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Essays in International Trade:

Comparative Advantage, Market Power, and Regional Divergence

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"At any rate, the lesson from history seems to be that continued globalization cannot be taken for granted. If its consequences are not managed wisely and creatively, a retreat from openness becomes a distinct possibility."

— *Dani Rodrik, Has Globalization Gone Too Far? (1997)*

Acknowledgements

I remember the 14th of September 2014 as if it was yesterday. That was the day I landed in Belgium for the first time. Moving to the land of frites, bières Trappistes, and Les Diables Rouges, I would have never thought to spend here so many years. Everything felt new and exciting at that time, but I can still recollect that sense of amazement and curiosity in entering the Grand Place of Brussels. I can confidently claim that these two feelings have been a fil rouge of my Ph.D. journey since its beginning six years ago. On the flip side of the coin, however, realizing a Ph.D. thesis is an arduous task, constantly requiring pushing one's boundaries and striving to overcome difficulties.

However, precisely like the magnificence of the Grand Place cannot be merely attributed to the Hôtel de Ville or only to one of the architects that envisioned it, this Thesis should be appreciated keeping in mind the multitude of people that concurred in its realization. A Ph.D. Thesis is a collective endeavor, and I want to do justice to everyone who supported me in its realization. This section is a tribute to my supervisor, professors, colleagues, friends, and family, without whom this Thesis would not have seen the light and that made my Ph.D. a memorable journey.

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Introduction

Recent developments in the global economic landscape have breathed new life into discussions surrounding the benefits and disadvantages generated by trade and economic globalization. Over the decades, the world experienced the partial dissolution of the national borders which generated freer movements of goods, services, people, and capital (Baldwin, 2016). The premise behind these achievements was the collective political effort taking place across international institutions, such as the World Trade Organization (WTO), in pursuing the consolidation of a global economy.

However, *all that glitters is not gold*, and the events that occurred in the last five years have been a wake-up call for policymakers and academics whose efforts have concentrated on exalting the progress and economic gains brought by openness to the world markets. After years of trade liberalizations and tariff reductions, in fact, political discontent culminated in large protectionist and inward-looking policies, with a few iconic examples being the escalation in tariff retaliation between the United States and China, the so-called Trade War, on the one hand, and the withdrawal from the European Union of the United Kingdom, also known as Brexit, on the other.

This backlash against globalization is evocative of a significant degree of malaise that is at odds with the general view of international trade as an engine of prosperity. Despite the enduring doctrine of free trade, certain arguments against it have proven particularly resilient. Among others, these arguments pertain to the effects of trade liberalization on inequality, the dismantling of strategic industries, and the perception of unfairness with respect to large multinationals in choosing, or even setting, the rules of the game (Rodrik, 2021).

This Ph.D. thesis provides a rigorous study of some of the aspects that are particularly relevant in order to understand the distortions and the disadvantages that international trade might generate across countries, regions, and industries. Using modern tools in the field of international trade, namely general equilibrium frameworks and state-of-the-art econometric identifications, the three chapters address some of the challenges that policymakers are confronting and will confront in the coming years when addressing economic globalization.

Chapter 1 provides a framework to study the role of trade in the rise and decline of industries across countries. The theory of comparative advantage provides a rationale for international trade with the idea that countries tend to specialize in making and exporting those products they are relatively good at producing. The international trade literature suggests that among the factors influencing a country's ability to specialize in a specific production industry size should play an important role. The bigger the industry, the more efficient it can become, with large expected productivity gains. However, understanding the magnitude of the so-called "scale effect" has posed substantial challenges and a consensus has not been achieved.

The aim of this chapter is quantify the impact of production scale on a country's comparative advantage by testing a general equilibrium model of trade using cross-country trade data. On the demand side, the model looks at how preferences shape consumption for products from different countries. On the supply side, it considers how industries become more efficient as they grow. This relationship between efficiency and size is key to identifying the "scale effect" at the industry level. The identification is achieved by exploiting exogenous variation in international demand and theory-based instrumental variable strategy to separate the effects of production scale from other factors that might play a role, such as pure technology. Estimating the model using data from different countries and industries allows to obtain robust and comprehensive results.

The results of this research show that production scale does matter. It positively affects how much a country produces locally and exports. On average, for the industries and countries studied, a 10% increase in production scale leads to an 18% increase in local production. Interestingly, when comparing different industries, there is some variation in how much production scale matters. Some industries benefit more from scale than others. When a country experiences a boost in production due to scale, it continues to benefit from it for years to come. This dynamic effect might prove pivotal in thinking about whether and how industrial policy should target an industry. Moreover, this result emphasizes that temporary international shocks can induce long-lasting impacts on industries and their ability to compete globally.

Chapter 2 (co-authored with Catherine Fuss and Lorenzo Trimarchi) analyzes the role played by international competition on firms' market power in the context of the Belgian manufacturing sector. Recent years have witnessed a growing concern about the competitiveness of markets in Europe and the United States. Several studies have shown that big companies have gained more control, and they're charging higher prices, which can have negative effects on businesses and workers.

This study looks at the role of international trade in affecting the ability of firms to dominate markets by focusing on the manufacturing sector of Belgium over the 2000-2015 period. The steady takeover of China in global manufacturing is exploited as a quasi-natural experiment to pin down the impact of increasing competition on market power. Market power in an industry is proxied by the aggregate level of markups charged by firms in that industry, where markups are defined as the wedge between the price charged by firms for their products and the relative marginal cost incurred for their production. According to the standard textbook definition, companies having more market power are able to influence prices and charge higher markups.

Standard international trade theory suggests that, by trading more, countries should increase domestic competition and reduce prices. However, this study finds that when China's imports increased, markups in the affected sectors went up. In fact, Chinese import competition explains a fourth of the increase in prices in the Belgian manufacturing sector. Belgium is an interesting country to study because of its small size and the heavy reliance on international trade. China's rise as a manufacturing powerhouse had a big impact on Belgium, and the study uses detailed data to measure how it affected individual companies.

The study also explores why markups are changing and finds that firms surviving tougher competition are able to increase their market share in the long run and take advantage of a less competitive environment. Additionally, the study looks at how the competition shock affects firms' productivity. Surprisingly, in this respect, the impact is very small which suggests that the experienced increase in market power is not supply-driven as it is found for the United States. Therefore, even though markups are going up, companies are not becoming more efficient.

In Chapter 3 (co-authored with Gonzague Vannoorenberghe and Florian Mayneris), we explore the determinants of the regional divide between urban and rural areas in France between 1995 and 2015. In the experience of the layman, a sizable gap has grown in terms of job opportunities and wages between big cities and smaller towns. Such a divide is believed to have fueled populist movements and political divisions in various countries, like the U.S., the U.K., and France. Various explanations have been put forward, like the role played by globalization, automation, and new technologies that have transformed the job market. However, the idea that these fundamental changes might have weakened the economic connections between different regions, leaving some places behind while others thrive, is held among many, but no formal test has been provided.

This study sets out to investigate this idea more deeply. It looks at two kinds of connections between regions: one is the network of firms that have multiple plants across locations, and the other is how much workers and firms in one area purchase from other regions through final consumption and input-output linkages. The analysis focuses on regional employment trends in France from 1995 to 2015 and a new set of stylized facts is proposed. First, employment in large urban areas grew faster than in the rest of France during this period, and this trend got even stronger from 2005 to 2015. Second, smaller areas did benefit from being close to the large, fast-growing cities in the early years, but this advantage disappeared over time. These findings held up even when taking into account factors like the size of companies, international trade, and local amenities like climate or natural attractions.

