794)	18.296*** (df = 7; 792)	17.001*** (df = 8; 791)

Note: *p<0.1; **p<0.05; ***p<0.01.
Note: The results are derived from the authors own calculations.
Note: the results are derived from the authors own calculation.

would be representative of the whole country.

A note of caution should be given, however, when interpreting the markup estimates. Even though the markup is the most ideally suited measure available to estimate market power for the purposes of this paper, it is not infallible. Numerous papers have surfaced demonstrating theoretically that markups might be influenced by changes other than pricing and marginal cost of production. The changes include an altering of the cost structure such as; the variable costs relative to marginal costs (Syverson, 2019) and changes to the fixed costs of production (Berry et al., 2019), rent seeking behavior by firms and networking effects. Any of the previously mentioned changes, particularly within the cost structure, could, potentially, influence the markup – even if no change in market power actually occurred. Moreover, the use of aggregate information blends out intra-industrial product differentiation. Differences in food quality and the difficulty for consumers to determine pricing (information asymmetries) leads to differences in pricing for foodstuffs (Bonanno et al., 2017). According to the approach presented in this paper, the output of the whole industry is produced by one firm (concordant to input-output theory), thereby only one price is given – generating loss of information. Several of the papers mentioned previously focus on describing the problems of markups using a micro-, firm-level perspective. The examples given in those papers naturally find an equivalence at the macro-level as presented in this paper. The firm-level aggregation to give macro results, gives a bottoms-up, micro to macro point of view. However, analyzing markups at a purely macroeconomic level among a large variety of countries may also potentially open up new avenues of research, by examining other dimensions not as readily accessible using firm-level data. The results of which, may complement micro-level research. One potential dimension is the role institutional quality could play explaining the differences in markups. There could be two channels at play. The first is the increase of fixed costs caused by poor institutional quality. Substantial literature has found that poor institutional quality raises costs of doing business, and thereby generates a barrier to entry into the market. The second channel might be institutional quality reducing existing market power through creating and enforcing relevant policy. The relationship between institutional quality and country-wide markups is, nevertheless, relatively unknown (as well as possible reverse causality).

6. Conclusions

This paper derived global markup estimation for the primary foods industry by employing a Generalized Maximum Entropy (GME) -based approach. The estimates were determined using aggregate data from input-output tables, that track flows of goods and services from country to country. This approach, together with the usage of macro-data, allows for the estimation of measures of market power for the Primary Foods Industry (defined as agriculture, hunting, fishing and logging) for nearly all countries in Asia. This analysis tests the role economic globalization in the form of Global Value Chains has on market power, across countries with a wide range of characteristics, including income levels and economic and political systems.

In summary, markups for the primary food industry have risen on aggregate between 1995 and 2015. Nevertheless, this rise has been unequal between regions and income levels. The results suggest that markups are systematically higher for countries classified as low-income than for high-income countries. Further ingrained nationwide characteristics do impact markups. Measures of globalization in the form of value chain positioning and foreign value added used for production are both seen to reduce markups significantly. Opening up to trade and foreign investments can help increase economic efficiencies in the critical primary foods industry.

Table 5
Summary statistics by country; markup (μ) mean estimates and variability 1995–2015.

Variable	Country	Income Group	n	Min	Max	$\bar{x}$	s
GME Markup (μ)	Afghanistan	L	21	1.45	2.53	2.00	0.30
	Armenia	LM	16	1.06	1.49	1.30	0.15
	Azerbaijan	UM	16	1.19	1.60	1.44	0.12
	Bahrain	H	21	1.58	2.19	1.83	0.20
	Bangladesh	LM	21	1.28	1.41	1.34	0.04
	Bhutan	LM	21	1.16	1.32	1.23	0.04
	Brunei	H	21	1.33	1.52	1.44	0.06
	Cambodia	LM	21	1.50	2.53	1.97	0.27
	China	UM	21	0.95	1.63	1.04	0.16
	Cyprus	H	21	1.21	1.93	1.57	0.19
	Georgia	UM	16	1.93	2.17	2.02	0.07
	India	LM	21	1.91	2.19	2.08	0.08
	Indonesia	LM	21	2.05	2.33	2.16	0.06
	Iran	UM	21	1.79	2.05	1.93	0.07
	Iraq	UM	21	2.13	4.62	3.11	0.72
	Israel	H	21	1.02	1.15	1.10	0.04
	Japan	H	21	1.50	1.63	1.58	0.04
	Jordan	UM	21	1.00	1.28	1.19	0.09
	Kazakhstan	UM	16	1.84	2.40	2.17	0.19
	Kuwait	H	21	1.44	1.95	1.60	0.13
	Kyrgyzstan	LM	16	1.29	1.67	1.42	0.11
	Laos	LM	21	1.47	2.92	2.30	0.47
	Lebanon	UM	21	1.62	2.13	1.88	0.16
	Malaysia	UM	21	1.07	1.69	1.57	0.12
	Maldives	UM	21	1.54	2.88	2.17	0.40
	Mongolia	LM	21	1.13	1.55	1.37	0.12
	Myanmar	LM	21	0.91	1.21	1.12	0.07
	Nepal	L	21	1.70	2.75	2.14	0.28
	Oman	H	21	1.90	2.54	2.28	0.16
	Pakistan	LM	21	1.76	2.21	1.85	0.11
	Philippines	LM	21	1.97	2.66	2.36	0.16
	Saudi Arabia	H	21	1.58	2.20	1.94	0.21
	South Korea	H	21	1.89	2.19	2.02	0.10
	Sri Lanka	LM	21	1.45	1.73	1.58	0.09
	Syria	LM	21	0.94	1.22	1.10	0.08
	Tajikistan	LM	16	1.85	2.93	2.34	0.25
	Thailand	UM	21	1.58	1.81	1.66	0.07
	Turkey	UM	21	2.88	3.45	3.20	0.15
	Turkmenistan	UM	16	1.52	1.83	1.72	0.08
	UAE	H	21	1.30	1.88	1.65	0.20
	Uzbekistan	LM	16	2.24	2.46	2.33	0.07
	Viet Nam	LM	20	0.89	1.09	1.00	0.07
	Yemen	LM	21	0.96	1.30	1.14	0.07
	all		862	0.89	4.62	1.77	0.55

