# External Economies of Scale and Dynamic Comparative Advantage*

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**Abstract**

Sector featuring external economies of scale are characterized by potentially large benefits in scaling up the level of production. However, there is scant evidence about the magnitude of such benefits and their potential contribution in affecting countries' comparative advantage. In this paper, I develop a multi-country multi-sector general equilibrium model of trade featuring inter-temporal sector-level externalities. The model highlights the channel linking a sector production size and its productivity, moreover it delivers at the equilibrium a dynamic gravity model of trade that can be empirically tested. I structurally estimate the dynamic scale parameter by exploiting exogenous demand shocks uncorrelated to supply-side determinants of the level of production. Results points at the existence of positive external economies of scale as a source of comparative advantage, with an estimated dynamic scale parameter of 0.18. However, such gains are heterogeneous across industries with some benefitting little from scaling up the production level.

**Keywords:** External economies of scale, dynamic comparative advantage, international demand shocks

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*A district which is dependent chiefly on one industry is liable to extreme depression, in case of a falling-off in the demand for its produce, or of a failure in the supply of the raw material which it uses.*

— Alfred Marshall, *Principle of Economics* (1890)

# 1 Introduction

A key insight in the theory of international trade is that countries tend to specialize in the production and export of those goods in which they are relatively more productive. As formulated by Ricardo (1817), the law of comparative advantage is a powerful predictive tool and received empirical validation in recent years.[1] The international trade literature has provided various mechanisms explaining cross-country productivity differences and their impact on countries' trade patterns.[2] In particular, since the work of Marshall (1890), trade economists have considered the scale of production at the industry level as a source for productivity growth, hence, a potential determinant of comparative advantage.[3] However, despite the anecdotal evidence identifying the so-called scale effect remains challenging, and we have little evidence of its magnitude across industries and countries.

This paper aims to provide a quantitative framework to estimate the role of production scale in determining a country's comparative advantage. To discipline the empirical strategy, I propose a general equilibrium trade model that builds on the most influential works in the structural gravity literature (Anderson, 1979; Anderson and Van Wincoop, 2003). On the demand side, the model features Armington preferences across varieties nested within an industry-level Cobb-Douglas structure. This preference structure allows for origin-specific product differentiation within sectors. On the supply side, production is characterized by

[1] Among others, Bernhofen and Brown (2004) provide evidence of the relationship between prices and trade by exploiting Japan's sudden opening to foreign markets in 1860, which ended 250 years of autarky in the country. Costinot and Donaldson (2012) show that cross-country productivity differences are important for understanding specialization. In particular, they study crops since these are less heterogeneous than standard manufacturing goods and allow them to disentangle the role of productivity from demand-specific determinants.

[2] A long-lasting tradition has investigated the source of relative productivity differences theoretically and empirically. Among others, Dornbusch et al. (1977) study the role of pure technological differences in explaining trade patterns in a general equilibrium model. Eaton and Kortum (2002) and Costinot et al. (2012) generalize their analysis to account for trade frictions and sector-level productivity heterogeneity. Romalis (2004) and Bernard et al. (2007) study the role of cross-country differences in factor endowments and generalize the Heckscher-Ohlin framework to account for trade frictions and firms' heterogeneity. Other important trade determinants consist of differences in institutions' quality (Nunn, 2007; Manova, 2013), differences in the degree of external economies of scale (Grossman and Rossi-Hansberg, 2010; Kucheryavyy et al., 2023), or the presence of non-homothetic preferences (Fieler, 2011).

[3] For an early survey about the role of external economies of scale in determining a country's comparative advantage, see Chipman (1965). Graham (1923) motivates adopting infant industry protection policies as a tool to take advantage of external economies of scale at the industry level. Ethier (1982) provides the theoretical foundation for such intuition by showing that the ex-ante presence of comparative advantage in industries characterized by diseconomies of scale can generate substantial welfare losses. Theoretically, this result occurs when trade takes place between countries that are similar in size and economies of scale are weak in magnitude.

dynamic sector-level economies of scale. This assumption delivers a structural relationship between the level of productivity and the past sector-level scale of production akin to standard gravity models. This assumption is necessary to break the simultaneity between the realized production scale and the productivity level that hinders the identification of this parameter.[4] Since these economies of scale generate positive productivity gains only through an externality effect, firms set prices and quantities as if they were in a perfectly competitive environment.

Using the structure of the model, I build an empirical strategy for estimating the scale elasticity. From the equilibrium conditions, in any sector, idiosyncratic productivity differences simultaneously affect the size of production and total sales to each destination market. Identification requires breaking such simultaneity; I, therefore, exploit an Instrumental Variable (IV) strategy using variation in domestic production stemming solely from its foreign demand. In particular, I exploit a shift-share instrument using initial import shares and variation in aggregate demand over time to identify exogenous shocks. Intuitively, the instrument's validity hinges on the orthogonality between a country's export capability within a sector and its relative change in demand from a destination country. This assumption ensures any observed change in the total quantity produced to be induced by the sectoral scale of production. In a reduced-form exercise, I provide additional estimates for the scale elasticity using the dynamic structure of the model. In the same spirit, identification relies on the orthogonality between past productivity and the current level of demand.

For the baseline exercise, I estimate the scale elasticity for a sample of 21 OECD countries and 26 ISIC Rev. 4 manufacturing industries for which both production and trade data were available. Results show that industry-level economies of scale are present across sectors and positively impact local production. Conservative estimates point to an average scale elasticity of 0.18, with a weak heterogeneity across industries ranging from 0.12 to 0.20. In the second empirical exercise, I extend the analysis to a panel of 40 countries and 25 SITC Rev. 2 manufacturing industries retrieved from Comtrade over the 1986-2015 period. The estimates for the scale elasticity are very close to the first exercise and equal to 0.17. Notably, the IV estimate is roughly half the magnitude of its corresponding OLS estimate, suggesting the existence of the discussed simultaneity bias. Moreover, lagged estimates from the dynamic gravity equation point to a sizable persistence of the effect over time, implying that current shocks to production can have a long-lasting impact on a country's comparative advantage. This finding is significant for understanding how relative productivity evolves across countries and sectors on top of the standard innovation and technology diffusion mechanisms (Hanson et al., 2016; Gaubert and Itskhoki, 2021).

**Related Literature.** This paper contributes to several strands of literature. First, it contributes to the quantitative trade literature employing multi-country, multi-sector Ricardian

[4]The standard identification issue is due to the compatibility assumption. Theoretically, the coexistence of increasing returns, perfect competition, and the simultaneous productivity adjustment to scale lead to a multiplicity of equilibria. For a detailed discussion on this issue, see Kucheryavyy et al. (2023).

models to estimate fundamental elasticities in an international trade setup. Eaton and Kortum (2002) paved the way for quantitative theory through the lenses of Ricardian trade models. Subsequent work has been devoted to extending their framework to incorporate many other features such as non-tradable sectors (Alvarez and Lucas, 2007), multiple sectors (Costinot et al., 2012), input-output linkages (Caliendo and Parro, 2015), non-homothetic preferences (Fieler, 2011).[5] Most of this literature aimed at identifying the trade elasticity and performing welfare analysis in an international trade context (Arkolakis et al., 2012). Relative to this literature, in which production technology is exogenous, this paper introduces sector-level economies of scale arising from the dynamic externality generated by local production. In this setup, the model's structure helps guide the identification strategy of the scale elasticity. The intuition is that trade data inherently contain information about relative costs and could be used to infer productivity differences across countries and sectors, as first discussed in Antweiler and Trefler (2002).

This paper is closely related to two concurrent ones. First, it relates to Kucheryavyy et al. (2023), which provide conditions for the equilibrium existence and uniqueness in a large class of quantitative Ricardian trade models featuring external economies of scale. We depart from their characterization of industry-level scale economies by allowing for dynamic gains. This approach bridges the external economies of scale literature with external learning-by-doing literature. [6] Second, this paper is closely related to Bartelme et al. (2019), which provide parametric restrictions for directly identifying the scale parameter in a multi-sector Ricardian framework featuring external economies of scale. Despite exploiting a similar intuition for the identification strategy, their instrumental variable strategy is driven by a static model, while this paper proposes to take advantage of a dynamic identification setup. Reassuringly, their estimate for the sector-level scale elasticity is quantitatively comparable to the one of this paper. In addition, they perform a welfare analysis to study the optimal industrial policy.

This paper also contributes to the trade literature on the evolution of comparative advantage. Evidence suggests that a country's comparative advantage is far from persistent over time. Levchenko and Zhang (2016) find evidence of a systematic productivity catch-up within countries of less-productive sectors, suggesting that domestic and international technological spillovers might play a non-trivial role in generating the observed patterns of relative productivity growth. Hanson, Lind, and Muendler (2016) document a continuous turnover in top exporting industries across countries. They find evidence that churning in export advantage

[5] For a comprehensive survey of recent extensions of the Ricardian model of trade, see Eaton and Kortum (2012).

[6] For a recent quantitative exploration of external learning-by-doing in the context of post-war Korea, see Choi and Levchenko (2023). Krugman (1987) introduces learning-by-doing in a two-country multi-industry model to study the patterns of trade with dynamic comparative advantage. Redding (1999) extends the analysis to account for dynamic welfare evaluation and identifies conditions for industrial policy to be welfare-improving. In the same spirit, Young (1991) develops a general equilibrium growth model featuring bounded learning-by-doing along with national spillover effects and analyzes the impact of free trade on a country's development. Melitz (2005) analyzes a model of external learning-by-doing and product differentiation to evaluate the welfare effects of trade policy.

is relatively fast, with over half of the top 5% of exporting industries losing their comparative advantage within two decades.

Various mechanisms can be at the core of the aforementioned dynamic processes. Costinot et al. (2016) find evidence that changes in the natural environment are a source of productivity changes. They exploit changes in average temperature around the world induced by climate change to estimate the effect of crops' yields and the patterns of trade. Sampson (2023) focuses on the role of innovation, in particular by highlighting how R&D activities and knowledge spillovers contribute to shaping the cross-country distribution of comparative advantage. Focusing on a historical setup, Juhász (2015) exploits the temporary trade protection imposed by France to England in the nineteen century to explain the subsequent take-off of the cotton industry in the North of France. In particular, she takes advantage of the spatial heterogeneity in the exposure induced by the Napoleonic blockade to claim causality. Such findings are coherent with the idea that industry protection can drive the patterns of production specialization.