To explain these trends, a general equilibrium model of the French economy is proposed. This model endogenizes regional linkages through multi-region firms' economies of scale. The model allows quantifying the role of preferences and productivity shocks in shaping the evolution of employment across locations. Using theory-consistent measures of linkages, we show that the break of urban-rural linkages does partially explain the employment trends across French locations.

Chapter 1

Demand Shocks, Sector-level Externalities, and the Evolution of Comparative Advantage

"*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)

1.1 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

[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.

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 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

[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.

[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).

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 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

[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.

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 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.

[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).

Outline. The rest of the paper is organized as follows. Section 1.2 develops the theoretical model and highlights its predictions in linking productivity growth and economies of scale. Section 1.3 describes the methodology adopted to estimate the theoretical model. Section 1.4 presents the data. Section 1.5 discusses the results. Finally, Section 1.6 concludes.

1.2 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 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.

1.2.1 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:

$$U_d = \prod_{i=1}^{I} (C_{id})^{\mu_{id}}, \tag{1.1}$$

where C_{id} represents total consumption in sector i from country d, and μ_{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:

$$C_{id} = \left(\sum_{o=1}^{N} \beta_{iod}^{\frac{1}{\sigma_i}} c_{iod}^{\frac{\sigma_i - 1}{\sigma_i}} \right)^{\frac{\sigma_i}{\sigma_i - 1}}, \tag{1.2}$$

where c_{iod} represents the consumption of variety o in sector i from country d, β_{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.

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

$$c_{iod} = \beta_{iod} \mu_{id} Y_d p_{iod}^{-\sigma_i} P_{id}^{\sigma_i - 1}, \tag{1.3}$$

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:

$$P_{id} = \left(\sum_{o=1}^{N} \beta_{iod} p_{iod}^{1-\sigma_i} \right)^{\frac{1}{1-\sigma_i}}. \tag{1.4}$$

The interpretation of equation (1.3) is standard, demand for any variety should increase when consumers prefer such variety relatively more, β_{iod} , when it is cheap, p_{iod} , when

[10] In this context, the elasticity σ_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.

they spend a higher share of income on its relative sector, μ_{id}, or when it is relatively expensive to substitute it with other varieties, P_{id}.

1.2.2 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 :

$$Q_{io} = A_{io} L_{io} E\left(Q_{io}\right), \tag{1.5}$$

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 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:

[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.

$$p_{iod} = \frac{w_o \tau_{od}}{A_{io} E\left(Q_{io}\right)}. \tag{1.6}$$

The optimal price charged by firms is a function of three components. The sectoral production cost, w_o/A_{io}, the bilateral shipping cost τ_{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 ψ_i being the production scale elasticity:[13]

[12] This follows immediately from the production technology in equation (1.5). 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).

$$E\left(Q_{iot}\right) = Q_{iot-1}^{\psi_i}, \tag{1.7}$$

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.

1.2.3 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:

$$L_o = \sum_{i=1}^{I} L_{io}. \tag{1.8}$$

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 (1.6) into the optimal demand in equation (1.3). Goods market clearing condition implies:

$$q_{iod} = \frac{\beta_{iod}\tau_{od}^{-\sigma_i}\Phi_{io}^{-\sigma_i}}{\sum_{\zeta=1}^{N}\beta_{i\zeta d}\tau_{i\zeta d}^{1-\sigma_i}\Phi_{i\zeta}^{1-\sigma_i}}\mu_{id}Y_d, \tag{1.9}$$

where :

$$\Phi_{io} = \frac{w_o}{A_{io}Q_{io,-1}^{\psi_i}}. \tag{1.10}$$

The price parameter, Φ_{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:

$$X_{iod} = \frac{\beta_{iod}\tau_{od}^{1-\sigma_i}\Phi_{io}^{1-\sigma_i}}{\sum_{\zeta=1}^{N}\beta_{i\zeta d}\tau_{i\zeta d}^{1-\sigma_i}\Phi_{i\zeta}^{1-\sigma_i}}\mu_{id}Y_d. \tag{1.11}$$

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, β_{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, Φ_{io}, the lower the trade costs, τ_{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 $o, X_{io} = \sum_{d=1}^{N} X_{iod}$:

$$\pi_{iod} = \frac{\beta_{iod}\tau_{od}^{1-\sigma_i}}{\sum_{\zeta=1}^{N}\beta_{i\zeta d}\tau_{i\zeta d}^{1-\sigma_i}\Phi_{i\zeta}^{1-\sigma_i}}\frac{\Phi_{io}^{1-\sigma_i}}{X_{io}}\mu_{id}Y_d. \tag{1.12}$$

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:

$$W_d = \frac{\sum_{i=1}^{I}\sum_{o=1}^{N} p_{iod}c_{iod}}{P_d} \equiv \frac{w_d L_d}{P_d}, \tag{1.13}$$

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

$$P_d = \sum_{i=1}^{I}\left\{\sum_{o=1}^{N}\beta_{iod}\tau_{od}^{1-\sigma_i}\Phi_{io}^{1-\sigma_i}\right\}^{\frac{1}{1-\sigma_i}}. \tag{1.14}$$

Dynamic Gravity Model. In this setup, the novelty stems from the functional form of the competitiveness index in equation (1.10). As discussed in Appendix A.1, we can replace equation (1.11) 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:

[14] Appendix A.1 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.

$$X_{iodt} = \frac{\beta_{iodt}\tau_{odt}^{1-\sigma_i}\left(\frac{A_{iot}}{w_{ot}}\right)^{\sigma_i-1}}{\sum_{\zeta=1}^{N}\beta_{i\zeta dt}\tau_{i\zeta dt}^{1-\sigma_i}\Phi_{i\zeta t}^{1-\sigma_i}}\mu_{idt}Y_{dt}\Pi_{n=1}^{t}\left[\frac{A_{iot-n}}{w_{ot-n}}X_{iot-n}\right]^{\psi_i^n(\sigma_i-1)}. \tag{1.15}$$

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, ψ_i, and the elasticity of substitution, σ_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 (1.15) over destination markets d :

$$X_{iot} = A_{iot}^{\sigma_i-1}w_{ot}^{1-\sigma_i}\Lambda_{iot}\Pi_{n=1}^{t}\left[\frac{A_{iot-n}}{w_{ot-n}}\sum_{d=1}^{N}X_{iodt-n}\right]^{\psi_i^n(\sigma_i-1)}, \tag{1.16}$$

where:

$$\Lambda_{iot} = \sum_{d=1}^{N}\frac{\beta_{iodt}\tau_{odt}^{1-\sigma_i}\mu_{idt}Y_{dt}}{\sum_{\zeta=1}^{N}\beta_{i\zeta dt}\tau_{i\zeta dt}^{1-\sigma_i}\Phi_{i\zeta t}^{1-\sigma_i}}, \tag{1.17}$$

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.

1.3 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

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[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.

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:

$$\ln\left(X_{iodt}\right) = k_{iot} + m_{idt} + \sum_{n=1}^{t} \psi_i^n z_{iot-n} + (1-\sigma_i)\ln\left(\tau_{odt}\right) + \ln\left(\beta_{iodt}\right). \tag{1.18}$$

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:

$$k_{iot} = (\sigma_i - 1)\ln\left(A_{iot}\right) - (\sigma_i - 1)\ln\left(w_{ot}\right). \tag{1.19}$$

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:

$$m_{idt} = \ln\left(\frac{\mu_{idt} Y_{dt}}{\sum_{\zeta=1}^{N} \beta_{i\zeta dt} \tau_{i\zeta dt}^{1-\sigma_i} \Phi_{i\zeta t}^{1-\sigma_i}}\right). \tag{1.20}$$

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:

$$z_{iot-n} = (\sigma_i - 1)\ln\left(\frac{A_{iot-n}}{w_{ot-n}} X_{iot-n}\right). \tag{1.21}$$

[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).