Notes: the income classification is displayed for 2015.

Table 6
Summary statistics of the markup disaggregated by the income group using current income classifications.

Variable	Income Group	n	Min	Max	$\bar{x}$	s
GME Markup (μ)	H	180	1.02	2.54	1.65	0.34
	L	245	0.91	2.75	1.69	0.48
	LM	293	0.89	4.62	1.80	0.64
	UM	144	1.01	3.45	1.99	0.57
	all	862	0.89	4.62	1.77	0.55

Source: the authors own calculations.

Recognizing the impact of globalization and Global Value Chain positioning on markups can guide strategies aiming to balance market power and enhance sustainable economic growth.

It might be of further interest for policymakers and academia to study the impact of several recent trade agreements signed by ASEAN members in 2017, to better evaluate how this has causally impacted the evolution of markups Some papers have already presented a notable increase in efficiency resulting from this agreement. It is conceivable that these trade agreements may replicate the economic success seen in the EU's integrated market approach.

Table 7
Summary Statistics of the markup disaggregated by subregions.

Variable	UN Sub-region	n	Min	Max	$\bar{x}$	s
GME Markup (μ)	Central Asia	80	1.29	2.93	1.99	0.40
	Eastern Asia	84	0.95	2.19	1.50	0.38
	South-eastern Asia	188	0.89	2.92	1.73	0.51
	Southern Asia	189	1.16	2.88	1.82	0.38
	Western Asia	321	0.94	4.62	1.78	0.67
	all	862	0.89	4.62	1.77	0.55

Source: the authors own calculations.

Table 8
Summary statistics of the foreign value added, disaggregated by country.

Variable	Country	n	Min	Max	$\bar{x}$	s
Foreign VA	Afghanistan	21	4.65	8.54	6.80	1.23
	Armenia	16	3.32	13.69	6.57	3.70
	Azerbaijan	16	4.53	12.18	7.25	2.75
	Bahrain	21	10.99	20.90	16.97	3.23
	Bangladesh	21	3.80	8.16	5.40	1.42
	Bhutan	21	5.30	19.42	11.56	3.36
	Brunei	21	7.63	14.26	10.96	2.02
	Cambodia	21	7.09	16.13	12.09	2.04
	China	21	4.16	6.06	5.13	0.66
	Cyprus	21	20.06	24.15	22.00	1.25
	Georgia	16	5.99	16.81	11.71	4.32
	India	21	1.71	3.82	2.75	0.83
	Indonesia	21	3.67	6.57	4.59	0.64
	Iran	21	6.23	10.92	8.37	1.43
	Iraq	21	2.46	4.51	3.17	0.65
	Israel	21	16.31	23.09	19.88	2.11
	Japan	21	4.19	11.36	7.62	2.55
	Jordan	21	20.81	29.06	24.78	2.48
	Kazakhstan	16	2.68	4.97	3.79	0.73
	Kuwait	21	9.65	18.11	14.89	1.90
	Kyrgyzstan	16	14.67	27.89	22.07	4.28
	Laos	21	2.90	8.77	5.78	1.87
	Lebanon	21	13.56	21.61	17.51	2.45
	Malaysia	21	20.06	30.90	22.41	2.22
	Maldives	21	13.98	22.22	18.97	2.52
	Mongolia	21	5.11	15.15	9.33	3.12
	Myanmar	21	0.12	1.22	0.55	0.40
	Nepal	21	5.93	9.32	7.98	0.95
	Oman	21	7.62	13.40	9.80	1.68
	Pakistan	21	2.87	4.57	3.63	0.54
	Philippines	21	6.65	9.32	8.17	0.79
	Saudi Arabia	21	8.01	11.79	9.84	1.39
	South Korea	21	7.63	10.67	9.12	0.83
	Sri Lanka	21	7.21	9.78	8.40	0.70
	Syria	21	5.44	9.77	6.96	1.35
	Tajikistan	16	7.63	13.09	9.74	1.64
	Thailand	21	9.28	12.79	11.07	1.00
	Turkey	21	3.04	5.79	4.41	0.82
	Turkmenistan	16	15.26	19.79	17.58	1.69
	UAE	21	9.63	15.91	12.88	1.65
	Uzbekistan	16	1.64	3.43	2.71	0.46
	Viet Nam	20	13.52	35.45	22.20	7.76
	Yemen	21	5.18	9.72	6.91	1.29
	all	862	0.12	35.45	10.57	6.65

Source: the authors own calculations.