Finally, the paper builds on the insights from the empirical economic geography literature for the identification strategy. Among others, Davis and Weinstein (2002) disentangle the role of natural comparative advantage, unrelated to the scale of production, and the scale effect on the evolution of localization of activities. The intuition is that shocks would be followed by a reversion to the mean if economies of scale were unimportant. Most of this literature has studied the role of agglomeration economies within well-defined spatial boundaries such as cities or local labor markets.[7] The presence of agglomeration economies at the regional level can be an important rationale for place-based policies, as shown by Kline and Moretti (2014).[8] In an international trade context, empirical works on the home-market effect have exploited domestic demand shocks to pin down the role of scale (Costinot et al., 2019).[9] In this project, I apply a similar conceptual framework to an international trade context with a focus on externalities at the sectoral level.

**Outline.** The rest of the paper is organized as follows. Section 2 develops the theoretical model and highlights its predictions in linking productivity growth and economies of scale. Section 3 describes the methodology adopted to estimate the theoretical model. Section 4 presents the data. Section 5 discusses the results. Finally, Section 6 concludes.

## 2 A Trade Model with External Economies of Scale

I consider a world economy at a point in time $t$, with a discrete number $N$ of countries indexed by $o$ and $d$, referring respectively to the origin and the destination, and a discrete number $I$ of

[7] For a recent survey, see Combes and Gobillon (2015).

[8] In their evaluation of the long-run effects of the Tennessee Valley Authority's regional development program, Kline and Moretti (2014) estimate the agglomeration elasticity to be around 0.2.

[9] The home-market effect was first discussed by Linder (1961).

sectors indexed by $i$. To keep the notation compact, I abstract from the time notation. I follow Armington (1969) in assuming that varieties within sectors are differentiated by country of origin so that subscript $o$ both represents origin countries and varieties. Each country is endowed with a fixed amount of units of labor, $L_d$, which is assumed to be inelastically supplied, immobile across countries, and perfectly mobile between sectors, such that factor price equalization holds within countries and across industries. Labor is the only factor of production; therefore, total income in country $d$, $Y_d$, is given by the product between the country-level wage rate, $w_d$, and the total supply of labor, $L_d$. I abstract from intertemporal consumption decisions by assuming trade to be balanced at any point in time.

### 2.1 Demand Side

**Preferences.** Preferences are represented by a two-tier utility function. The representative consumer optimizes consumption over a Cobb-Douglas bundle of different sectors taking the following form:

$$U_d = \prod_{i=1}^{I} (C_{id})^{\mu_{id}} , \tag{1}$$

where $C_{id}$ represents total consumption in sector $i$ from country $d$, and $\mu_{id}$ the exogenous sector-specific Cobb-Douglas expenditure share. The second tier of the preference structure is a CES bundle over origin-specific varieties and takes the following form:

$$C_{id} = \left( \sum_{o=1}^{N} \beta_{iod}^{\frac{1}{\sigma_i}} c_{iod}^{\frac{\sigma_i - 1}{\sigma_i}} \right)^{\frac{\sigma_i}{\sigma_i - 1}} , \tag{2}$$

where $c_{iod}$ represents the consumption of variety $o$ in sector $i$ from country $d, \beta_{iod}$ is an idiosyncratic demand shifter incorporating both quality and consumer tastes, and $\sigma_i > 1$ is the sector-level elasticity of substitution between varieties. In particular, the elasticity of substitution determines the trade elasticity, which is given by $1 - \sigma_i$.[10]

To give the intuition about the preferences structure, let us consider a simple two-country and two-sector model. In this example, Belgium and Italy produce and exchange beers and fashion clothes. Consumers in each country allocate a constant fraction of their income on both products and subsequently split such an amount to purchase Belgian and Italian beer and fashion clothes. The Armington assumption ensures that consumers in the two countries perceive beers in Italy and Belgium as different varieties; the same holds for fashion clothes. The general model extends this logic to multiple destinations and sectors.

[10] In this context, the elasticity $\sigma_i$ is the only parameter disciplining the substitution between varieties, implying that consumers substitute domestic and foreign varieties at the same constant elasticity. For a generalization of the demand structure, Feenstra et al. (2014) assume two distinct substitution elasticities, one between varieties produced domestically and one between domestic and foreign varieties, estimating the second higher than the first.

**Demand for Varieties.** Solving the maximization problem of the representative consumer, we can retrieve the Marshallian demand:

$$c_{iod} = \beta_{iod}\mu_{id}Y_d p_{iod}^{-\sigma_i} P_{id}^{\sigma_i - 1}, \tag{3}$$

where $p_{iod}$ is the price of variety $o$ produced in sector $i$ and faced by country $d$ and $P_{id}$ the price index faced by consumers in country $d$ in sector $i$. The latter takes the following form:

$$P_{id} = \left( \sum_{o=1}^{N} \beta_{iod} p_{iod}^{1-\sigma_i} \right)^{\frac{1}{1-\sigma_i}}. \tag{4}$$

The interpretation of equation (3) is standard, demand for any variety should increase when consumers prefer such variety relatively more, $\beta_{\text{iod}}$, when it is cheap, $p_{\text{iod}}$, when they spend a higher share of income on its relative sector, $\mu_{id}$, or when it is relatively expensive to substitute it with other varieties, $P_{id}$.

## 2.2 Production Side

**Technology.** We assume each country $o$ and sector $i$ to be populated by a representative firm competing to acquire both the domestic and foreign markets. Firms incur a shipping cost reflected in the iceberg trade cost $\tau_{od} > 1$, which is interpreted as the quantity of variety $o$ necessary to be produced in order for one unit of product to arrive at the destination market $d$. This implies that the price faced by consumers is given by $p_{iod} = p_{io}\tau_{od}$. We also assume the arbitrage-free condition to hold, $\tau_{od} \leq \tau_{oj}\tau_{jd}$, ensuring that country o cannot serve country $d$ at a cheaper price by funneling the variety through a third country $j$.

In each origin country and sector pair, total output is produced using the following technology:

$$Q_{io} = A_{io}L_{io}E\left(Q_{io}\right), \tag{5}$$

where $A_{io}$ is the standard Ricardian productivity level in origin country $o$ and sector $i$, $L_{io}$ is the amount of labor in country o employed in sector $i$, and $E\left(Q_{io}\right)$ is the additional effect on output determined by the economies of scale in production at the sectoral level. Keeping the notation general, the shape of the scale function $E(\cdot)$ is required to be concave and twice differentiable, such that $E'(\cdot) > 0$ and $E''(\cdot) < 0$.

Sector-level economies of scale are isomorphic to external economies of scale at the firm level. Despite several mechanisms could play a role in generating such externalities, $E\left(Q_{io}\right)$ captures the existence of scale effects without resorting to any specific modeling choice.[11] The representative firm does not take the scale of production into account in the profit

[11] Marshallian externalities can be very different in nature. Puga (2010) identifies three different micro-mechanisms: input market externalities, labor market externalities, and knowledge externalities. The magnitude of the scale effect may vary depending on the simultaneous co-existence of all three mechanisms or, rather, the presence of only one of them.

maximization problem; therefore, factory-gate prices charged for variety $o$ in industry $i$ account only indirectly for the level of externalities. Consumers in destination $d$ will be charged the full price that comprises shipping costs:

$$p_{iod} = \frac{w_o \tau_{od}}{A_{io} E\left(Q_{io}\right)}. \tag{6}$$

The optimal price charged by firms is a function of three components. The sectoral production cost, $w_o/A_{io}$, the bilateral shipping cost $\tau_{od}$, and the efficiency gain driven by the externality, $1/E\left(Q_{io}\right)$. Intuitively, an increase in the production scale puts downward pressure on the equilibrium level of prices.

**Dynamic Economies of Scale.** To make the model amenable for parametric estimation, it is necessary to assign a functional form to the externality function $E\left(Q_{io}\right)$. Building on the insights of Krugman (1987), the scale effect is modeled as a dynamic process generated by expansions in production. Differently from his paper, I assume the externality to be bounded by national boundaries and not spill over to foreign ones. Compared to the classic formulation of external economies of scale, this approach has two advantages. First, it takes into account the dynamic process of productivity growth, which is essential to understand how the comparative advantage of countries evolves over time. Second, it provides a general interpretation of the productivity gains induced by the externality. Such gains can materialize either because of standard Marshallian motives or a learning-by-doing process at the sectoral level.

An important difference between the modeling approach of learning-by-doing and external economies of scale is the role played by total production versus total employment. Choosing production over employment has an important consequence for the later identification strategy and the source of variation exploited. From a modeling point of view, production, and employment are closely linked in standard quantitative trade theory.[12] A more practical aspect concern the availability of production data that the OECD STAN Database provides, which makes the choice of the first over the latter the preferred option.

Since little evidence is available for what concerns the actual parametrization, I follow the literature in assuming an exponential functional form for the scale effect, with $\psi_i$ being the production scale elasticity:[13]

$$E\left(Q_{iot}\right) = Q_{iot-1}^{\psi_i}, \tag{7}$$

with $\psi_i \in (0, 1)$ defining the sector-specific scale elasticity. This intertemporal scale component characterizes the relationship between the current level of gains from scale and the past level of production in the same sector.

[12]This follows immediately from the production technology in equation (5). Under the assumption of a productivity parameter equal to one, production, $Q_{io}$ and employment $L_{io}$ equalize.

[13]Such parametrization is standard in the literature, see among others Krugman (1987), Kucheryavyy et al. (2023), and Bartelme, et al. (2019).

## 2.3 Competitive Equilibrium

**Equilibrium.** In equilibrium, both the labor market and the goods market should clear. In the origin country $o$, total labor demand needs to meet total labor supply, therefore the labor market clearing condition implies:

$$L_o = \sum_{i=1}^{I} L_{io}. \tag{8}$$

For the goods market, the supply of variety $o$ in sector $i$ to destination market $d$ needs to meet its demand. The optimal price and production levels are retrieved by substituting firms' optimal price from equation (6) into the optimal demand in equation (3). Goods market clearing condition implies:

$$q_{iod} = \frac{\beta_{iod}\tau_{od}^{-\sigma_i}\Phi_{io}^{-\sigma_i}}{\sum_{\zeta=1}^{N}\beta_{i\zeta d}\tau_{i\zeta d}^{1-\sigma_i}\Phi_{i\zeta}^{1-\sigma_i}}\mu_{id}Y_d, \tag{9}$$

where :

$$\Phi_{io} = \frac{w_o}{A_{io}Q_{io,-1}^{\psi_i}}. \tag{10}$$

The price parameter, $\Phi_{io}$, measures the competitiveness of firms producing variety $o$ in sector $i$. Firms are more competitive when producing more efficiently, $A_{io}$, when paying lower production costs $w_o$, and when subject to greater gains from the scale of production $Q_{io,-1}^{\psi_i}$.