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, ψ_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 ψ_i would result in a validation of the assumed structure.

Equation (1.18) 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:

$$\ln(X_{iodt}) = \delta_{iot} + \delta_{idt} + \sum_{n=1}^{t} \beta_n z_{iot-n} + \ln(\tau_{odt}) + \varepsilon_{iodt}, \tag{1.22}$$

where δ_{iot} and δ_{idt} are directional fixed effects, β_n is the sector-level dynamic scale coefficient, and $\tau_{\text{odt}} = \exp[\mathbb{X}'_{\text{odt}}\, \eta_m]$ 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 τ_{odt}, and past trade flows are directly observed. The elasticity of substitution, σ_i, is taken from Broda and Weinstein (2006). The demand shifter, β_{iodt}, cannot be observed, furthermore, it enters equation (1.18) 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 β_{iodt} would be sufficiently small to not pose a threat to the identification strategy.

Identification. The identification of the scale elasticity, ψ_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

[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.

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 A.2 discusses a reduced form estimation as a robustness check.

By manipulating the dynamic gravity model in equation (1.15), 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:

$$X_{iot} = \left(A_{iot}/w_{ot}\right)^{\sigma_i - 1} Q_{iot-1}^{\psi_i(\sigma_i-1)} \Lambda_{iot}. \tag{1.23}$$

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

$$Q_{iot} = \Phi_{iot}^{-\sigma_i} \sum_{d=1}^{N} \frac{\beta_{iodt}\tau_{odt}^{1-\sigma_i}\mu_{idt}Y_{dt}}{\sum_{\zeta=1}^{N}\beta_{i\zeta dt}\tau_{i\zeta dt}^{1-\sigma_i}\Phi_{i\zeta t}^{1-\sigma_i}} = \Phi_{iot}^{-\sigma_i}\Lambda_{iot}. \tag{1.24}$$

In fact, while the price parameter Φ_{iot} summarizes all the information related to the labor market conditions and the industrial structure, Λ_{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, Λ_{iot}, over time to identify the scale parameter, ψ_i.

One way to address this issue is to directly construct Λ_{iot} . However, this approach comes with the problem of finding appropriate counterparts in the data. Both β_{iodt} and μ_{idt} are not directly observable, and at best τ_{odt} and Φ_{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:

[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).

$$\Lambda_{iot}^{Bartik} = \sum_{d=1}^{N} W_{iod} \hat{E}_{dt}, \tag{1.25}$$

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_{iod} :

$$\Lambda_{iodt-1} = \frac{\beta_{iodt-1} \tau_{odt-1}^{1-\sigma_i} \mu_{idt-1}}{\sum_{\zeta=1}^{N} \beta_{i\zeta dt-1} \tau_{i\zeta dt-1}^{1-\sigma_i} \Phi_{i\zeta t-1}^{1-\sigma_i}} Y_{dt-1}. \tag{1.26}$$

Bringing the model to the data, total income can be proxy by GDP, while the measure W_{iod} needs to be estimated. It is possible to retrieve the ratio component of the previous equation by exploiting a particular odds specification:[20]

$$\frac{X_{iodt-1}}{X_{iot-1}} = \frac{\beta_{iodt-1} \tau_{odt-1}^{1-\sigma_i} \mu_{idt-1} Y_{dt-1}}{\sum_{\zeta=1}^{N} \beta_{i\zeta dt-1} \tau_{i\zeta dt-1}^{1-\sigma_i} \Phi_{i\zeta t-1}^{1-\sigma_i}} \left[\sum_{d=1}^{N} \frac{\beta_{iodt-1} \tau_{odt-1}^{1-\sigma_i} \mu_{idt-1} Y_{dt-1}}{\sum_{\zeta=1}^{N} \beta_{i\zeta dt-1} \tau_{i\zeta dt-1}^{1-\sigma_i} \Phi_{i\zeta t-1}^{1-\sigma_i}} \right]^{-1} \equiv \frac{\Lambda_{iodt-1}}{\Lambda_{iot-1}}. \tag{1.27}$$

Using X_{iodt-1}/X_{iot-1} as a substitute for Λ_{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 $\hat{Y}_{dt} = \partial \text{Log}\left(Y_{dt}\right) / \partial t$, it is possible to define the weighted idiosyncratic demand shock as follows:

$$\hat{D}_{iodt-1} = \frac{1}{\Lambda_{iot-1}} \frac{\beta_{iodt-1} \tau_{odt-1}^{1-\sigma_i} \mu_{idt-1}}{\sum_{\zeta=1}^{N} \beta_{i\zeta dt-1} \tau_{i\zeta dt-1}^{1-\sigma_i} \Phi_{i\zeta t-1}^{1-\sigma_i}} \hat{Y}_{dt}, \tag{1.28}$$

where the weight is the inverse of the total world demand Λ_{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:

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

$$\hat{D}_{iot-1} = \frac{1}{\Lambda_{iot-1}} \sum_{d=1}^{N} \frac{\beta_{iodt-1}\tau_{odt-1}^{1-\sigma_i}\mu_{idt-1}}{\sum_{\zeta=1}^{N}\beta_{i\zeta dt-1}\tau_{i\zeta dt-1}^{1-\sigma_i}\Phi_{i\zeta t-1}^{1-\sigma_i}}\hat{Y}_{dt}. \tag{1.29}$$

Equation (1.29) 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:

$$\hat{B}_{iot} = \frac{1}{\Lambda_{ist-3}} \sum_{d=1}^{N} \frac{\beta_{isdt-3}\tau_{sdt-3}^{1-\sigma_i}\mu_{idt-3}}{\sum_{\zeta=1}^{N}\beta_{i\zeta dt-3}\tau_{i\zeta dt-3}^{1-\sigma_i}\Phi_{i\zeta t-3}^{1-\sigma_i}}\hat{Y}_{dt}. \tag{1.30}$$

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 ψ_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, $\hat{X}_{iot}$.

1.4 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 A.4. I consider import value, which are of the CIF (cost, insurance, and freight) type.[22] Following Hanson, Lind,

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

[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

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, σ_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 A.2.

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.

1.5 Results

1.5.1 Baseline Estimation

Turning to the estimation of scale elasticities ψ_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 (1.23). In particular, the empirical model on which to focus reads:

$$\operatorname{Log}\left(X_{iot}\right) = \beta_1 \operatorname{Log}\left(\tilde{Q}_{iot}\right) + \delta_{it} + \varepsilon_{iot}, \tag{1.31}$$

where $\operatorname{Log}\left(X_{\mathrm{iot}}\right)$ defines the export level in Log for the origin country o and industry i at time $t, \operatorname{Log}\left(Q_{iot}\right)$ 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, δ_{it} defines an industry-time fixed effect and ε_{iot} the error term.

As previously highlighted, we expect the magnitude of the coefficient β_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:

$$X_{iot} = \exp\left[\beta_1 \operatorname{Log}\left(\tilde{Q}_{iot}\right) + \delta_{it}\right] \times \varepsilon_{iot}, \tag{1.32}$$

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

Column (1) of Table 1.1 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,

Table 1.1: Baseline Estimation, Reduced Form

	Log(X_{iot})	X_{iot}
	LSDV	PPML
	(1)	(2)
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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

however, its introduction would confound the estimation of β_1. This issue is addressed by using the instrumental variable as described in Section 1.3.