Appendix

Estimating Markups using Entropy Econometrics

The generalized maximum entropy (GME) strategy applied in this research shares similarities to the one applied in (Rodriguez del Valle and Fernandez-Vazquez, 2023) for the estimation of market power at the industry level. It is based on the estimators proposed in (Golan et al., 1996) and (Golan and Vogel 2000). The GME estimator reparametrizes the element of a typical linear regression $y = X\beta + u$ in terms of probability distributions. Each element of the vector of parameters $\boldsymbol{\beta}$ is assumed to be a discrete random variable with

Table 9
Summary statistics of upstreamness, disaggregated by country.

Variable	Country	n	Min	Max	$\bar{x}$	s
Upstreamness	Afghanistan	21	2.09	2.38	2.25	0.08
	Armenia	16	3.34	6.75	4.50	1.22
	Azerbaijan	16	2.94	3.91	3.39	0.31
	Bahrain	21	2.30	3.14	2.61	0.31
	Bangladesh	21	3.13	3.84	3.51	0.16
	Bhutan	21	2.38	2.96	2.67	0.17
	Brunei	21	3.06	3.77	3.42	0.23
	Cambodia	21	2.55	2.99	2.82	0.12
	China	21	2.14	2.42	2.28	0.08
	Cyprus	21	2.57	3.07	2.80	0.14
	Georgia	16	1.63	1.74	1.68	0.04
	India	21	1.59	1.84	1.72	0.10
	Indonesia	21	1.81	2.05	1.99	0.05
	Iran	21	1.68	1.77	1.74	0.03
	Iraq	21	1.23	1.87	1.53	0.19
	Israel	21	1.99	2.29	2.17	0.10
	Japan	21	2.03	2.14	2.09	0.03
	Jordan	21	2.82	4.34	3.30	0.47
	Kazakhstan	16	2.09	2.66	2.34	0.19
	Kuwait	21	1.13	1.27	1.19	0.04
	Kyrgyzstan	16	1.70	2.18	1.90	0.12
	Laos	21	3.00	3.50	3.29	0.15
	Lebanon	21	2.01	2.27	2.10	0.06
	Malaysia	21	1.61	2.11	1.98	0.15
	Maldives	21	2.63	3.34	2.92	0.17
	Mongolia	21	3.07	3.97	3.42	0.22
	Myanmar	21	3.52	27.93	6.11	6.35
	Nepal	21	2.21	2.41	2.32	0.06
	Oman	21	2.40	2.51	2.45	0.03
	Pakistan	21	2.50	2.79	2.65	0.08
	Philippines	21	1.75	2.06	1.83	0.06
	Saudi Arabia	21	2.11	3.09	2.55	0.33
	South Korea	21	1.97	2.32	2.18	0.10
	Sri Lanka	21	2.62	2.94	2.78	0.10
	Syria	21	3.69	6.74	4.37	0.87
	Tajikistan	16	1.99	2.30	2.15	0.10
	Thailand	21	2.37	2.74	2.59	0.11
	Turkey	21	1.47	1.61	1.53	0.03
	Turkmenistan	16	2.15	2.59	2.33	0.13
	UAE	21	2.05	2.64	2.24	0.18
	Uzbekistan	16	2.11	2.36	2.26	0.07
	Viet Nam	20	1.69	2.16	1.97	0.12
	Yemen	21	2.96	6.97	4.30	0.75
	all	862	1.13	27.93	2.61	1.37

Source: the authors own calculations.

Table 10
Summary statistics of Foreign Added and Upstreamness, disaggregated by the current income group.

Variable	Income Group	n	Min	Max	$\bar{x}$	s
Foreign VA	H	180	4.19	24.15	14.00	5.09
	L	245	0.16	30.45	8.27	5.76
	LM	293	0.12	35.45	9.56	6.95
	UM	144	2.46	30.90	12.25	7.05
	all	862	0.12	35.45	10.57	6.65
Upstreamness	H	180	1.13	3.77	2.34	0.61
	L	245	1.59	27.93	2.97	2.20
	LM	293	1.23	6.74	2.65	0.96
	UM	144	1.47	3.34	2.26	0.49
	all	862	1.13	27.93	2.61	1.37

Source: the authors own calculations.

Table 11
Summary statistics of Foreign Value Added and Upstreamness disaggregated by year.