**Expenditure Shares.** To relate the model to the standard gravity literature, it is possible to define the product between the Marshallian demand and the optimal price level.[14] Total expenditure for variety $o$ in sector $i$ from destination country $d$ reads:

$$X_{iod} = \frac{\beta_{iod}\tau_{od}^{1-\sigma_i}\Phi_{io}^{1-\sigma_i}}{\sum_{\zeta=1}^{N}\beta_{i\zeta d}\tau_{i\zeta d}^{1-\sigma_i}\Phi_{i\zeta}^{1-\sigma_i}}\mu_{id}Y_d. \tag{11}$$

The interpretation of the gravity model is standard. Destination country d's expenditure for variety $o$ in sector $i$ is greater the higher the taste shifter, $\beta_{\text{iod}}$ , the higher the share of total income spent by $d$ in sector $i$, $\mu_{id}Y_d$, the lower the marginal cost of production in origin country $o$ and sector $i, \Phi_{io}$, the lower the trade costs, $\tau_{od}$, and the lower the competitiveness of its competitors.

The expenditure share for variety $o$ can be obtained by dividing the gravity model by the world expenditure on variety $o$ from origin country $o, X_{io} = \sum_{d=1}^{N} X_{iod}$ :

[14] Appendix 6 describes in detail how to use the trade balanced condition to retrieve the standard gravity formula for the total expenditure for variety $o$ in sector $i$ from destination country $d$ as a function of the inward and outward multilateral resistance terms and the economic sizes of the origin and destination countries.

$$\pi_{iod} = \frac{\beta_{iod}\tau_{od}^{1-\sigma_i}}{\sum_{\zeta=1}^{N}\beta_{i\zeta d}\tau_{i\zeta d}^{1-\sigma_i}\Phi_{i\zeta}^{1-\sigma_i}}\frac{\Phi_{io}^{1-\sigma_i}}{X_{io}}\mu_{id}Y_d. \tag{12}$$

**Welfare.** Destination country $d$'s welfare is given by the real expenditure of its consumers, $W_d = Y_d/P_d$. Trade balance implies that total income is entirely spent, therefore the real welfare is given by:

$$W_d = \frac{\sum_{i=1}^{I}\sum_{o=1}^{N} p_{iod}c_{iod}}{P_d} \equiv \frac{w_d L_d}{P_d}, \tag{13}$$

where $P_d$ is the aggregate price index faced by local consumers:

$$P_d = \sum_{i=1}^{I}\left\{\sum_{o=1}^{N}\beta_{iod}\tau_{od}^{1-\sigma_i}\Phi_{io}^{1-\sigma_i}\right\}^{\frac{1}{1-\sigma_i}}. \tag{14}$$

**Dynamic Gravity Model.** In this setup, the novelty stems from the functional form of the competitiveness index in equation (10). As discussed in Appendix 6, we can replace equation (11) in the gravity equation to get a dynamic (or path-dependent) gravity model of trade. Introducing subscript $t$ for the time period, we can express the dynamic gravity equation as:

$$X_{iodt} = \frac{\beta_{iodt}\tau_{odt}^{1-\sigma_i}\left(\frac{A_{iot}}{w_{ot}}\right)^{\sigma_i-1}}{\sum_{\zeta=1}^{N}\beta_{i\zeta dt}\tau_{i\zeta dt}^{1-\sigma_i}\Phi_{i\zeta t}^{1-\sigma_i}}\mu_{idt}Y_{dt}\Pi_{n=1}^{t}\left[\frac{A_{iot-n}}{w_{ot-n}}X_{iot-n}\right]^{\psi_i^n(\sigma_i-1)}. \tag{15}$$

The model conveys an inverse exponential relationship between current and past levels of production, therefore quantitatively the effect is entirely driven by production shock happening more recently in time.[15] This feature breaks the equilibrium indeterminacy curse driven by the interplay between the scale elasticity, $\psi_i$, and the elasticity of substitution, $\sigma_i$.[16] When economies of scale are dynamic, the need to introduce such an assumption is less stringent.

Total export of variety $o$ in sector $o$ at time $t$ is given by summing equation (15) over destination markets $d$ :

$$X_{iot} = A_{iot}^{\sigma_i-1}w_{ot}^{1-\sigma_i}\Lambda_{iot}\Pi_{n=1}^{t}\left[\frac{A_{iot-n}}{w_{ot-n}}\sum_{d=1}^{N}X_{iodt-n}\right]^{\psi_i^n(\sigma_i-1)}, \tag{16}$$

where:

$$\Lambda_{iot} = \sum_{d=1}^{N}\frac{\beta_{iodt}\tau_{odt}^{1-\sigma_i}\mu_{idt}Y_{dt}}{\sum_{\zeta=1}^{N}\beta_{i\zeta dt}\tau_{i\zeta dt}^{1-\sigma_i}\Phi_{i\zeta t}^{1-\sigma_i}}, \tag{17}$$

[15] Because of the scale parameter range, $0 \leq \psi_i \leq 1$, the impact of a production shock taking place with a four-year lag has a marginal contribution close to zero.

[16] Grossman and Rossi-Hansberg (2010) show that in order for a unique equilibrium to exist in a model with external returns to scale, $\psi_i\sigma_i < 1$ needs to hold across sector.

represents the real world demand for variety $o$ in sector $i$ at time $t$. This term becomes particularly relevant in the identification strategy because it allows to exploit a potential exogenous source of variation in past total production in order to underpin the role of scale on the current level of production. The next section will discuss the identification strategy and the estimation procedure at length.

# 3 Model Estimation

Bringing the theory to data requires retrieving the empirical model from the dynamic gravity equation. Conversely to the standard specifications, the model makes explicit the relationships between current and past levels of production, hence highlighting the potential for an omitted variable bias in standard estimation procedures of the gravity model.[17]

I follow Hanson, Lind, and Muendler (2016) by re-expressing the dynamic gravity equation in its log-linear form. For simplicity, I will discuss how to bring this standard model to the data, but I will later consider Poisson Pseudo-Maximum Likelihood (PPML) estimation to account for the presence of zeros and the heteroskedasticity of the error term. The estimating equation becomes:

$$\ln\left(X_{iodt}\right) = k_{iot} + m_{idt} + \sum_{n=1}^{t} \psi_i^n z_{iot-n} + (1-\sigma_i)\ln\left(\tau_{odt}\right) + \ln\left(\beta_{iodt}\right). \tag{18}$$

The first term of the decomposition is the export capability and it summarizes all variety-specific characteristics that affect the export flow from country $o$ in sector $i$ at time $t$. The first structural term is defined as:

$$k_{iot} = (\sigma_i - 1)\ln\left(A_{iot}\right) - (\sigma_i - 1)\ln\left(w_{ot}\right). \tag{19}$$

The second term is the potential demand from country $d$ in sector $i$ at time $t$ and captures the destination market's demand taking into account all the other competitors. The second structural term takes the following form:

$$m_{idt} = \ln\left(\frac{\mu_{idt} Y_{dt}}{\sum_{\zeta=1}^{N} \beta_{i\zeta dt} \tau_{i\zeta dt}^{1-\sigma_i} \Phi_{i\zeta t}^{1-\sigma_i}}\right). \tag{20}$$

The third structural component is the dynamic production contribution and captures the productivity effect induced by the past production level of variety $o$ in sector $i$ on the current level of bilateral trade:

[17] The gravity model is by now considered the workhorse model in the literature of empirical international trade (Head and Mayer, 2013). Dynamic considerations have been kept at the margin of the debate, however, recent evidence suggests that they might play an important for understanding trade flows. See among others Olivero and Yotov (2012).

$$z_{iot-n} = (\sigma_i - 1) \ln \left( \frac{A_{iot-n}}{w_{ot-n}} X_{iot-n} \right). \tag{21}$$

Eventually, the last two terms of the equation, $\ln(\tau_{\text{odt}})$ and $\ln(\beta_{\text{iodt}})$, capture the idiosyncratic demand shifter and the bilateral trade costs respectively, with $\sigma_i - 1 > 0$ being the trade elasticity.

The scale elasticity, $\psi_i$, decays exponentially at a factor $n$. However, this is the result of assuming the dynamic scale parameter to take the exponential functional form. Despite the assumption might not hold generally, the finding of an exponential decay of $\psi_i$ would result in a validation of the assumed structure.

Equation (18) can be estimated in a stochastic setting by allowing for an additive error term capturing any type of measurement error and unaccounted determinants. The log transformation allows to estimate of a linear parametric model:

$$\ln(X_{iodt}) = \delta_{iot} + \delta_{idt} + \sum_{n=1}^{t} \beta_n z_{iot-n} + \ln(\tau_{odt}) + \varepsilon_{iodt}, \tag{22}$$

where $\delta_{iot}$ and $\delta_{idt}$ are directional fixed effects, $\beta_n$ is the sector-level dynamic scale coefficient, and $\tau_{\text{odt}} = \exp\left[\mathbb{X}'_{\text{odt}} \eta_m\right]$ sum up the vector of $m$ covariates, $\mathbb{X}_{\text{odt}}$, related to bilateral trade costs.[18] The error term $\varepsilon_{\text{iodt}}$ can be structurally interpreted as the idiosyncratic demand shock. Nonetheless, the residual might contain additional information due to any misspecification of the model.

Bilateral trade costs, summarized in $\tau_{\text{odt}}$, and past trade flows are directly observed. The elasticity of substitution, $\sigma_i$, is taken from Broda and Weinstein (2006). The demand shifter, $\beta_{\text{iodt}}$, cannot be observed, furthermore, it enters equation (18) both linearly in the fourth term and non-linearly in the potential demand. This is less of a problem if the number of source countries is big enough, in such case the marginal effect of $\beta_{\text{iodt}}$ would be sufficiently small to not pose a threat to the identification strategy.