Instrumental Variable Strategy. Moving to the instrument variable specification, the 2SLS scale elasticity is identified by estimating the dynamic counterpart of equation (1.31). In particular, the dynamic empirical model reads:

$$\hat{X}_{iot} = \beta_1 \hat{Q}_{iot} + \delta_{it} + \varepsilon_{iot}, \tag{1.33}$$

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, δ_{it} is the industry-time fixed effect and ε_{iot} the error term. The 2SLS implies instrumenting $\hat{Q}_{iot}$ with the shift-share, $\hat{B}_{\text{iot-1}}$, in equation (1.30).

Table 1.2 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 ψ, which is significant at the 1% and equal to 0.18.

Table 1.2: 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 A.1 in Appendix A.5 shows the scatter plot of the first stage. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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.

Heterogeneity. Table 1.2 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 1.3 reports the estimated scale coefficient from equation (1.33), breaking down industry by industry. Results are reported at a more

Table 1.3: 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 (1.33) 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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".

1.5.2 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 (1.18). The empirical model read:

$$\ln\left(X_{iodt}\right) = \delta_{it} + \delta_{idt} + \delta_{odt} + \sum_{n=1}^{t} \psi_i^n Z_{iot-n} + \varepsilon_{iodt}, \tag{1.34}$$

where $\delta_{it}, \delta_{idt}$, and δ_{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 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 A.2 discusses the main assumptions of this reduced-form approach. In a nutshell, the idea is to construct the Z_{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 (1.21) exploiting observable information on trade data and trade elasticities.

Table 1.4 displays the point estimates for the average ψ 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 1.1. 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]

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.

[24] Table A.1, in Appendix A.3, reports the estimates for specification in equation (1.34). 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 1.4: 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 (1.18) 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.

1.6 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.

Chapter 2
The Anticompetitive Effect of Trade Liberalization

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"*Price hikes are rarely so clear that consumers notice them. Sometimes headline prices remain unchanged but hidden fees increase. Sometimes prices drift so slowly that it takes several years to notice any significant difference. Stealth, however, can allow harm to go unnoticed.*"

— Thomas Philippon, *The Great Reversal* (2019)

2.1 Introduction

Recent years have witnessed a growing concern, among academics and policy-makers, about market competition in Europe and the United States (Syverson, 2019). Recent studies document that concentration (e.g., Gutiérrez and Philippon, 2018) and markups (e.g., De Loecker et al., 2020) rose over the last forty years,[25] suggesting a surge in aggregate market power with potential negative consequences for business dynamism (De Loecker et al., 2021) and workers' conditions (Deb et al., 2022).

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

A debate is open about the possible rationales explaining the rising in market concentration and markups. Autor et al. (2020) propose the "superstar firms" hypothesis. They show that higher concentration is driven by reallocation to large and productive firms. This shift results from competitive forces turning leading firms into dominating superstars. Other studies (e.g., Philippon, 2019) propose the "declining competition" hypothesis where they associate the rise in market power with weak antitrust enforcement.[26] The main idea behind this theory is that regulatory capture by large firms generated entry barriers preventing competitors from entering the market.[27] Alternatively, the "intangible assets" hypothesis (e.g., Eeckhout, 2021) postulates that industry leaders gain a competitive edge by investing more in intangibles (e.g., patents) to increase entry barriers.[28]

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

In a standard trade model with firm heterogeneity and variable markups, trade openness is pro-competitive because it induces a reallocation of market shares from low-productive to high-productive firms, and forces the latter to reduce their level of markups with consequential positive welfare effects (Melitz and Ottaviano, 2008).[29] Surprisingly, our

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

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

[28]For the U.S. context, Crouzet and Eberly (2021) provide empirical evidence of this mechanism. De Ridder (2023) propose a framework to quantify the impact of intangibles investment on productivity slowdown for the U.S. and France.

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

results indicate that the rise in competition driven by the China shock has a positive effect on aggregate industry-level markups and concentration, hence it is anti-competitive. In our benchmark estimates, we find that Chinese import competition explains one-fourth of the variation in aggregate markups.

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

To retrieve markups, we employ the control function approach developed by Ackerberg et al. (2015) (hereafter, ACF) to estimate production functions using information on revenues. Having obtained the relevant parameters, it is possible to adopt the optimal input demand approach popularized by De Loecker and Warzynski (2012). This approach has become standard in the industrial organization and macro literature, and builds on the insights of Hall (1986) regarding the relationship between input and output growth under imperfect competition. In particular, positive markups should be captured when the former causes a disproportional growth of the latter. [30]

Our empirical model aims to test how the cross-industry variation in the rise of Chinese

(e.g., Edmond et al., 2015, Asturias et al., 2019). Nevertheless, Arkolakis et al. (2019) show that variable markups play a limited role in explaining gains from trade.

[30] A growing body of literature has highlighted some limitations with the current approach and has provided some extensions or refinements. Klette and Griliches (1996) highlight the importance to account for the potential correlation between output prices and firms' input choices, namely the input price bias. Following the critique, several works have proposed the use of output and input quantities to generate unbiased estimates of the input elasticities (Foster et al., 2008; De Loecker, 2011; Garcia-Marin and Voigtländer, 2019; Bond et al., 2021; Doraszelski and Jaumandreu, 2021). Grieco et al. (2016) propose a framework to estimate production functions when input quantities are not observed that relies on the CES production function. An additional aspect concerns the lack of independent variation in input expenditure that can potentially hinder the identification of input elasticities in the ACF framework. To circumvent the issue, Gandhi et al. (2020) propose to rely on factor share and a non-parametric estimation derived from the flexible input first-order condition.

import exposure caused a change in markups. However, OLS estimates might suffer from an omitted variable bias. For instance, a sector's unobservable positive demand shock might induce a simultaneous increase in markups and imports. Therefore, building upon Acemoglu et al. (2016), we construct an instrumental variable (IV) using sector-level Chinese import data for eight other high-income economies to identify the impact of the China shock. In our strategy, the identifying assumption requires cross-country sectoral demand for Chinese imports to be uncorrelated.[31]

We test the empirical model over two sub-periods, 2000-08 and 2008-15, and on the stacked version to account for short- and long-term impacts. The 2SLS estimates indicate that sectors relatively more exposed to Chinese import competition experienced increasing markups. In line with the insights of Chen et al. (2009), we find this anticompetitive effect to prevail in the second part of our sample period, suggesting that market structure adjustments realize in the long-run. We also inquire about potential drivers behind the rise in markups by applying the dynamic aggregate decomposition strategy proposed by Melitz and Polanec (2015). Our findings are driven by an increase in the average firm-level markup rather than a reallocation of market shares towards high-markup firms. Oppositely, we find evidence of a negative effect on markups on the reallocation and exit margins suggesting the presence of pro-competitive effects that are not sufficiently strong to compensate for the rise in the within-firm component.

Additionally, we find a positive impact on sector-level Total Factor Productivity (TFP) in the second period, suggesting a comovement between markups and productivity, as in De Ridder (2023). To explain the increase in markups, we test the impact of the China shock on industry concentration. We find that the increase in China import competition raises market concentration, suggesting that exposure to Chinese competition increases incumbents' market power. To understand the potential implication of trade for resource misallocation, we assess the impact of the China shock on the evolution of markup dispersion.[32] In this respect, we estimate a positive effect suggesting a potential worsening

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

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

of allocative efficiency in the period 2008-2015. Overall, our findings suggest that Chinese import competition only impacts the market structure in the long run.