Variable	Year	n	Min	Max	$\bar{x}$	s
Foreign VA	1995	35	1.18	30.90	10.31	7.52
	1996	35	1.09	29.01	10.08	6.60
	1997	35	1.18	26.02	10.24	6.19
	1998	35	1.22	23.03	10.13	6.02
	1999	35	1.00	22.88	9.83	5.99
	2000	43	0.82	23.19	10.09	6.11
	2001	43	0.77	22.70	9.82	5.71
	2002	43	0.54	23.13	9.79	5.70
	2003	43	0.62	24.93	10.12	5.78
	2004	43	0.56	27.18	10.73	6.35
	2005	43	0.49	28.04	10.64	6.49
	2006	43	0.40	27.41	10.92	6.82
	2007	43	0.30	28.73	11.22	7.31
	2008	43	0.23	30.45	11.30	7.40
	2009	43	0.17	27.86	10.28	6.86
	2010	43	0.17	35.45	11.02	7.62
	2011	42	0.16	27.89	11.26	6.90
	2012	43	0.16	34.80	11.64	7.67
	2013	43	0.16	34.32	11.53	7.55
	2014	43	0.16	27.72	10.79	6.87
	2015	43	0.12	26.99	9.81	6.46
	all	862	0.12	35.45	10.57	6.65
Upstreamness	1995	35	1.14	22.02	3.20	3.49
	1996	35	1.15	27.93	3.39	4.41
	1997	35	1.15	4.82	2.59	0.85
	1998	35	1.13	4.96	2.54	0.86
	1999	35	1.13	4.49	2.50	0.75
	2000	43	1.16	5.79	2.52	0.80
	2001	43	1.15	6.75	2.64	1.03
	2002	43	1.16	6.51	2.62	1.00
	2003	43	1.17	5.83	2.60	0.92
	2004	43	1.18	5.42	2.59	0.85
	2005	43	1.20	4.90	2.58	0.80
	2006	43	1.22	4.89	2.57	0.77
	2007	43	1.23	4.33	2.56	0.72
	2008	43	1.23	4.42	2.56	0.72
	2009	43	1.21	4.44	2.53	0.73
	2010	43	1.23	4.49	2.54	0.74
	2011	42	1.27	4.44	2.56	0.74
	2012	43	1.26	4.38	2.54	0.74
	2013	43	1.23	4.39	2.54	0.75
	2014	43	1.21	4.27	2.46	0.73
	2015	43	1.21	4.17	2.43	0.70
	all	862	1.13	27.93	2.61	1.37

Source: the authors own calculations.

$M \geq 2$ possible realizations. These potential values of the unknown parameter are included in a support vector $\mathbf{b}'_{\mathbf{h}} = b_{h1}, ..., b_{hM}$ with corresponding –-unknown– probabilities $\mathbf{p}'_{\mathbf{h}} = (p_{h1}, ..., p_{hM})$ and each parameter β_h is specified as follows:

$$\beta_h = \mathbf{b}'_{\mathbf{h}}\mathbf{p}_{\mathbf{h}} = \sum_{m=1}^{M} b_{hm}p_{hm};\ h = 1, ..., H \tag{4a}$$

A similar approach is followed for the random disturbances. Although GME does not require specific assumptions about the probability distribution function of the noise term, some assumptions are necessary. First, the uncertainty about the realizations of this element is addressed by treating each element u_i as a discrete random variable with $J \geq 2$ possible outcomes contained in a convex set $v' = v_1, ..., v_J$ which, for the sake of simplicity, will be common for all the realizations of the random disturbance u_t. Second, we also assume that these possible outcomes of the random disturbance are symmetric and centered on zero ($-v_1 = v_J$). As a result, $\mathbf{u}$ has mean $E[\mathbf{u}] = 0$ and a finite covariance matrix $\boldsymbol{\Sigma}$. Additionally, it is common practice to establish the upper and lower limits of the vector v applying the three-sigma rule (see (Pukelsheim 1994)). Under these conditions, the value of the random term for an observation i equals:

$$u_i = \mathbf{v}'\mathbf{w}_{\mathbf{i}} = \sum_{j=1}^{J} v_j w_{ij};\ i = 1, ..., n \tag{5}$$

This specification of the original model transforms the estimation of the coefficients of the regression equation into the estimation of probability distributions. At this point, the principle of Maximum Entropy (ME) is used to recover unknown probability distributions of discrete random variables that can take M different values. Specifically, ME estimates $\widehat{\mathbf{p}}$ by maximizing the Shannon Entropy measure (see (Shannon 1948)) $E(\mathbf{p})$:

$$\max_{\mathbf{p}} E(\mathbf{p}) = \sum_{m=1}^{M} p_m \ln(p_m) \tag{6}$$

$E(\mathbf{p})$ achieves a maximum when all the M values are equally probable –-i.e., $\mathbf{p}$ is uniform–. However, if some additional data are available, the uniform distribution could not be a reasonable estimate if it fails to generate the observed data. Therefore, a reasonable approach is to use as an estimate the probability distribution closer to the uniform that can generate the observed data. In other words, the probability distribution that maximizes the Entropy measure is subject to being able to generate the observed data. The underlying idea of the ME methodology can be applied to recovering the parameters of the re-parameterized equation $y = X\beta + u$, defining the GME estimator. Matrices $\mathbf{P}$ and $\mathbf{W}$ are estimated by maximizing the entropy function $E(\mathbf{P}, \mathbf{W})$, subject to consistency with the sample and normalization (i.e., non-negativity and unitary sums) constraints.

In addition, the following basic assumptions guarantee consistency and asymptotically normality (see, (Golan et al., 1996), p. 96–100):

1. The support for the errors $\mathbf{v}'$ is symmetric around zero.
2. The support space $\mathbf{b}'$ bounds the true value of each one of the unknown parameters and it has a finite lower and upper bound b_1 and b_M, respectively.
3. The errors are i.i.d.
4. $\lim_{n\to\infty} n^{-1}\mathbf{X}'\mathbf{X}$ exist and is non-singular.