**Identification.** The identification of the scale elasticity, $\psi_i$, requires additional assumptions. Ricardian productivities, $A_{iot}$, are unobservable to the econometrician and pose an identification challenge. Relying on existing sector-level productivity estimates would not be a choice, in fact, they would confound the pure technological component with externality effects driven by the scale of production. To solve the simultaneity issue, an instrumental variable (IV) strategy leveraging the exogeneity of demand shocks is proposed. In addition to the IV approach, Appendix 6 discusses a reduced form estimation as a robustness check.

[18]CEPII provides a set of time-invariant bilateral trade costs: bilateral distance ($dist$), the sharing of a geographical border ($border$), of the same language ($lang$), of a minority language ($lang9perc$), of colonial linkages in the past ($colony$, $after_45_colonial$) or in the present ($curr_colonial$), of a common colonizer ($comm_colonizer$), being the same country ($same_country$), being in a regional trade agreement ($RTA$). I also rely on time-varying fixed effects to control for bilateral costs.

By manipulating the dynamic gravity model in equation (15), it is possible to express the total trade for variety $o$ in sector $i$ as the product of the export capability at time $t$, the variety real demand at time $t$, and the total size of production at time $t-1$. Mathematically:

$$X_{iot} = (A_{iot}/w_{ot})^{\sigma_i - 1} Q_{iot-1}^{\psi_i(\sigma_i - 1)} \Lambda_{iot}. \tag{23}$$

Total production is made of a supply-specific and a demand-specific component:

$$Q_{iot} = \Phi_{iot}^{-\sigma_i} \sum_{d=1}^{N} \frac{\beta_{iodt} \tau_{odt}^{1-\sigma_i} \mu_{idt} Y_{dt}}{\sum_{\zeta=1}^{N} \beta_{i\zeta dt} \tau_{i\zeta dt}^{1-\sigma_i} \Phi_{i\zeta t}^{1-\sigma_i}} = \Phi_{iot}^{-\sigma_i} \Lambda_{iot}. \tag{24}$$

In fact, while the price parameter $\Phi_{iot}$ summarizes all the information related to the labor market conditions and the industrial structure, $\Lambda_{iot}$ refers to the level of the world's real demand. Being the supply side serially correlated over time, it is possible to exploit the variation from the real demand, $\Lambda_{iot}$, over time to identify the scale parameter, $\psi_i$.

One way to address this issue is to directly construct $\Lambda_{\text{iot}}$. However, this approach comes with the problem of finding appropriate counterparts in the data. Both $\beta_{\text{iodt}}$ and $\mu_{idt}$ are not directly observable, and at best $\tau_{\text{odt}}$ and $\Phi_{\text{iot}}$ would need a first round of estimations. For this reason, I will adopt a structural Bartik shock as an indirect approach to identify demand-driven variations over time.[19] This strategy is adopted to take full advantage of the longitudinal structure of trade data allowing to effectively disentangle supply- and demand-driven shocks. This is an important difference with Bartelme et al. (2019) who exploit a contemporaneous IV strategy to underpin the scale elasticity. For the model previously developed, the Bartik shock has the following form:

$$\Lambda_{iot}^{Bartik} = \sum_{d=1}^{N} W_{iod} \hat{E}_{dt}, \tag{25}$$

where $W_{iod}$ is the beginning-of-the-period share of demand directed to country $o$ in sector $i$ from destination $d$ and $\hat{E}_{dt}$ is destination $d$ expenditure shock. Guided by the theoretical structure of a shift-share of world demand, it is possible to construct the structural counterpart using the dynamic gravity equation. Changes in destination $d$ income, $\hat{Y}_{dt}$, can be used to construct the shift component $\hat{E}_{dt}$, while the remaining ratio to construct the constant share $W_{\text{iod}}$ :

$$\Lambda_{iodt-1} = \frac{\beta_{iodt-1} \tau_{odt-1}^{1-\sigma_i} \mu_{idt-1}}{\sum_{\zeta=1}^{N} \beta_{i\zeta dt-1} \tau_{i\zeta dt-1}^{1-\sigma_i} \Phi_{i\zeta t-1}^{1-\sigma_i}} Y_{dt-1}. \tag{26}$$

Bringing the model to the data, total income can be proxy by GDP, while the measure $W_{\text{iod}}$ needs to be estimated. It is possible to retrieve the ratio component of the previous equation

[19] The Bartik shift-share instrument is a widely applied tool used to isolate demand shocks from supply shocks, it has been shown to be a reliable instrument to tackle endogeneity, and to be robust to microfoundation. Some notable studies exploiting a shift-share instrument are Card (2001) and Autor, Dorn, and Hanson (2013).

by exploiting a particular odds specification:[20]

$$\frac{X_{iodt-1}}{X_{iot-1}} = \frac{\beta_{iodt-1}\tau_{odt-1}^{1-\sigma_i}\mu_{idt-1}Y_{dt-1}}{\sum_{\zeta=1}^{N}\beta_{i\zeta dt-1}\tau_{i\zeta dt-1}^{1-\sigma_i}\Phi_{i\zeta t-1}^{1-\sigma_i}}\left[\sum_{d=1}^{N}\frac{\beta_{iodt-1}\tau_{odt-1}^{1-\sigma_i}\mu_{idt-1}Y_{dt-1}}{\sum_{\zeta=1}^{N}\beta_{i\zeta dt-1}\tau_{i\zeta dt-1}^{1-\sigma_i}\Phi_{i\zeta t-1}^{1-\sigma_i}}\right]^{-1} \equiv \frac{\Lambda_{iodt-1}}{\Lambda_{iot-1}}. \tag{27}$$

Using $X_{iodt-1}/X_{iot-1}$ as a substitute for $\Lambda_{iodt-1}$ has the advantage of not imposing any further assumption, it is immediately available from data on export, and it can be further manipulated to obtain the constant share to plug in the Bartik shock. By defining the variation over time of $Y_{dt}$ as $\hat{Y}_{dt} = \partial \mathrm{Log}\left(Y_{dt}\right)/\partial t$, it is possible to define the weighted idiosyncratic demand shock as follows:

$$\hat{D}_{iodt-1} = \frac{1}{\Lambda_{iot-1}}\frac{\beta_{iodt-1}\tau_{odt-1}^{1-\sigma_i}\mu_{idt-1}}{\sum_{\zeta=1}^{N}\beta_{i\zeta dt-1}\tau_{i\zeta dt-1}^{1-\sigma_i}\Phi_{i\zeta t-1}^{1-\sigma_i}}\hat{Y}_{dt}, \tag{28}$$

where the weight is the inverse of the total world demand $\Lambda_{iot-1}$. Eventually, it is possible to sum up the weighted idiosyncratic demand shocks across all destinations to obtain a measure of the world demand shock:

$$\hat{D}_{iot-1} = \frac{1}{\Lambda_{iot-1}}\sum_{d=1}^{N}\frac{\beta_{iodt-1}\tau_{odt-1}^{1-\sigma_i}\mu_{idt-1}}{\sum_{\zeta=1}^{N}\beta_{i\zeta dt-1}\tau_{i\zeta dt-1}^{1-\sigma_i}\Phi_{i\zeta t-1}^{1-\sigma_i}}\hat{Y}_{dt}. \tag{29}$$

Equation (29) is the structural shift-share that can be used to instrument the change in the production level over time, $\hat{Q}_{iot}$. To avoid the risk of introducing a simultaneity bias, the share adopted for the estimation will be lagged by three periods.[21] The exclusion restriction requires no autocorrelation in demand for a specific industry located in a certain country. This can be potentially problematic if demand from one destination country is large enough to account for the largest fraction of a variety's sales. The concern is attenuated if a large panel of countries is taken into consideration and various demand shocks occur each year. The data section will provide information about the degree of world trade coverage exploited for the identification.

Finally, the shift-share instrument adopted in the empirical analysis is given by:

$$\hat{B}_{iot} = \frac{1}{\Lambda_{ist-3}}\sum_{d=1}^{N}\frac{\beta_{isdt-3}\tau_{sdt-3}^{1-\sigma_i}\mu_{idt-3}}{\sum_{\zeta=1}^{N}\beta_{i\zeta dt-3}\tau_{i\zeta dt-3}^{1-\sigma_i}\Phi_{i\zeta t-3}^{1-\sigma_i}}\hat{Y}_{dt}. \tag{30}$$

This measure is used in the first stage of a 2SLS estimation to capture the variation of production over time that comes from the world demand. The second step aims at estimating the elasticity $\psi_i$ associated with a change in the predicted production variation, $\tilde{Q}_{iot}$, on the change in the aggregate export variation for variety $o$ in sector $i$, $\hat{X}_{iot}$.

[20] See Head and Mayer (2013) for a discussion about the use of odds specification in a gravity model setup.

[21] The long time span of the database is such to reduce estimation problems induced by the Nickell bias.

# 4 Data

Data are collected from different sources. The United Nations Statistics Division Database on Commodity Trade (Comtrade) provides bilateral trade flows for the period between 1986 and 2015. Product classification is based on the Standard International Trade Classification (SITC), revision 2, at the 2-digit level. This level of disaggregation broadly identifies industries, which are reported in Appendix 6. I consider import value, which are of the CIF (cost, insurance, and freight) type.[22] Following Hanson, Lind, and Muendler (2016), I introduce a set of restrictions on the choice of the sample of importers and exporters. First, it is required that destination countries import a product in all years so that coefficients on exporting-industries dummies are comparable over time. Second, it is necessary to consider only exporters shipping to overlapping groups of importing countries, in order to correctly identify destination-industries dummies. Overall, this strategy ensures that all importer and exporter fixed effects are separately identified. Combined, these restrictions leave 85 exporters, 55 importers, and 52 industries, which account for 85% of overall world trade in the same period. This one is the sample used to estimate the baseline dynamic gravity equation.

Data for gravity control variables are retrieved by CEPII and consist of a set of dummy pair variables on the adjacency of the countries, the share of a common language, and the existence of a colonial relationship. Egger and Larch (2008) provide data on regional trade agreements (RTA, hereafter) for the same period. In such a database RTAs are defined according to four different, not mutually exclusive, classes: free trade agreements (FTA), customs unions (CU), economic integration agreements (EIA), and partial scope agreement (PS), the subsequent gravity trade estimation will take into account only the existence of any of these different agreements between any two countries. The industry-specific elasticities of substitution, $\sigma_i$, are taken from Broda and Weinstein (2006).