Related Literature. Our paper relates to several strands of the literature. First, we contribute to the ongoing debate on the rise of market power. In their pioneering contribution, De Loecker et al. (2020) are the first to systematically document a steady rise in markups since the 80 s for the U.S. economy.[33] According to their estimates, the rise in market power is induced by a reallocation of market shares toward high-markup and large firms. This result is consistent with the "superstar firm" hypothesis (Autor et al., 2020). The evidence about industry concentration also confirms the rise in market power. Covarrubias et al. (2020) and Grullon et al. (2019) show increasing concentration in U.S. markets, but the evidence for European countries is mixed.[34] We contribute to this literature by providing systematic evidence on the role of international competition in explaining the surge in market power.

We also contribute to the empirical literature on the relationship between import competition and markups. Early empirical evidence finds that trade liberalization reduces markups (Levinsohn, 1993; Harrison, 1994; Krishna and Mitra, 1998).[35] Recently, Impullitti and Kazmi (2022) exploit Spain's accession to the European Customs Union as an exogenous competition shock. They show that pro-competitive effects are weaker in sectors characterized by high entry barriers, suggesting that the domestic market structure plays a role in determining the benefits of a trade liberalization. More generally, trade liberalization can affect firms both on the input and the output sides. Chen et al. (2009) test the predictions of Melitz and Ottaviano (2008) for seven EU countries over the 1989-1999 period. They find that trade openness reduces the average industry markup in the short run; however, in the long run, the effect of import competition is reversed and becomes anti-competitive, in line with our findings. De Loecker et al. (2016) exploit the 1991 Indian trade liberalization episode and find that lower output tariffs put downward pressure on markups, while lower input tariffs increase them. This result provides evidence of an incomplete pass-through for input cost shocks.[36] Related

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

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

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

[36]The literature also addresses the impact of export liberalization on market power and markups. De

to input liberalization, access to cheaper inputs can also induce within-firm reallocation of resources generating productivity improvements (Vandenbussche and Viegelahn, 2018; Boehm et al., 2022). [37]

Closely related to our paper, Aghion et al. (2021) exploit the Chinese accession to WTO as an exogenous shock to pin down the competition effect French firms' performance and innovation. They distinguish the effect driven by direct competition in the output market from the input cost shock and find a negative impact of tougher competition on firm-level sales, employment, and innovation. Compared to their work, we focus on the import competition channel and its effect on firms' markups in the manufacturing sectors of Belgium, a small open economy. [38]

Finally, we contribute to the literature on the China shock. Several studies document how the swift rise of Chinese import competition in the U.S. manufacturing sector has negatively affected the domestic labor market.[39] Moving beyond the labor market implications, Bloom et al. (2016) use the termination of the Multi-Fiber Agreement to assess the impact of import exposure on productivity and innovation of the European textile sector. We contribute to this line of research by showing how import competition from China impacted the Belgian manufacturing market structure, markups, and productivity across all manufacturing sectors.

Outline. The remainder of the paper is structured as follows: Section 2.2 describes the data sources. Section 2.3 presents the main theoretical and empirical methodology. Section 2.4 discusses the liberalization episode and the source of variations used in the

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

[37] A large literature has focused on the role of sourcing and input liberalization on firms' performance. Among others, see Amiti and Konings (2007), Goldberg et al. (2010), and Topalova and Khandelwal (2011) for the role of cheaper inputs on productivity, and Bas and Strauss-Kahn (2015) and Fieler et al. (2018) for the role of access to inputs on quality upgrading.

[38] Specifically for Belgium, De Loecker et al. (2014) provide evidence for the anti-competitive effect induced by Chinese competition. However, they only consider a subset of manufacturing firms and perform the analysis at the firm level, completely abstracting from the aggregate implications of the shock.

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

empirical analysis. Section 2.5 presents the industry-level empirical results and discusses the mechanisms at play. Finally, Section 2.6 concludes.

2.2 Data

In our analysis, we construct a panel of Belgian manufacturing firms over the 19962015 period by combining balance-sheet information with trade data at the firm level. Additionally, we compute a measure of exposure to Chinese import competition and the relative instrument using aggregate trade data.

Balance sheet data are retrieved from the Annual Accounts and the VAT declarations provided by the Central Balance Sheet Office of the National Bank of Belgium and the Belgian Ministry of Finance (SPF Finance). The Annual Accounts report balance sheet information for the universe of Belgian firms. In particular, the dataset provides yearly information about firms' 4-digit NACE Rev. 2 (NACE4) industry code, total turnover (Y), value added (VA), fixed (K) and intangible (INT) capital, the number of full-time equivalent (FTE) employees (L), the wage bill (WB) and the value of total intermediates (M) used in production. All nominal values are deflated and reported in real terms. Concerning the capital stock, we use the net value of a firm's fixed assets. The VAT Declarations are collected by the Belgian tax authority and complement firm-level information about turnover and intermediate inputs for those Belgian firms below certain employment, turnover, and total assets thresholds.[40] Finally, we extract information about workers' occupations at the firm level from the Social Security data. This information allows us to distinguish between blue-collar and white-collar employees we use to build beginning-of-the-period controls at the firm and industry levels.

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

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

match to the corresponding NACE4 industry level. Appendix B.1 details our matching procedure to link HS6 product categories to the corresponding NACE4 industry code.

Table 2.1: Summary Statistics for Manufacturing Firms, 1996-2015

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

Notes: The full sample contains 195,118 firm-year observation, for 21,597 firms. The sample with only trading firms counts 93,601 firm-year observations, for 12.354 firms. Among these, 4.112 firms sourced at least once from China over the period. The table reports firm-level output and factors of production used later in the estimation procedure. Sales, capital, intermediates, wage bill, and trade are expressed in million of euros, employment is in full-time equivalent. All nominal variables are deflated as described in Appendix B.2.

We perform a data cleaning routine to correct our sample from data misreporting. The details of our data cleaning procedure are reported in Appendix B.2. In particular, we drop any observation reporting negative values for sales, value-added, or total assets from the original sample. The final sample contains 195,118 firm-year observations identifying 21,597 unique firms over 184 manufacturing industries for the 1996-2015 period. Table 2.1 shows the summary statistics. Panel A reports total sales, the stock of fixed and intangible capital, the amounts of intermediate inputs purchased, the level of employment in FTE, and the total wage bill for all firms. Looking at the variables' distribution, the skewed nature of the manufacturing sector along all dimensions emerges, with roughly half a standard deviation separating the firm at the 75 th compared to the one at the 95th percentile. Panel B reports information for the 12,354 firms involved in international trade. These are, on average, larger and more capital-intensive than their domestic counterparts. We will consider this information for estimating markups and productivity by introducing controls for the firm's export activity.