Under these assumptions, GME estimates distribute as $\widehat{\beta} \rightarrow N[\boldsymbol{\beta}, \widehat{\sigma}^2(\mathbf{X}'\mathbf{X})^{-1}]$ and it is possible to obtain their approximate variance matrix as $\widehat{\sigma}^2(\mathbf{X}'\mathbf{X})^{-1}$. Applying the GME estimator requires the specification of supporting vectors for the parameters and the error terms. The parameters be estimated are the output elasticities α_{it} and β_{it} and the factor productivities Ω_{it}. For the term Ω_{it} we set support vectors with $M = 3$ values ($b_{\Omega m}$) centered at 0 and with bounds at ± 10. For the output elasticities we define supporting vectors with $M = 3$ points ($b_{\alpha m}$ and $b_{\beta m}$ respectively) centered at the corresponding mean value of the shares of variable inputs and the stock of capital, being the limits of these vectors set as these means plus and minus 1 to assure having wide enough supports. Note that this approach implies that in absence of information the GME estimator produces uniform probabilities and the point estimates of the parameters will be equal to the central value in the vectors. Consequently, the uninformative GME solution makes the mean markup μ_{itc} equal to one by construction. In other words, our prior assumption is that there is no market power and only if data contains information that contradicts this initial assumption, the GME estimator will produce a different result. Finally, for the error term in our equations, the usual three-sigma rule applies (Pukelsheim, 1994), setting this support vector centered at 0 with symmetric bounds at ± 3 times the standard deviation of the dependent variable.

Country List and Code

Regression Results

Descriptive Statistics – Markups

Descriptive Statistics – Independent Variables

References

Antràs, Pol, Chor, Davin, Fally, Thibault, Hillberry, Russell, 2012. Measuring the upstreamness of production and trade flows. Amer. Econ. Rev. 102 (3), 412–416. https://doi.org/10.1257/aer.102.3.412.isac.

Baqaee, David, Farhi, Emmanuel, 2017. Productivity and Misallocation in General Equilibrium. Quar. J. Econ.

Barrett, Christopher B., Reardon, Thomas, Swinnen, Johan, Zilberman, David, 2022. Agri-food value chain revolutions in low- and middle-income countries. J. Econ. Lit 60 (4), 1316–1377.

Berry, Steven, Gaynor, Martin, Morton, Fiona Scott, 2019. Do Increasing Markups Matter? Lessons from Empirical Industrial Organization. J. Econ. Perspec. 33 (3), 44–68.

Bonanno, Alessandro, Russo, Carlo, Menapace, Luisa, 2017. Market power and bargaining in agrifood markets: a review of emerging topics and tools. Agribusiness. https://doi.org/10.1002/agr.21542.

Colonescu, Constantin, 2021. Price markups and upstreamness in world input-output data. *Acta. Universitatis. Sapientiae,. Econ. Business* 9 (April), 71–85. https://doi.org/10.2478/auseb-2021-0004.

Corral, P., Kuehn, D., Jabir, E., 2017. Generalized maximum entropy estimation of linear models. Stata. J 17 (1), 240–249. https://doi.org/10.1177/1536867X1701700113.

Creedy, John, Dixon, Robert, 1998. The relative burden of monopoly on households with different incomes. Economica 65 (258), 285–293. http://www.jstor.org/stable/2555148.

De Loecker, Jan, Eeckhout, Jan, 2018. Global market power." NBER working papers 24768. National Bureau. Econ. Res., Inc. https://ideas.repec.org/p/nbr/nberwo/24768.html.

De Loecker, Jan, Eeckhout, Jan, Unger, Gabriel, 2020. The rise of market power and the macroeconomic implications*. Q. J. Econ 135 (2), 561–644. https://doi.org/10.1093/qje/qjz041.

Deconinck, Koen. 2021. "Concentration and market power in the food chain," no. 151. https://doi.org/10.1787/3151e4ca-en.

Dethier, Jean-Jacques, Effenberger, Alexandra, 2012. Agriculture and development: a brief review of the literature. Econ. Syst. 36 (2), 175–205. https://doi.org/10.1016/j.ecosys.2011.09.003.

Diez, Federico J, Leigh, Daniel, Tambunlertchai, Suchanan, 2018. Global market power and its macroeconomic implications." IMF working papers 18/137. Int. Monetary Fund. https://ideas.repec.org/p/imf/imfwpa/18-137.html.

Golan, Amos, Vogel, Stephen J., 2000. Estimation of non-stationary social accounting matrix coefficients with supply-side information. Econ. Syst. Res. 12 (4), 447–471. https://doi.org/10.1080/09535310020003775.

Golan, Amos, Judge, George, Perloff, Jeffrey M., 1996. Estimating the size distribution of firms using government summary statistics. J. Ind. Econ 44 (1), 69–80. http://www.jstor.org/stable/2950561.

Hall, Robert E., Blanchard, Olivier Jean, Glenn Hubbard, R., 1986. Market structure and macroeconomic fluctuations. Brookings Pap. Econ. Act 1986 (2), 285–338. http://www.jstor.org/stable/2534476.