For implementing the IV strategy, I rely on the OECD Structural Analysis (STAN) Database that allows to match production and trade data at the sector level. STAN data used in the analysis span a period between 1990 to 2015 and are based on the International Standard Industrial Classification of all economic activities (ISIC), revision 4. For such a dataset, I use free on board (FOB) export trade data, this choice is justified by the fact that I can perform the estimation only on a small sample of exporters,[23] for which both trade and production data are available. Similarly to what done for the Comtrade database, a restriction will be imposed on exporters and importers, overall will be considered 23 exporters, 68 importers, and 26 industries, more information can be found in Appendix 6.

[22] For the sample of countries considered, I aggregate pre- and post-unification German trade data, and Belgium and Luxembourg in order to uniquely identify the gravity-type controls that are aggregated over the two countries

[23] The subsample of OECD countries is composed by: Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Italy, Japan, Latvia, Mexico, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Sweden, Switzerland, and United States.

# 5 Results

## 5.1 Baseline Estimation

Turning to the estimation of scale elasticities $\psi_i$, let us start by considering the OLS results for the baseline estimation. As discussed in Section 1.3, the baseline specification relies on trade and production data from the OECD Structural Analysis. This dataset allows to take advantage of the relationship between the industry-level production size and exports, as expressed in equation (23). In particular, the empirical model on which to focus reads:

$$\text{Log}\left(X_{iot}\right) = \beta_1 \text{Log}\left(\tilde{Q}_{iot}\right) + \delta_{it} + \varepsilon_{iot}, \tag{31}$$

where $\text{Log}\left(X_{\text{iot}}\right)$ defines the export level in Log for the origin country $o$ and industry $i$ at time $t$, $\text{Log}\left(Q_{iot}\right)$ the logarithm of the product between the production level for origin country $o$ and industry $i$ at time $t$, $Q_{iot}$, and the trade elasticity $(\sigma_i - 1)$. Finally, $\delta_{it}$ defines an industry-time fixed effect and $\varepsilon_{iot}$ the error term.

As previously highlighted, we expect the magnitude of the coefficient $\beta_1$ to be greater in the OLS specification due to the compounding effect of past production levels on the current level of productivity. The bias will be accounted for in the instrumental variable strategy. A second aspect to consider is the presence of zeros in trade data. To correct for potential biases, a Poisson Pseudo Maximum-Likelihood (PPML) estimation is proposed. The empirical model to estimate reads:

$$X_{iot} = \exp\left[\beta_1 \text{Log}\left(\tilde{Q}_{iot}\right) + \delta_{it}\right] \times \varepsilon_{iot}, \tag{32}$$

where the export level for the origin country $o$ and industry $i$ at time $t$, $X_{\text{iot}}$, can take any non-negative value.

Column (1) of Table 1 reports the coefficient for the average scale elasticity using the LSDV estimation. Column (2) reports the point estimate for the Poisson-Pseudo Maximum Likelihood (PPML) estimation. The coefficient is significant at the 1% and in the neighbor of 0.3 across specifications. An important limitation of this exercise is the impossibility of accounting for origin-sector-time fixed effects. Such a component would capture the outward multilateral resistance term in the gravity literature. In this setup, however, its introduction would confound the estimation of $\beta_1$. This issue is addressed by using the instrumental variable as described in Section 3.

**Instrumental Variable Strategy.** Moving to the instrument variable specification, the 2SLS scale elasticity is identified by estimating the dynamic counterpart of equation (31). In particular, the dynamic empirical model reads:

$$\hat{X}_{iot} = \beta_1 \hat{Q}_{iot} + \delta_{it} + \varepsilon_{iot}, \tag{33}$$

**Table 1:** Baseline Estimation, Reduced Form

| | $\text{Log}(X_{iot})$ | $X_{iot}$ |
|---|---|---|
| | LSDV | PPML |
| | (1) | (2) |
| $\text{Log}(Q_{iot-1})$ | $0.30^{***}$ | $0.28^{***}$ |
| | (0.03) | (0.04) |
| Source × Time FE | ✓ | ✓ |
| Observations | 14.352 | 14.950 |
| KP F-stat | 57.54 | × |

*Note*: The table reports Least Square Dummy Variable (LSDV) and Poisson Pseudo Maximum-Likelihood (PPML) estimates for the dynamic gravity model using volumes of production. The dependent and independent variables are expressed in log changes and represent the growth in total export and total production for the origin country $o$ in sector $i$, respectively. Values equal to zero have been included only in the specification in column (2). Column (1) is estimated using the Stata command reghdfe, developed by Correia (2016), while column (2) using poi2hdfe, developed by Guimarães (2014). Standard errors are clustered at the industry-source level and are reported in parentheses. $^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.10$.

where $\hat{X}_{iot}$ defines the export growth in log-difference for the origin country $o$ and industry $i$ at time $t$, $\hat{Q}_{iot}$ the product between the production growth in log-difference for origin country $o$ and industry $i$ at time $t$ and the trade elasticity $(\sigma_i - 1)$. Again, $\delta_{it}$ is the industry-time fixed effect and $\varepsilon_{iot}$ the error term. The 2SLS implies instrumenting $\hat{Q}_{iot}$ with the shift-share, $\hat{B}_{\text{iot-1}}$, in equation (30).

Table 2 reports the first and second stages of the 2SLS estimation. Column (1) shows a very strong first stage with a KP F-statistics larger than the usual threshold of 10. Column (2) reports the average scale elasticity $\psi$, which is significant at the 1% and equal to 0.18.

First, it is reassuring to obtain a 2SLS coefficient smaller than the OLS one, as the theory would predict. Importantly, the impact remains statistically significant and sizable. To gauge the magnitude of the effect, it is possible to compare the estimated coefficient with previous studies. For example, the scale elasticity estimated by Caballero and Lyons (1992) using US manufacturing micro-level data takes an average value of 0.15. A much smaller coefficient of 0.06 is estimated in Basu and Fernald (1997). Closely comparable to this paper are the coefficients from Antweiler and Trefler (2002) and Bartelme et al. (2019) both estimated using international trade data. The first work provides a very low estimate of 0.05, while the second an average value of 0.17, in line with this paper.

Table 2: Baseline Estimation, 2SLS

| | $\hat{Q}iot$ | $\hat{X}iot$ |
|---|---|---|
| | I Stage 2SLS | II Stage 2SLS |
| | (1) | (2) |
| $\hat{Q}iot$ | | 0.18*** |
| | | (0.08) |
| $\hat{B}iot-1$ | 7.32*** | |
| | (1.43) | |
| Source × Time FE | ✓ | ✓ |
| Observations | 14.352 | 14.352 |
| $R^2$ | 0.81 | × |

*Note*: The table reports the first and second stages of the estimated static gravity model using volumes of production. 2SLS is estimated using the STATA command ivreg2. Klainbergen-Paap (KP) F-statistics is reported. Standard errors are clustered at the industry-source level and are reported in parentheses. Figure B.1 in Appendix 6 shows the scatter plot of the first stage. *** p < 0.01, ** p < 0.05, * p < 0.10.

**Heterogeneity.** Table 2 provides an average coefficient for the scale elasticity. However, from a theoretical viewpoint, different industries should be characterized by different scale elasticities (Ellison et al., 2010). Table 3 reports the estimated scale coefficient from equation (33), breaking down industry by industry. Results are reported at a more aggregated ISIC Rev. 4 level to have a greater predictive power of the instrument. As expected, scale effects range between 0.12 to 0.20, with stronger scale elasticities associated with "Food, Beverage & Tobacco" and "Chemicals & Pharmaceutical". For comparison purposes, these two sectors are ranked among the top in the estimates of Bartelme et al. (2019), along with "Rubber & Plastics".

## 5.2 Robustness

As a robustness exercise, I use the more exhaustive Comtrade data, which allow to have a greater coverage of the world trade data. I use these data to estimate a modified version of equation (18). The empirical model read:

$$\ln\left(X_{iodt}\right) = \delta_{it} + \delta_{idt} + \delta_{odt} + \sum_{n=1}^{t} \psi_i^n Z_{iot-n} + \varepsilon_{iodt}, \tag{34}$$

where $\delta_{it}, \delta_{idt}$, and $\delta_{\text{odt}}$ are respectively the outward multilateral resistance term, the inward multilateral resistance term, and the time-variant bilateral trade cost. The measure $Z_{iot-n}$ summarizes the past production contribution to the current level of production, which allows to estimate the scale elasticity. Note that the outward multilateral resistance term is identified up to the sector-time level, and its introduction implies the same identification issues discussed

**Table 3:** Heterogeneous Effects, 2SLS

| | LSDV | $R^2$ | KP F-stat | Obs. |
|---|---|---|---|---|
| Food, Beverages & Tobacco | 0.19*** | 0.75 | 47.84 | 693 |
| | (0.06) | | | |
| Textiles | 0.15*** | 0.63 | 52.56 | 1,548 |
| | (0.02) | | | |
| Wood & Paper | 0.16*** | 0.76 | 55.74 | 976 |
| | (0.04) | | | |
| Chemicals & Pharmaceutical | 0.19*** | 0.80 | 52.84 | 1,264 |
| | (0.08) | | | |
| Plastics, Metals, Fabricated | 0.18*** | 0.86 | 54.34 | 4,212 |
| | (0.08) | | | |
| Machinery & Equipment | 0.12*** | 0.67 | 57.12 | 1,303 |
| | (0.05) | | | |
| Miscellaneous Manufacturing | 0.15*** | 0.68 | 54.15 | 1,776 |
| | (0.06) | | | |

*Note*: The table reports the baseline model results in equation (33) broken down by industry. for the seven 1-digit SITC Rev.2 aggregate industries. "Coke & Petroleum" manufacturing is omitted due to the lack of sufficient variation for identification. 2SLS is estimated using the STATA command ivreg2. Standard errors are clustered at the industry-source level and are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

for the baseline model. In particular, the model cannot capture idiosyncratic country-level shocks affecting bilateral trade such as changes in trade or industrial policy or the adoption of cross-sector technologies.