2.3 Methodology

2.3.1 Markups Estimation

A key issue for our empirical strategy is to choose an appropriate measure of firms' market power. A natural candidate is the price-to-marginal cost ratio, namely the price markup. This ratio measures the wedge between the price level charged by firms in a world of perfect competition with no distortions and the observed one.[41] However, despite the extensive access to production price data, it is hardly feasible to retrieve information about firms' marginal costs.[42]

For this reason, we follow the markup estimation methodology developed by De Loecker and Warzynski (2012) that builds on the insights of Hall (1986) and relies on the use of available firm-level balance sheet data. The intuition is that, with perfect competitive markets, input cost shares should be equal to the output elasticity of its respective input. Therefore, any price deviation from this benchmark should be considered as a result of firm market power. Furthermore, this methodology is flexible enough to encompass various market structures and it does not require to impose a specific demand system.[43]

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

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

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

We consider a firm i at time t with the following production function:[44]

$$Q_{it} = F_{it}\left(L_{it}, K_{it}, M_{it}, \Omega_{it}\right), \tag{2.1}$$

where Q_{it} denotes gross output, $F_{it}(\cdot)$ the production function defined over labor, L_{it}, capital, K_{it}, intermediates, M_{it}, and the productivity shock, Ω_{it}. We assume the production function, $F_{it}(\cdot)$, to be continuous and twice differentiable in its arguments. The markup identification strategy proposed by De Loecker and Warzynski (2012) relies on the firm's capability to flexibly adjust at least one of the inputs in production. Plenty of evidence points to the fact that firms' input choices are subject to adjustment costs, as in the case of capital due to its durable nature, or the case of labor due to labor market regulation. Following the literature, we assume capital to be a dynamic input in production, conversely, intermediate inputs can be freely adjusted at each period t. Variation in the firm use of intermediate inputs is key to identifying markups. Given that the Belgian economy is characterized by a rigid labor market, we do not assume labor to be flexible, differently from De Loecker and Warzynski (2012).[45]

As shown by De Loecker and Warzynski (2012), we can derive from the minimization problem of equation (2.1) the following expression for markups:

$$\mu_{it} = \theta_{it}^{M}\left(\alpha_{it}^{M}\right)^{-1}, \tag{2.2}$$

where θ_{it}^{M} is the output elasticity of intermediate inputs, and α_{it}^{M} is the share of intermediate input expenditures on total sales. A revision of the theoretical model can be found in Appendix B.3, here it is sufficient to highlight how the main advantage of the framework is to allow the estimate of markups by means of only two parameters.

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

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

[45]As discussed in Konings and Marcolin (2014), Belgium has a centralized hierarchical system of collective bargaining for wages, in particular, they show that productivity-wage differential is significant and strongly persistent, indicating the extent of rigidity in which Belgian firms operate. In addition, Dhyne et al. (2022) provide evidence of high adjustment costs for net labor changes in the context of Belgium. In light of this evidence, we assume labor to be a dynamic input in production like capital.

rectly pinpoint input elasticities by controlling for unobserved productivity shocks. To retrieve the parameter θ_{it}^{M}, the key challenge in estimating production functions is to deal with the endogeneity of the productivity to the input choices. Thus, we estimate the production function using the control function methodology proposed by Ackerberg et al. (2015).[46]

Production function estimation is performed for each aggregate manufacturing sector, in particular, we bring to the data a log-linearized version of equation (2.1):

$$q_{it} = f_{it}\left(l_{it}, k_{it}, m_{it}; \beta\right) + \omega_{it} + \varepsilon_{it}, \tag{2.3}$$

where the production function $f_{it}(\cdot)$ is assumed to be translog, ω_{it} is the Hicks neutral productivity level observed by the firm, potentially correlated to the level of the inputs in production, while ε_{it} is the unanticipated productivity shock assumed to be independent and identically distributed across firms. A limitation in our setup is the need for more data on quantities that can induce a price bias in the estimates. However, De Ridder et al. (2022) show that this bias is attenuated when studying markup changes over time, which is the focus of our empirical exercise. Appendix B.4 presents the production function methodology in detail, with an exposition of the set of assumptions and the identification strategy.

Table 2.2 reports the estimated output elasticities and markups at the aggregate industry level. The reported coefficients are averages across the entire sample period and feature sizable variation within and across industries. We find intermediate inputs to generate higher marginal revenues for labor and capital, with values ranging between 0.70 and 0.75 for the former and around 0.05 and 0.25 for the latter. Notice that elasticities do not necessarily sum up to one since we are not imposing constant returns to scale.

Figures B.1 and B.2 in Appendix B.6 show the evolution of the aggregate markup respectively revenue-weighted and unweighted. Figure B.3 shows the evolution of the dis-

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

tribution of firm-level markups for the years 2000, 2008, and 2015. All the figures show an increase in the markups, both in the aggregate and in the dispersion.

Table 2.2: Output Elasticities and Markups, Aggregate NACE Sector Level

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

Notes: Estimation is performed on the sub-sample that went through the second round of cleaning as described in Appendix B.2. We estimate output elasticities and markups using the algorithm from De Loecker Warzynski (2012). We assume a firm-level translog production function and we treat capital and labor as predetermined. Firm-level markup is calculated as the ratio between the intermediate output elasticity and the relative revenue share, the latter corrected for the first stage error.

2.3.2 Aggregate Markup Decomposition

As described in Table 2.2, we observe a considerable heterogeneity in markups within sectors and across firms. To investigate the mechanism behind aggregate changes, we decompose them into changes in the within-firm average markup, the reallocation of market shares across firms, and the entry/exit of competitors in the market following the decomposition by Melitz and Polanec (2015).[47] As shown in Appendix B.5, it is possible to express the change in the aggregate markup between the two periods as:

$$\Delta M_j = \Delta \bar{M}_{c,jt} + \Delta \operatorname{cov}_{c,jt} + s_{e,j2}\left(M_{e,j2} - M_{c,j2}\right) + s_{x,j1}\left(M_{c,j1} - M_{x,j1}\right), \tag{2.4}$$

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

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

Figure 2.1: Aggregate Dynamic Decomposition of Markups, 2000-2015

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

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

Figure 2.1 reports the decomposition of the aggregate markup growth (dark blue) for the two sub-periods, 1995-2008 and 2008-2015, and the entire 2000-2015 period. First, we can see that the aggregate markup level rose by 9% over the period. Roughly, a 90% increase over the 1995-2015 period is due to the within-firm component. Reallocation of market share between firms accounts for less than 10%, even though the sign is negative in the first period, meaning that market shares were relocated to low-markup firms between 2000 and 2008. On the opposite, the effect is positive in the second half and dominates over the full sample period.

The role played by the extensive margin is minor, and the net effect of entry and exit is negative overall, suggesting that what matters is the high-markup firms exiting the market. This result is intuitive: firms entering the market account for a tiny fraction of the total market share in general while exiting firms might come from more consolidated positions. Another reason for the lack of action in terms of entry and exit is the lack of business dynamism in the Belgian manufacturing sector, as highlighted in Figure B.4, with a share of entry and exit firms well below 10% each year since the beginning of the sample.

2.3.3 Other Measures of Market Power

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

Concentration Indices. Concentration measures are widely used to infer the degree of market competition. As discussed in Covarrubias et al. (2019), concentration is not a sufficient statistic about the functioning of the market. In particular, high concentration can be associated with high entry barriers and incumbents' anti-competitive behaviors. However, it can also result from competition between market leaders that devote most of their revenues to capital investments and innovation.[48]

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

$$\mathrm{HHI}_{jt} = \sum_i (s_{i,jt})^2 , \tag{2.5}$$

[48]Standard Cournot model of competition delivers equilibrium outcomes relating positively a firm market share with its markup and market power, as in Brander and Krugman (1983); however, models of innovation and endogenous growth might generate a negative correlation between the two measures, as in Aghion et al. (2005).