Harilal, K.N., 2021. Globalization of agriculture and atomization of farming: small farms crisis in Asia. Millennial. Asia 12 (3), 298–315. https://doi.org/10.1177/09763996211059964.

Irz, Xavier, Lin, Lin, Thirtle, Colin, Wiggins, Steve, 2001. Agricultural Productivity Growth and Poverty. Alleviation 19 (4), 449–466. https://doi.org/10.1111/1467-7679.00144.

Johnston, Bruce F., Mellor, John W., 1961. The role of agriculture in economic development. Am. Econ. Rev 51 (4), 566–593. http://www.jstor.org/stable/1812786.

Koopman, Robert, Wang, Zhi, Wei, Shang-Jin, 2014. Tracing value-added and double counting in gross exports. Amer. Econ. Rev. 104 (2), 459–494. https://doi.org/10.1257/aer.104.2.459.

Lenzen, Manfred, Kanemoto, Keiichiro, Moran, Daniel, Geschke, Arne, 2012. Mapping the structure of the world economy. Environ. Sci. Technol. 46 (15), 8374–8381. https://doi.org/10.1021/es300171x.

Lenzen, Manfred, Moran, Daniel, Kanemoto, Keiichiro, Geschke, Arne, 2013. Building eora: a global multi-region input–output database at high country and sector resolution. Econ. Syst. Res. 25 (1), 20–49. https://doi.org/10.1080/09535314.2013.769938.

Li, Junpeng, Ma, Wanglin, Gong, Binlei, 2023. Market participation and subjective well-being of maize farmers. Econ. Anal. Policy 80. https://doi.org/10.1016/j.eap.2023.09.037.

Liu, Ernest, Mian, Atif, Sufi, Amir, 2022. Low interest rates, market power, and productivity growth. Econometrica 90 (1), 193–221. https://doi.org/10.3982/ECTA17408.

Lowder, S.K., Skoet, J., Raney, T., 2016. The number, size, and distribution of farms, smallholder farms, and family farms worldwide. World. Dev 87, 16–29.

Miller, Ronald E., Blair, Peter D., 2009. Input-Output Analysis: Foundations and Extensions, 2nd ed. Cambridge University Press. https://doi.org/10.1017/CBO9780511626982.

Miroudot, Sébastien, Ye, Ming, 2022. Decomposing value added in gross exports from a country and bilateral perspective. Econ. Lett. 212, 110272 https://doi.org/10.1016/j.econlet.2022.110272.

Otsuka, Keijiro, Liu, Yanyan, Yamauchi, Futoshi, 2016. The future of small farms in Asia. Develop. Policy. Rev. 34 (3), 441–461. https://doi.org/10.1111/dpr.12159.

Perekhozhuk, Oleksandr, Glauben, Thomas, Grings, Michael, Teuber, Ramona, 2016. Approaches and methods for the econometric analysis of market power: a survey and empirical comparison. J. Econ. Surv. https://doi.org/10.1111/joes.12141 n/a–n/a.

Pukelsheim, Friedrich., 1994. The three sigma rule. Am. Stat 48 (2), 88–91. http://www.jstor.org/stable/2684253.

Rodríguez del Valle, Adrián, Fernández-Vázquez, Esteban, 2023. Estimating market power for the European manufacturing industry between 2000 and 2014. Empirica 50 (1), 141–172. https://doi.org/10.1007/s10663-022-09559-4.

Saitone, T., Sexton, R., 2017. Concentration and consolidation in the US food supply chain: the latest evidence and implications for consumers, farmers, and policymakers. Federal Reserve Bank Kansas. City Econ. Rev.

Sexton, Richard, Zhang, Mingxia, Chalfant, James, 2007a. Grocery retailer behavior in perishable fresh produce procurement. J. Agricul 3. https://doi.org/10.2202/1542-0485.1090 (February): 1090–90.

Sexton, Richard J., Sheldon, Ian, McCorriston, Steve, Wang, Humei, 2007b. Agricultural trade liberalization and economic development: the role of downstream market power, 36 (2), 253–270. https://doi.org/10.1111/j.1574-0862.2007.00203.x.

Shannon, Claude E., 1948. A mathematical theory of communication. Bell. Syst. Tech. J. 27 (3), 379–423. http://dblp.uni-trier.de/db/journals/bstj/bstj27.html#Shannon48.

Syverson, Chad., 2019. Macroeconomics and market power: context, implications, and open questions. J. Econ. Perspec. 33 (3), 23–43. https://10.1257/jep.33.3.23.

Timmer, Marcel P., Dietzenbacher, Erik, Los, Bart, Stehrer, Robert, de Vries, Gaaitzen J., 2015. An illustrated user guide to the world input–output database: the case of global automotive production. Rev. Int. Econ 23 (3), 575–605. https://doi.org/10.1111/roie.12178.

Urzúa, Carlos., 2013. Distributive and regional effects of monopoly power. *Economía. Mexicana. NUEVA. ÉPOCA*. XXII (2), 279–295. https://EconPapers.repec.org/RePEc:emc:ecomex:v:22:y:2013:i:2:p:279-295.

Van der Donckt, Marie, Chan, Philip, Silvestrini, Andrea, 2021. A new global database on agriculture investment and capital stock. Food Pol. 100, 101961 https://doi.org/10.1016/j.foodpol.2020.101961.