Appendix 6 discusses the main assumptions of this reduced-form approach. In a nutshell, the idea is to construct the $Z_{\text{iot}}$ measure by estimating the export capability for each country in the sample. This is accomplished by taking advantage of the standard static gravity model. Equipped with the export capabilities, it is possible to build the measure $Z_{iot-n}$ in equation (21) exploiting observable information on trade data and trade elasticities.

Table 4 displays the point estimates for the average $\psi$ using a LSDV estimation. The coefficient of interest is the one associated with $Z_{\text{iot-1}}$. In Column (1), it takes a value of 0.30, which compares directly to the OLS specification of the baseline specification in Table 1. Introduction additional lags the coefficient stabilizes at 0.17. This suggests that adding more lags increases the precision and reduces the bias under the assumption that the instrumental variable strategy is unbiased.[24]

[24] Table .5, in Appendix 6, reports the estimates for specification in equation (34). However, the source-destination-year fixed effect is able to account for each of the bilateral controls provided by CEPII plus the unobservable ones, making the main robustness exercise the preferred specification. The results for the two models are relatively close.

**Table 4:** Reduced Form Dynamic Gravity Model Estimation

| | $Log(X_{iot})$ | | | |
|---|---|---|---|---|
| | LSDV | | | |
| | (1) | (2) | (3) | (4) |
| $z_{iot-1}$ | 0.30*** | 0.19*** | 0.17*** | 0.17*** |
| | (0.002) | (0.002) | (0.001) | (0.001) |
| $z_{ist-2}$ | | 0.11*** | 0.06*** | 0.05*** |
| | | (0.002) | (0.001) | (0.001) |
| $z_{ist-3}$ | | | 0.07*** | 0.04*** |
| | | | (0.001) | (0.001) |
| $z_{ist-4}$ | | | | 0.05*** |
| | | | | (0.001) |
| Source × Destination × Time FE | ✓ | ✓ | ✓ | ✓ |
| Industry × Destination × Time FE | ✓ | ✓ | ✓ | ✓ |
| Source × Time FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 128,184 | 124,763 | 119,342 | 115,926 |
| Adjusted $R^2$ | 0.55 | 0.63 | 0.67 | 0.70 |

*Note*: The table reports Least Square Dummy Variable estimates for equation (18) using CEPII bilateral controls. Estimation relies on the Stata command **reghdfe** developed by Correia (2016). Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Another important aspect concerns the persistence of the scale effect over time. This result is novel, and the empirical exercise provides evidence of an exponential decay, as the assumption about the functional form would suggest. This should not be considered as a direct test of the exponential effect of external economies of scale, rather, it should be thought of as a validation of the empirical model used to identify such elasticity. A final aspect to consider is that avoiding accounting for the dynamic effects of economies of scale can bias our estimate of its effect. This can be particularly problematic when running industrial or trade policy counterfactual exercises.

# 6 Conclusion

The international trade literature has primarily focused on the nature of comparative advantage from a static perspective. This paper revises and quantifies a potential mechanism that can help explain the observed changes in relative productivity over time, namely dynamic external economies of scale. The first contribution of the paper is to introduce dynamic scale economies to a quantitative Ricardian model of trade featuring three main characteristics: *i* ) Armington differentiation at the industry level, *ii* ) industry-level productivity heterogeneity, and iii) dynamic gains from scaling up industry-level production. In equilibrium, the model delivers a dynamic-augmented gravity trade model characterized by path dependency.

The second contribution of the paper is to provide an identification strategy for the dynamic scale elasticity using aggregate trade and production data without relying on micro-level data as in the standard Industrial Organization literature. Aggregate trade and production data are available for a large number of countries and industries, making it advantageous to replicate this study to estimate economies of scale for specific sectors and countries.

Identification is achieved following two complementary strategies. The first methodology takes advantage of the structure of the model to build a theory-consistent demand-driven Bartik shock. The shift-share is then used to instrument the total production volume and isolate the variation stemming solely from demand. In turn, this variation is used to explain the observed changes in aggregate export levels to identify the productivity gains realized from scaling up production. The second strategy follows a recent literature using gravity models of trade to estimate a country's export capability and then exploit the dynamic features of the model to identify the same scale elasticity. Results show that increasing industry-level production can generate productivity gains of 18% on average, depending on the industry considered. Point estimates are heterogeneous across industries, with scale elasticities ranging between 0.12 and 0.20.

With respect to the IO literature, the main contribution of this paper is a framework to estimate the sector-level scale parameter without using data on output and input. The advantage of using trade rather than production data lies in the availability of the former for a large number of countries and industries. Indeed, it is reassuring that my estimates do not go far from those relying on detailed sector-level production data.

In conclusion, this study contributes to a reviving literature about the role of industrial policy in an open economy. By providing new empirical evidence of the relevance of external economies of scale, considerations should be made concerning the role of the government in favoring long-run growth and reducing misallocation. At the very least, the existence of potential gains from production size should make policymakers reconsider the role of industrial policy among their tools to increase social welfare. A second important aspect concerns the role that sudden changes in international demand conditions might have in generating long-run losses or gains at the national and sectoral levels.

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# Appendix A

## (

)Solving the Model

This section covers the steps required to solve the model. As explained in Section 2, preferences are represented by the following two-tier utility function:

$$U_d = \prod_{i=1}^{I} \left[ \sum_{o=1}^{N} \beta_{iod}^{\frac{1}{\sigma_i}} c_{iod}^{\frac{\sigma_i - 1}{\sigma_i}} \right]^{\frac{\mu_{id}\sigma_i}{\sigma_i - 1}} \qquad \sum_{i=1}^{I} \mu_{id} = 1, \quad \sum_{o=1}^{N} \beta_{iod} = 1, \tag{A.1}$$

where $c_{\text{iodt}}$ represents the consumption of variety $o$ in sector $i$ from country $d$, $\beta_{\text{iodt}}$ is an idiosyncratic demand shifter incorporating both quality and consumer tastes, $\mu_{idt}$ is the Cobb-Douglas expenditure share, and $\sigma_i > 1$ is the sector-level elasticity of substitution between varieties. The budget constraint faced by the representative consumer follows from the balanced trade condition and reads:

$$Y_d \equiv w_d L_d = \sum_{i=1}^{I} \sum_{o=1}^{N} p_{iod} c_{iod}. \tag{A.2}$$

The utility function, $U_d$, is weakly separable. Hence, it is possible to find the optimal demand by applying a two-stage budgeting procedure. Given the Cobb-Douglas structure, the representative consumer devotes a share $\mu_{id}$ of real income to each sector:

$$M_{id} = \frac{\mu_{id} Y_d}{P_{id}}, \tag{A.3}$$

where the price index associated with the bundle of consumption in sector $i$ and destination country $d$ is given by:

$$P_{id} = \left( \sum_{o=1}^{N} \beta_{iod} p_{iod}^{1-\sigma_i} \right)^{\frac{1}{1-\sigma_i}}. \tag{A.4}$$

The lower-tier maximization regards the choice of the sector-level consumption bundle, and it takes into account the income partition derived from the first stage. The problem can be expressed as follows:

$$\max_{\{c_{iod}\}} \left[ \sum_{o=1}^{N} \beta_{iod}^{\frac{1}{\sigma_i}} c_{iod}^{\frac{\sigma_i - 1}{\sigma_i}} \right]^{\frac{\sigma_i}{\sigma_i - 1}} \qquad \text{s.t.} \quad \mu_{id} Y_d - \sum_{s=1}^{N} p_{iod} c_{iod} = 0, \tag{A.5}$$

and it is solved by the following Marshallian demand:

$$c_{iod} = \beta_{iod} \mu_{id} Y_d p_{iod}^{-\sigma_i} P_{id}^{\sigma_i - 1}. \tag{A.6}$$

On the production side, the representative firm in country $o$ and sector $i$ maximizes profits across all destination markets $d$. I follow the standard assumption that firms break even in each market.[25] Therefore, the profit maximization reads:

[25]This assumption rules out the possibility for the industry to compensate for losses in some destination markets by making large profit margins in others.

$$\max_{\{q_{iod}\}} \quad \Pi_{io} = \sum_{d=1}^{N} \left[ p_{iod} q_{iod} - \frac{\tau_{od} w_{ot}}{A_{io} E\left(Q_{io}\right)} q_{iod} \right]. \tag{A.7}$$

The First Order Condition of the profit maximization problem is given by:

$$p_{iod} = \frac{w_o \tau_{od}}{A_{io} E\left(Q_{io}\right)}, \tag{A.8}$$

where the competitiveness index is given by:

$$\Phi_{io} = \frac{w_o}{A_{io} E\left(Q_{io}\right)}. \tag{A.9}$$

At the equilibrium, the labor market clearing condition implies:

$$L_o = \sum_{i=1}^{I} L_{io}. \tag{A.10}$$

The goods market clearing condition implies:

$$q_{iod} = \frac{\beta_{iod} \tau_{od}^{-\sigma_i} \Phi_{io}^{-\sigma_i}}{\sum_{\zeta=1}^{N} \beta_{i\zeta d} \tau_{i\zeta d}^{1-\sigma_i} \Phi_{i\zeta}^{1-\sigma_i}} \mu_{id} Y_d. \tag{A.11}$$

Total expenditure for variety $o$ in sector $i$ from destination country $d$ is obtained by multiplying both sides by the equilibrium level of prices:

$$X_{iod} = \frac{\beta_{iod} \tau_{od}^{1-\sigma_i} \Phi_{io}^{1-\sigma_i}}{\sum_{\zeta=1}^{N} \beta_{i\zeta d} \tau_{i\zeta d}^{1-\sigma_i} \Phi_{i\zeta}^{1-\sigma_i}} \mu_{id} Y_d. \tag{A.12}$$

Using the sector-level balance trade condition, $Y_{io} = \sum_{d=1}^{N} X_{iod}$, and the expression for the variety demand in equation (A.6), we can express the total income generated by origin country $o$ in sector $i$ as:

$$Y_{io} = \Phi_{io}^{1-\sigma_i} \sum_{d=1}^{N} \beta_{iod} \mu_{id} Y_d P_{id}^{\sigma_i - 1}. \tag{A.13}$$