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

$$\mathrm{CR4}_{jt} = \sum_{i=1}^{4} (s_{i,jt})^2 , \tag{2.6}$$

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

Misallocation. To analyze the potential efficiency loss determined by the presence of market power, we construct a measure of industry dispersion of markups. From a theoretical point of view, the greater the dispersion of markups, the higher the efficiency losses due to misallocation. This result is theoretically driven by the presence of high-markup firms producing below their optimal level and low-markup firms producing above.[49] In this paper, we measure the markup dispersion by the Theil index. For industry j at time t, we define:

$$\mathrm{Theil}_{jt} = \frac{1}{N} \sum_{i} \frac{\mu_{ijt}}{\bar{\mu}_{jt}} \ln \left(\frac{\mu_{ijt}}{\bar{\mu}_{jt}} \right) . \tag{2.7}$$

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

2.4 Exploiting the "China Shock"

To identify the international trade shock to the Belgian economy, we exploit the remarkable surge of China as a world manufacturing producer and exporter. The rising Chinese role in world trade is well suited for being used as a quasi-natural trade shock due to a concurrence of various factors, as extensively discussed in various seminal works (Autor, Dorn, and Hanson, 2013; 2016). First, among the key drivers explaining the progressive increase of trade flows originating from China, there is a policy change, namely its accession to the WTO in 2001. This implied not only massive cuts in trade barriers with the

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

Western economies, but also the reduction of uncertainty in those industries for which low tariffs were already put in place.[50] Second, both the trade liberalization and the massive induced migration from the rural areas of the West to the urban areas of the East allowed China to build a comparative advantage in the labor-intensive manufacturing industries, in which it eventually specialized. Finally, the realized shift in trade patterns was swift and largely unanticipated. In addition, evidence suggests that Belgium was largely exposed to the shock over the course of the last two decades. In particular, Mion and Zhu (2013) show that despite the increase in imports of Chinese products starting in the 2000s, Belgium did not experience a similar change in trade patterns with other low-income economies. This aspect is important for the validity of our empirical analysis.

Import Exposure. We examine the degree of import exposure for the 184 Belgian 4-digit NACE industries, over our sample period 2000-2015. We follow Mion and Zhu (2013) and define our measure of import exposure as the industry-level change in Chinese import share weighted by the beginning-of-the-period industry imports and production values:[51]

$$\Delta IS_{j,t}^{BECH} = 100 \times \frac{\Delta M_{j,t}^{BECH}}{Q_{j,2000} + M_{j,2000}}, \tag{2.8}$$

where $\triangle M_{j,t}^{BECH}$ is the long-run change in Chinese imports values in industry j, while $Q_{j,2000}$ and $M_{j,2000}$ are respectively Belgian total production and total imports in industry j at the beginning of the period. Variation in $\triangle IS_{j,t}^{BECH}$ across industries stems from the reliance on both intermediate inputs and final products sourced from exporters located in China. In particular, import-intensive industries are expected to be relatively more exposed to the surge in trade with China.

To get a sense of the magnitude of the shock for the Belgian economy, Figure 2.2 depicts the evolution of our aggregate measure of Chinese import exposure over the sample

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

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

period. While in 2000 the share of Chinese import on total production and import was slightly above 1%, by 2010 it was more than 2 times larger, plateauing since. With respect to the U.S. pattern, the rise in trade exposure seems to lag a few years with the change in trend only happening from 2004 onward. This is important later on for the discussion of our results. Figure B.5 in Appendix B.6 reports the growth rates at the 2-digit NACE sector level. Cross-industry variation in the exposure to the shock is crucial in our setup to pin down the effect of import competition on markups.

Endogeneity. It is important to recognize that OLS estimates might suffer from an omitted variable bias. To fix ideas, consider Figure 2.2 and the potential determinants behind the rise in Chinese import exposure over the decade. Chinese firms might become relatively more productive and be able to compete in various Belgian manufacturing sectors at the expense of local competitors. At the same time, however, some industries might experience a general expansion in sales induced by a change in consumers' preferences simultaneously raising demand for local and foreign producers. In the first case, we should expect a negative relationship between local firms' prices and imports from China. Conversely, in the second case, domestic firms would be able to exploit the rise in demand by potentially increasing prices introducing a mechanical correlation between markups and foreign imports.

To reduce concern about potential endogeneity arising from firms' optimization of their sourcing strategies, we follow the industry-level identification proposed by Acemoglu et al. (2016). We rely on an instrumental variable strategy that aims at capturing the variation in the rise of Chinese import share stemming from the country specialization in their comparative advantage over the period. In particular, we regress our measure of import exposure on the same measure constructed using import changes between China and other eight high-income economies:[52]

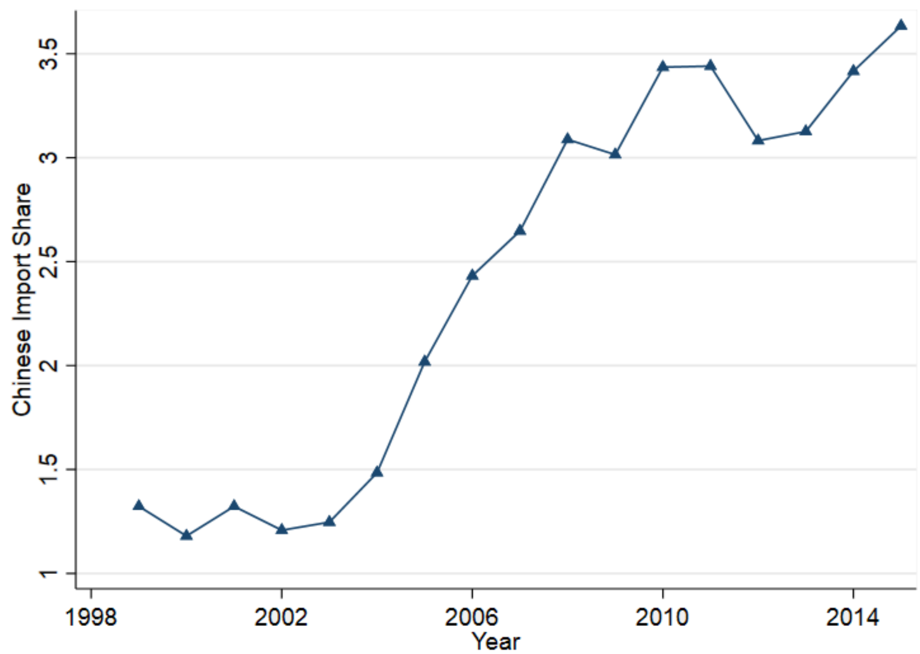
$$\Delta IS_{jt}^{OTCH} = 100 \times \frac{\Delta M_{jt}^{OTCH}}{Q_{j,1996} + M_{j,1996}}, \tag{2.9}$$

where $\Delta M_{j,\tau}^{oc}$ is now the long-run change in the average Chinese import value from the other eight high-income economies, and $Q_{j,1996}$ and $M_{j,1996}$ are again computed using

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

Belgian production and import data, but in 1996, in order to avoid mechanical correlation between the share components of the two measures.