Zepeda, Lydia., Food, and Agriculture Organization of the United Nations, 2001. Agricultural Investment and Productivity in Developing Countries /Edited by Lydia Zepeda. Book. Food; Agriculture Organization of the United Nations Rome.

Zheng, Hongyun, Ma, Wanglin, 2023. Impact of agricultural commercialization on dietary diversity and vulnerability to poverty: insights from Chinese rural households. Econ. Anal. Policy 80. https://doi.org/10.1016/j.eap.2023.09.007. Volume.

Chapter 6

Conclusions (English)

The thesis has proposed a new methodology to estimate the markups using macroeconomic data derived from input-output tables. The methodology is sufficiently reliable to produce results comparable to those derived from micro-data in Chapter 3. The methodology is used to derive results for the agriculture industry (or more concretely the Primary Foods Industry) in Chapter 4, producing estimates for 170 countries. This approach is not possible when using micro-economic data. Chapter 5 finds that Global Value Chains and value chain positioning significantly reduce the markups.

Furthermore, a country's political system and economic income classification affect country-wide markups in Asia. Concretely, communist countries (China, Vietnam, and Laos) generally have lower markups relative to other economic systems. Although this might seem advantageous on paper, exceedingly low markups are connected to relatively low levels of technology innovation and change. The paper presented in Chapter 4 shows that regions with predominantly low-income economies, particularly Africa, have considerably high levels of markups. The results should not be understood as Africa having exceedingly high levels of monopolistic power. It may be interpreted that fixed costs in this area are considerably high as explained in Section 2.1.1.

6.1 Methodological limitations (with respect to micro-data)

The methodology presents several notable advantages and a few limitations, which will be explained in more detail in this Section.

Several drawbacks might exist, such as:

- the assumption in input-output economics that each industry is produced by one representative firm. This can bias results in industries with a fat-tailed firm-size distribution i.e. many relatively smaller firms and a few large, dominant firms operating within a market.

- The results derived from macro-data cannot exceed markup estimates using micro-data in terms of precision. Any estimates of markups using micro-data will always be considered as the benchmark.

- product homogeneity. In micro-economic theory, goods within one market might have more market power because of the possibility of product differentiation. Macroeconomic data cannot discern these intricacies.

- the methodology cannot differentiate between product-level shocks, technological or otherwise. It can only capture country-level changes. This may constrain potential avenues of research.

- If the industry being examined within the macro-data is too broad, the results might not be interpretative as too much aggregation has occurred.

6.2 Methodological advantages

There are notable advantages of using the methodology, such as:

- the methodology allows to potentially estimate markups for any industry, and for most countries in the world. For example, the thesis has estimated the markup of the Primary Foods Industry for 170 countries.

- ease of calculation. Rather than having to process the data of every firm operating in a market, the methodology allows for a quick estimation using one macro table.

- the methodology avoids the difficulties of classifying a firm into an industry if said firm produces many different types of goods. To give an extreme example, if a firm produces wheels comprising 49% of its revenue, and clothing representing 51%, the micro-economist might be forced to classify the whole firm as producing only clothing. Biases might arise in such situations, as production technologies of two completely different goods are aggregated into one.

- the industrial classification is harmonious and homogeneous. The results between countries may be compared with one another effectively.

- there is no sample attrition i.e. the problem caused by firms entering bankruptcy within the sample and thereby causing bias. In input-output theory, there will always be one or zero "firms" producing output.

- Some input-output tables have data on physical quantities of output, capital, and intermediate inputs. This is the case with the World Input-output Database (see Timmer et al. (2015) for more). This limits the bias caused by pricing.

- the problem of one good having different markups depending on where it is being produced is avoided. This problem arises with large multinational firms, for example, large car firms, producing the same goods in different parts of the world with each having different cost structures.

6.3 Further avenues of research

The methodology opens up brand new fields of research, as it allows to estimate markups for industries that would otherwise not be possible. In particular, it might be interesting to further explore the determinants of the markup for the Primary Foods Industry in poor countries, as this has not been explored adequately to date. As mentioned extensively in Section 5, any structural rigidities in this industry might impede the development of low-income countries.

Capítulo 7

Conclusiones (Español)

La tesis ha propuesto una nueva metodología para estimar los markups utilizando datos macroeconómicos derivados de tablas input-output. La metodología es suficientemente fiable para producir resultados comparables a los derivados de datos microeconómicos en el Capítulo 3. La metodología se utiliza para obtener resultados para la industria agrícola (o más precisamente el sector primario) en el Capítulo 4, produciendo estimaciones para 170 países. Este enfoque no es posible cuando se utilizan datos microeconómicos. El Capítulo 5 encuentra que las Cadenas Globales de Valor y la posición en la cadena de valor reducen significativamente los markups.

Además, el sistema político de un país y la clasificación de ingresos económicos afectan los markups a nivel nacional en Asia. Concretamente, los países comunistas (China, Vietnam y Laos) generalmente tienen markups más bajos en comparación con otros sistemas económicos. Aunque esto podría parecer ventajoso en papel, markups excesivamente bajos están relacionados con niveles relativamente bajos de innovación tecnológica y cambio. El artículo presentado en el Capítulo 4 muestra que las regiones con economías predominantemente de bajos ingresos, particularmente África, tienen niveles considerablemente altos de markups. Los resultados no deben interpretarse como que África tiene niveles excesivamente altos de poder monopolístico. Puede interpretarse que los costos fijos en esta área son considerablemente altos, como se explica en la Sección 2.1.1.