By rearranging the terms, we can define the export capability of origin country $o$ in sector $i$ as:

$$\Phi_{io}^{1-\sigma_i} = \frac{Y_{io}}{\sum_{d=1}^{N} \beta_{iod} \mu_{id} Y_d P_{id}^{\sigma_i - 1}}. \tag{A.14}$$

Replacing equation (A.14) back in equation (A.12), we obtain the standard gravity model of trade:

$$X_{iod} = \left( \frac{Y_{io}}{\Pi_{io}^{1-\sigma_i}} \right) \left( \frac{\beta_{iod} \tau_{od}^{1-\sigma_i} \mu_{id} Y_d}{P_{id}^{1-\sigma_i}} \right), \tag{A.15}$$

where $\Pi_{io}^{1-\sigma_i} = \sum_{d=1}^{N} \beta_{iod} \mu_{id} Y_d P_{id}^{\sigma_i - 1}$ and $P_{id}^{1-\sigma_i}$ define respectively the outward and inward multilateral resistance term. In this setup, a convenient way to express the gravity model is by multiplying both sides of equation (A.12) for the equilibrium price level:

$$X_{iod} = \frac{\beta_{iod}\tau_{od}^{1-\sigma_i}\Phi_{io}^{1-\sigma_i}}{\sum_{\zeta=1}^{N}\beta_{i\zeta d}\tau_{i\zeta d}^{1-\sigma_i}\Phi_{i\zeta}^{1-\sigma_i}}\mu_{id}Y_d. \tag{A.16}$$

In order to compute the equilibrium level for total production at time $t$, it is possible to sum the gravity equation over all destination markets $d$ :

$$Q_{iot} \equiv \sum_{d=1}^{N} \frac{\beta_{iodt}\tau_{odt}^{1-\sigma_i}\Phi_{iot}^{-\sigma_i}}{\sum_{\zeta=1}^{N}\beta_{i\zeta dt}\tau_{i\zeta dt}^{1-\sigma_i}\Phi_{i\zeta t}^{1-\sigma_i}}\mu_{idt}Y_{dt} = \frac{X_{iot}}{\Phi_{iot}}. \tag{A.17}$$

Total production in country $o$, sector $i$, and time $t$ depends on the world demand directed to that variety and the competitiveness of the origin country. By solving recursively equation (A.12) using all past realizations of the output function, we can re-express the equation as follows:

$$\begin{aligned} Q_{iot} &= \frac{A_{iot}}{w_{ot}} X_{iot} \Pi_{n=1}^{t} \left[\frac{A_{iot-n}}{w_{ot-n}} X_{iot-n}\right]^{\psi_i^n} \underbrace{Q_{io0}^{-\psi_i^t}}_{\lim_{t\to\infty}=1}, \\ &= \frac{A_{iot}}{w_{ot}} X_{iot} \prod_{n=1}^{t} \left[\frac{A_{iot-n}}{w_{ot-n}} X_{iot-n}\right]_i^{\psi_i^n}. \end{aligned} \tag{A.18}$$

Equation (A.18) describes the cumulative effect of the scale effect by relating the current level of total production to all previous ones.

# Appendix B

## Reduced Form Estimation

This section describes an alternative identification strategy for the dynamic scale parameter, $\psi_i$. As discussed in Section 3, estimating the dynamic gravity equation requires constructing the dynamic scale measure, $z_{iot-n}$. However, the industry-level productivity level, $A_{\text{iot}}$, cannot be directly observed as it is the case for the average wage rate, $w_{ot}$.

One approach to circumvent the issue is to estimate the export capability by imposing additional assumptions. The main idea is to follow a two-step procedure related to the development accounting exercise proposed by Levchenko and Zhang (2016). At first, using the gravity model to estimate the origin-sector-year fixed effects is possible. In the second step, it is possible to exploit observable data on all the other variables to isolate the true values of the export capability $A_{\text{iot}}/w_{\text{ot}}$. This can be done for all the countries in the database.

The first aspect to consider is that by using fixed effects to estimate the stochastic gravity model, it would not be possible to disentangle the source of variation coming from $A_{\text{iot}}$ and $z_{iot-n}$. Hence, as a first-order simplification, the adopted strategy relies on estimating the country-level productivity parameter $k_{ot}$. In such a reduced-form approach, the latter is equal to:

$$k_{ot} = (\sigma - 1)\ln\left(A_{ot}/w_{ot}\right), \tag{B.1}$$

where $\sigma$ is the average elasticity of substitution across industries. The model allows to jointly estimate $A_{ot}$ and $w_{ot}$ by exploiting a log-linearize version of equation (A.17):

$$\ln\left(X_{iot}\right) = (\sigma_i - 1)\ln\left(A_{iot}/w_{ot}\right) + \ln\left(\Lambda_{iot}\right) + \sum_{n=1}^{t}\psi_i^n z_{iot-n}, \tag{B.2}$$

where:

$$\Lambda_{iot} = \sum_{d=1}^{N}\frac{\beta_{iodt}\tau_{odt}^{1-\sigma_i}\mu_{idt}Y_{dt}}{\sum_{\zeta=1}^{N}\beta_{i\zeta dt}\tau_{i\zeta dt}^{1-\sigma_i}\Phi_{i\zeta t}^{1-\sigma_i}}, \tag{B.3}$$

and:

$$z_{iot-n} = (\sigma_i - 1)\ln\left[\frac{A_{iot-n}}{w_{ot-n}}X_{iot-n}\right]. \tag{B.4}$$

I estimate the log total trade flows by employing Least Square Dummy Variable (LSDV) estimation of the following form:

$$\ln\left(X_{iot}\right) = \delta_{ot} + \delta_{is} + \delta_{it} + \varepsilon_{iot}, \tag{B.5}$$

where $\delta_{ot}$ is the source country-year fixed effect capturing the role played by $A_{ot}/w_{ot}, \delta_{is}$ and $\delta_{it}$ are respectively the sector-year and sector-country fixed effects. A huge part of the variance is hence not captured in such a specification; nonetheless, it is not of importance for the estimation of $\delta_{ot}$ as long as $\epsilon_{iot}$ and $\delta_{ot}$ are orthogonal.

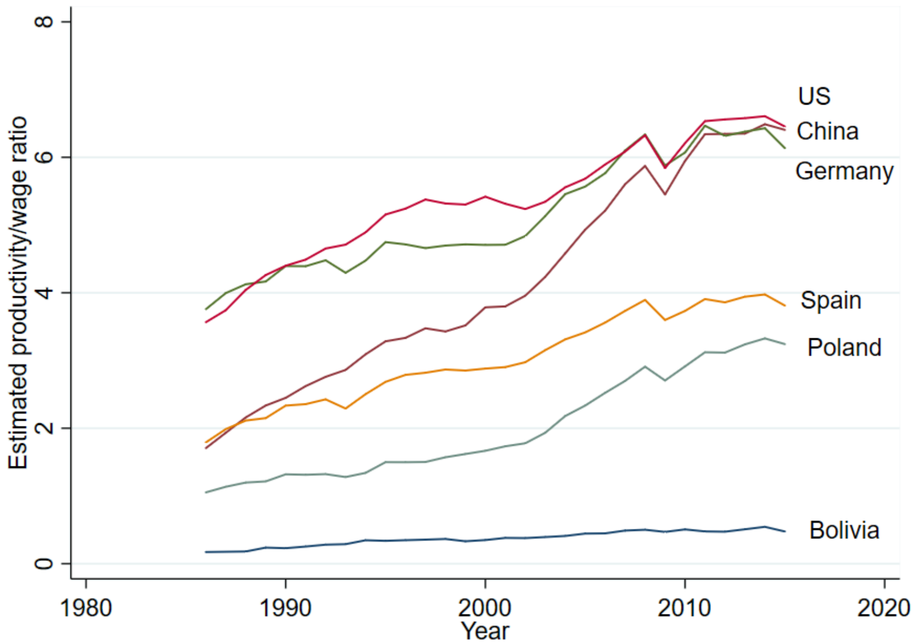
Since fixed effects are identified up to a reference group, for convenience, I will fix the reference to be the US at the beginning of the period. The estimated source country-year fixed effect is hence given by:

$$\delta_{ot} = (\sigma - 1)\frac{\ln\left(A_{ot}/w_{ot}\right)}{\ln\left(A_{USt^{init}}/w_{USt^{init}}\right)}. \tag{B.6}$$

This is very convenient since it is simply possible to correct for the adjusted average elasticity of substitution $(\sigma - 1)$ and the observable term $\ln\left(w_{USt^{\text{init}}}/A_{USt^{\text{init}}}\right)$ to retrieve $\ln\left(A_{ot}/w_{ot}\right)$.[26] With the estimates of $A_{ot}$ and $w_{ot}$ at hand, it is possible to construct the dynamic scale measure $Z_{iot-n}$, for different lagged periods and use it to estimate $\psi_i$.

Figure 1 and Figure 2 report the estimates of $\ln\left(A_{ot}/w_{ot}\right)$ for a small sample of countries. The United States and Germany feature the highest adjusted productivity through the period considered, followed by high-income OECD countries like France and Italy. China is characterized by a surge in adjusted productivity, bringing it to the top at the end of the period. Similar upward trends, but smaller in magnitude, are shared by transition economies of the eastern European block, like Poland and Hungary, and emerging economies like Mexico and the Korean Republic. Eventually, lagging economies of South America and Africa, like Bolivia and Kenya, are found at the bottom of the ranking.

**Figure B.1:** Estimated Productivity/Wage Ratios I, 1986-2015

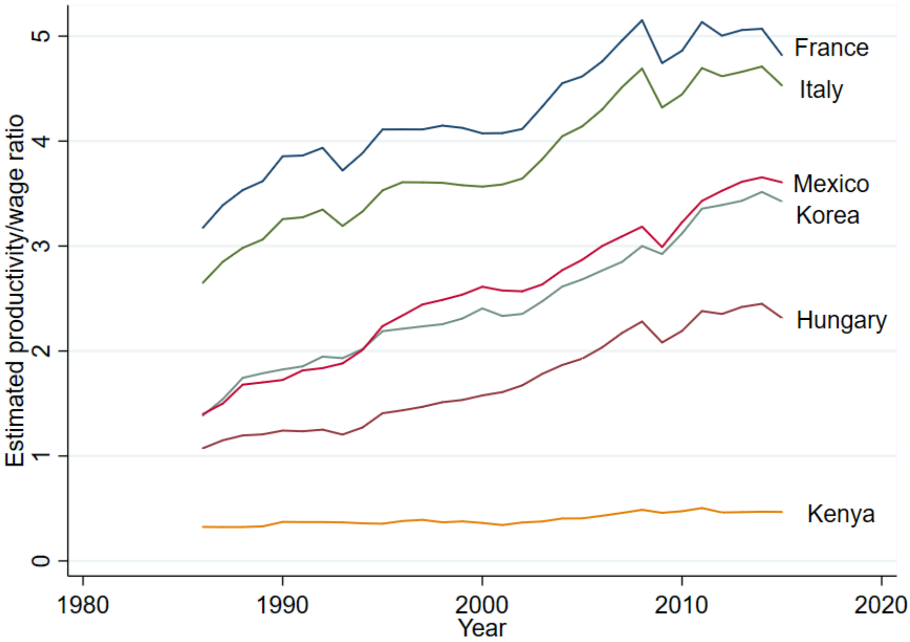



*Notes*: Estimated productivity/wage ratio between 1986 and 2015 for a sample of countries: Bolivia, China, Germany, Poland, Spain, United States. Confidence intervals are omitted for clarity.

Introducing $Z_{iot-n}$ for the estimation requires three additional assumptions. First, it requires $\beta_{\text{iodt}}$ to be uncorrelated with the industry-destination-time fixed effect. This is due to the fact that the real potential demand is inversely related to the idiosyncratic demand shifter. This is a minor issue in this context since the number of source countries $N$ is sufficiently large in the sample, although a country size granularity might prevent the law of large numbers from

[26] In controlling for a country-year fixed effect, I exploit the variation across sectors that prevents identifying the industry-specific elasticity of substitution $\sigma_i$. Nonetheless, the fixed effect will capture the measure of interest weighted by an average of such elasticity.

**Figure B.2:** Estimated Productivity/Wage Ratios II, 1986-2015




*Notes*: Estimated productivity/wage ratio between 1986 and 2015 for a sample of countries: France, Hungary, Italy, Kenya, Mexico, Rep. of Korea. Confidence intervals are omitted for clarity.

holding. Second, it is also necessary to assume orthogonality between $A_{iot}$ and $w_{ot}$ with $\Lambda_{\text{iot}}$ . The third assumption needed is the orthogonality of the country-level productivity and the wages' respective components over time. This third assumption is much stronger, as Figures B.1 and B.2 show.

# Appendix C

## Additional Robustness

**Table .5:** Reduced Form Dynamic Gravity Model Estimation, CEPII Controls

| | $Log(X_{iot})$ | | | |
|---|---|---|---|---|
| | LSDV | | | |
| | (1) | (2) | (3) | (4) |
| $z_{iot-1}$ | 0.29*** | 0.19*** | 0.17*** | 0.16*** |
| | (0.002) | (0.002) | (0.001) | (0.001) |
| $z_{ist-2}$ | | 0.11*** | 0.06*** | 0.05*** |
| | | (0.002) | (0.001) | (0.001) |
| $z_{ist-3}$ | | | 0.07*** | 0.04*** |
| | | | (0.001) | (0.001) |
| $z_{ist-4}$ | | | | 0.05*** |
| | | | | (0.001) |
| Source × Destination × Time FE | ✓ | ✓ | ✓ | ✓ |
| Industry × Destination × Time FE | ✓ | ✓ | ✓ | ✓ |
| Source × Time FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 128,184 | 124,763 | 119,342 | 115,926 |
| Adjusted $R^2$ | 0.55 | 0.63 | 0.67 | 0.70 |

*Notes*: The table reports Least Square Dummy Variable estimates for equation (18) using CEPII bilateral controls. Estimation relies on the Stata command **reghdfe** developed by Correia (2016). Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

# Appendix D

# Tables

**Table .6:** Comtrade Database SITC Rev. 2, 2-digit industries

| Industry (SITC Rev.2) | |
|---|---|
| Dairy products and birds' eggs (02) | Leather, leather manufactures, nes, and dressed furskins (61) |
| Fish, crustacean and molluscs, and preparations thereof (03) | Rubber Manufactures, nes (62) |
| Cereals and cereal preparations (04) | Cork and wood, cork manufactures (63) |
| Vegetables and fruit (05) | Paper, paperboard, and articles of pulp, of paper or of paperboard (64) |
| Sugar, sugar preparations and honey (06) | Textile yarn, fabrics, made-up articles, nes, and related products (65) |
| Coffee, tea, cocoa, spices, and manufactures thereof (07) | Non-metallic mineral manufactures, nes (66) |
| Feeding stuff for animals (not including unmilled cereals) (08) | Iron and steel (67) |
| Miscellaneous edible products and preparations (09) | Non-ferrous metals (68) |
| Beverages (11) | Manufactures of metals, nes (69) |
| Tobacco and tobacco manufactures (12) | Power generating machinery and equipment (71) |
| Crude rubber (including synthetic and reclaimed) (23) | Machinery specialized for particular industries (72) |
| Cork and wood (24) | Articles of apparel, accessories, knit or crochet (73) |
| Textile fibres (not wool tops) and their wastes (not in yarn) (26) | General industrial machinery and equipment, nes, and parts of, nes (74) |
| Crude fertilizer and crude minerals (27) | Office machines and automatic data processing equipment (75) |
| Metalliferous ores and metal scrap (28) | Telecommunications, sound recording and reproducing equipment (76) |
| Crude animal and vegetable materials, nes (29) | Electric machinery, apparatus and appliances, nes, and parts, nes (77) |
| Petroleum, petroleum products and related materials (33) | Road vehicles (78) |
| Fixed vegetables oils and fast (42) | Other transport equipment (79) |
| Animals and vegetables oils and fats, processed and waxed (43) | Sanitary, plumbing, heating, lighting fixtures and fittings, nes (81) |
| Organic chemicals (51) | Furniture and parts thereof (82) |
| Inorganic chemicals (52) | Travel goods, handbags and similar containers (83) |
| Dyeing, tanning, and colouring materials (53) | Articles of apparel and clothing accessories (84) |
| Medicinal and pharmaceutical products (54) | Footwear (85) |
| Oils and perfume materials: toilet and cleansing preparation (55) | Professional, scientific, controlling instruments, apparatus, nes (87) |
| Artificial resins and plastic materials, and cellulose esters etc. (58) | Photographic equipment and supplies, optical goods; watches, etc (88) |
| Chemical materials and products, nes (59) | Miscellaneous manufactured articles, nes (89) |

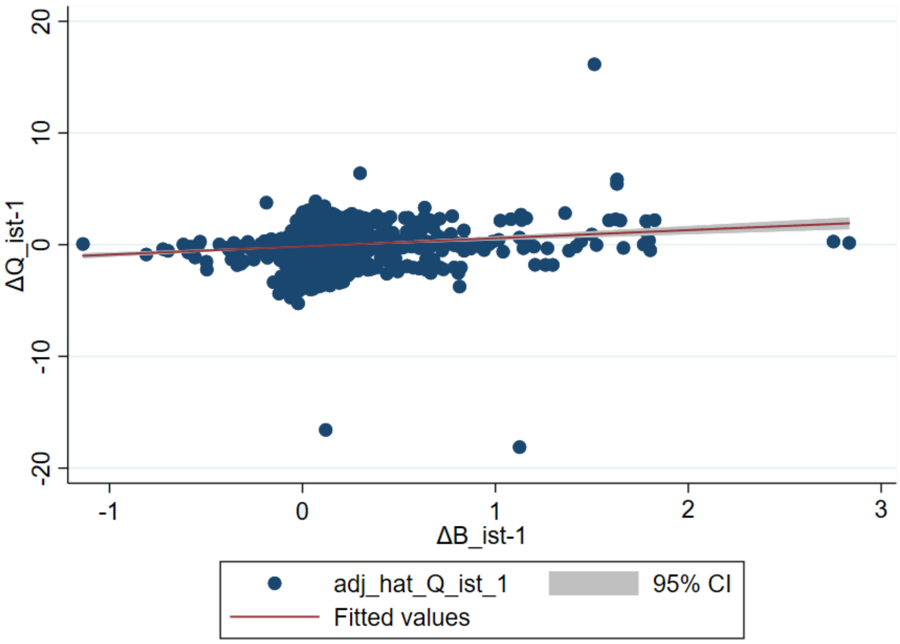
**Table .7:** STAN Database ISIC Rev. 4, 2-digit industries

| Industry | ISIC Rev. 4 |
|---|---|
| Crop and Animal Production, Hunting and Related Service Activities | D01 |
| Forestry and Logging | D02 |
| Fishing and Aquaculture | D03 |
| Manufacturing of Food Products | D10 |
| Manufacturing of Beverages | D11 |
| Manufacturing of Tobacco Products | D12 |
| Manufacturing of Textiles | D13 |
| Manufacturing of Wearing Apparels | D14 |
| Manufacturing of Leather and Related Products | D15 |
| Manufacturing of Wood and Products of Wood | D16 |
| Manufacturing of Paper and Paper Products | D17 |
| Printing and Reproduction of Recorded Media | D18 |
| Manufacturing of Coke and Refined Petroleum Products | D19 |
| Manufacturing of Chemicals and Chemical Products | D20 |
| Manufacturing of Pharmaceutical | D21 |
| Manufacturing of Rubber and Plastic Products | D22 |
| Manufacturing of Other Non-metallic Mineral Products | D23 |
| Manufacturing of Basic Metal | D24 |
| Manufacturing of Fabricated Metal Products | D25 |
| Manufacturing of Computer, Electronic, and Optical Products | D26 |
| Manufacturing of Electrical Equipment | D27 |
| Manufacturing of Machinery and Equipment n.e.c. | D28 |
| Manufacturing of Motor Vehicles, Trailers, and Semi Trails | D29 |
| Manufacturing of Other Transport Equipment | D30 |
| Manufacturing of Furniture | D31 |
| Other Manufacturing | D32 |

# Appendix E

## Figures

**Figure E.3:** First Stage IV Estimation




*Notes*: The figures reports the fitted line derived by regressing the Bartik instrument, $\hat{B}_{iot-1}$, on the volume of production $\hat{Q}_{iot-1}$. The grey band represents the confidence interval at the 95%.