7.1 Limitaciones metodológicas (respecto a los datos micro)

La metodología presenta varias ventajas notables y algunas limitaciones, que se explicarán con más detalle en esta sección.

Pueden existir varios inconvenientes, tales como:

- la suposición en la economía input-output de que cada industria es producida por una empresa representativa. Esto puede sesgar los resultados en industrias con una distribución de tamaño de empresas de cola gruesa, es decir, muchas empresas relativamente más pequeñas y unas pocas empresas grandes y dominantes que operan en el mercado.

- Los resultados derivados de datos macroeconómicos no pueden superar las estimaciones de markups utilizando datos microeconómicos en términos de precisión. Cualquier estimación de markups utilizando datos microeconómicos siempre se considerará como el referente.

- homogeneidad del producto. En la teoría microeconómica, los bienes dentro de un mercado pueden tener más poder de mercado debido a la posibilidad de diferenciación de productos. Los datos macroeconómicos no pueden discernir estas complejidades.

- la metodología no puede diferenciar entre choques a nivel de producto, tecnológicos u otros. Solo puede capturar cambios a nivel de país. Esto puede limitar posibles vías de investigación.

- Si la industria que se examina dentro de los datos macroeconómicos es demasiado amplia, los resultados podrían no ser interpretativos ya que se ha producido demasiada agregación.

7.2 Ventajas metodológicas

Algunas ventajas de la metodología son:

- la metodología permite potencialmente estimar markups para cualquier industria y para la mayoría de los países del mundo. Por ejemplo, la tesis ha estimado el markup de la Industria de Alimentos Primarios para 170 países.

- facilidad de cálculo. En lugar de tener que procesar los datos de cada empresa que opera en un mercado, la metodología permite una estimación rápida utilizando una tabla macro.

- la metodología evita las dificultades de clasificar una empresa en una industria si dicha empresa produce muchos tipos diferentes de bienes. Para dar un ejemplo extremo, si una empresa produce ruedas que comprenden el 49 % de sus ingresos y ropa que representa el 51 %, el microeconomista podría verse obligado a clasificar toda la empresa como productora únicamente de ropa. Pueden surgir sesgos en tales situaciones, ya que las tecnologías de producción de dos bienes completamente diferentes se agregan en uno.

- la clasificación industrial es armoniosa y homogénea. Los resultados entre países pueden compararse entre sí de manera efectiva.

- no hay desgaste de la muestra, es decir, el problema causado por empresas que entran en bancarrota dentro de la muestra y, por lo tanto, causan sesgos. En la teoría input-output, siempre habrá una o ninguna empresa produciendo output.

- Algunas tablas input-output tienen datos sobre cantidades físicas de output, capital e insumos intermedios. Este es el caso de la Base de Datos Mundial Input-Output (ver Timmer et al. (2015) para más detalles). Esto limita el sesgo causado por los precios.

- se evita el problema de que un bien tenga diferentes markups dependiendo de dónde se produzca. Este problema surge con grandes empresas multinacionales, por ejemplo, grandes empresas automotrices, que producen los mismos bienes en diferentes partes del mundo, cada una con diferentes estructuras de costos.

7.3 Futuras avenidas de investigación

La metodología abre nuevos campos de investigación, ya que permite estimar markups para industrias que de otro modo no serían posibles. En particular, podría ser interesante explorar más a fondo los determinantes del markup para la Industria de Alimentos Primarios en países pobres, ya que esto no se ha explorado adecuadamente hasta la fecha. Como se menciona extensamente en la Sección 5, cualquier rigidez estructural en esta industria podría impedir el desarrollo de los países de bajos ingresos.

Bibliography

Ackerberg, D. A., Caves, K., and Frazer, G. (2015). Identification Properties of Recent Production Function Estimators. *Econometrica*, 83:2411–2451.

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

Baqaee, D. and Farhi, E. (2017). Productivity and misallocation in general equilibrium. *Quarterly Journal of Economics*.

De Loecker, J., Eeckhout, J., and Unger, G. (2020). The Rise of Market Power and the Macroeconomic Implications*. *The Quarterly Journal of Economics*, 135(2):561–644.

Diez, F. J., Leigh, D., and Tambunlertchai, S. (2018). Global Market Power and its Macroeconomic Implications. IMF Working Papers 18/137, International Monetary Fund.

Lerner, A. P. (1934). The concept of monopoly and the measurement of monopoly power. *The Review of Economic Studies*, 1(3):157–175.

Levinsohn, J. and Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. Working Paper 7819, National Bureau of Economic Research.

Olley, G. S. and Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6):1263–97.

Rodríguez del Valle, A. and Fernández-Vázquez, E. (2023). Estimating market power for the european manufacturing industry between 2000 and 2014. *Empirica*, 50(1):141–172.

Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R., and de Vries, G. J. (2015). An illustrated user guide to the world input–output database: the case of global automotive production. *Review of International Economics*, 23(3):575–605.