Figure 2.2: Evolution of Chinese Import Share in Manufacturing, 2000-2015



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

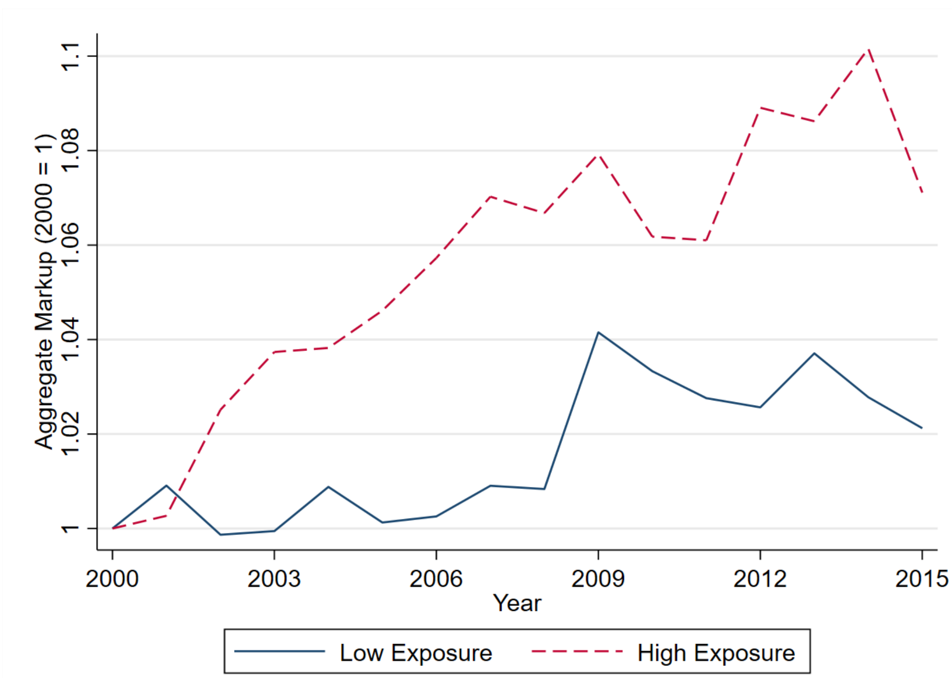
The identification by means of the proposed IV is valid as long as the change in the Belgian import exposure is not predicted by a simultaneous rise in sector-level demand across the other 8 high-income economies. For example, if over the period all Chinese trading partners experience a rise in demand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

2.5 Results

2.5.1 Graphical Patterns

To motivate our empirical strategy, in Figure 2.3 we plot the evolution of weighted aggregate markups for two sub-sample of industries over the period 2000-2015. On the one hand, the dashed red line represents the revenue-weighted aggregate markup for those industries facing an above-the-median change in Chinese import share; on the other, the solid blue line represents the same measure for those industries below the median of the exposure. As it is apparent, industries that are relatively more exposed to the China shock experience higher aggregate markup growth over time. Interestingly, specifically for 2000, this is not the case, with much of the action taking place in the years following China's accession to the WTO. This suggestive evidence excludes the presence of pre-trends that could potentially invalidate the analysis.

Figure 2.3: Evolution of the Aggregate Markup by Exposure to Chinese Competition, 2000-2015



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

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

2.5.2 Industry-Level Analysis

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

$$\Delta\,\text{Markup}_{j,t} = \beta_1 \Delta IS^{BECH}_{j,t} + \mathbf{X}'_{\mathbf{j,2000}}\beta + \gamma_j + \delta_t + \varepsilon_{j,t}, \tag{2.10}$$

where Δ Markup $_{j,t}$ denotes the (log) difference of the aggregate industry-level markup, γ_j is the industry fixed effect, capturing time-invariant characteristics across industries, δ_t is the year fixed effects, capturing common yearly shocks affecting the Belgian manufacturing, and $\mathbf{X_{j,2000}}$ is a vector containing beginning-of-the-period controls at the aggregate industry level. These controls are the capital-to-labor ratio, the labor share, the share of blue-collar workers, the value added labor productivity, and the Herfindahl index for market concentration. To control for heteroskedasticity and potential serial correlation of the error term, $\varepsilon_{j,t}$, we cluster at the 3-digit NACE industry level, moreover we weight regressions by the industry-level volume of sales at the beginning-of-the-period.

Baseline Results. Table 2.3 reports the results for the baseline regression in equation (2.10) for the long-run variation in the aggregate markups. In column (1), the first row reports the W2SLS estimates for markups of the stacked difference of import share in the two periods 2000-2008 and 2008-2015, where the weights are the beginning-of-the-period industry-level sales. In this specification, we control for 2-digit NACE industry and year fixed effects, and the set of beginning-of-the-period controls previously discussed. The second row reports the first stage estimated coefficient of the instrument which is associated with the Kleibergen-Paap F-stat at the bottom of the column. The instrument performs well, being higher than the rule of thumb of 10, while the coefficient on the stacked difference of markups is estimated to be positive at the 1% and equal to 0.038. The coefficient is identified from variation across industries. Column (2), instead, presents a more demanding specification with controls replaced by a 4-digit NACE fixed effects. Here we are exploiting variation over time within the same industry. The effect is stronger in this second specification, however the instrument is weaker, with the F statistics close to 6. Column (3) and (4) are comparable with specification (1), but look at the differential impact for the two sub-periods. It appears that much of the adjustment realizes starting from the second period.

Table 2.3: Industry-Level Chinese Import Competition, Markups

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

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

Two aspects are noteworthy to highlight, first, as from Figure 2.3, the rise in the Chinese import share takes place from 2004 onward, meaning that the cumulative effect might start to become significant relatively further in time; second, this might simply suggest a certain degree of sluggishness in markup adjustment over time, in particular this might due to the specific mechanism underlying the process. We will inquire the potential sources of the aggregate markup variation over time in the next section. Coming back to our estimates, taking our preferred specification in column (1), we have that a one standard deviation increment in Chinese import exposure increases the aggregate markups by 0.07.

Decomposition. We now move to inquiring what is the source of the aggregate change that we identify, by looking at the direct impact of Chinese trade exposure to the different components of the decomposition identified in equation (6). To test this empirically, we separately estimate an analogous of equation (16) for each component of the decomposition, using these same set of controls. Table 2.4 reports results for the two sub-periods and for the preferred stacked difference specification. Columns (1) to (3) look at the reallocation effect, which allows to capture whether market shares are reallocated towards high- or low-markup firms. The result is consistently negative across specifications, even if significantly estimated only when looking at the stacked difference. This implies that market share is reallocated towards low markup firms.

Table 2.4: Industry-Level Chinese Import Competition, Decomposition I

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

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

Columns (4) to (6) look at the within effect, which identifies changes in aggregate markups due to the average change in the unweighted aggregate markup. We see how this effect is statistically significant and stronger enough to dominate the negative reallocation effect, meaning that the Chinese import shock induces a strong reaction on incumbent firms to push upward their average charged markup. Put together with the negative sign of the reallocation effect, this evidence suggests that are firms with lower market shares that increase relatively more their markups. This is also coherent with the findings in Díez et al. (2021) for a large number of developed and developing economies.

Concentration. Having established that Chinese import exposure had an anticompetitive effect for Belgian manufacturing, we move to understand potential mechanisms behind this stylized fact. As highlighted theoretically in Impullitti and Kazmi (2022), trade liberalizations can indirectly lead to anticompetitive effects if the resulting market concentration increases due to tougher competition.

Table 2.5: Industry-Level Chinese Import Competition, Decomposition II

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

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

In particular they provide a general equilibrium model of oligopolistic competition with free entry. Trade liberalization has a double effect in this setup. On the one hand, more competition puts downward pressure on firms' markups. On the other, it allows surviving firms to exert a higher degree of market power as a result of the shrinking number of competitors forced to exit the market. This implies that when the concentration effect dominates the standard pro-competitive effect, markups can even increase in equilibrium. This is not the case in the standard Melitz and Ottaviano (2008) model because monopolistic competition ensures a monotonic relationship between competition and markups.

To test this potential mechanism we estimate the following equation:

$$\Delta \text{ Concentration }_{j,t} = \beta_1 \Delta IS_{j,t}^{BECH} + \mathbf{X'_{j,2000}}\beta + \gamma_j + \delta_t + \varepsilon_{j,t}, \tag{2.11}$$

where Δ Concentration $_{j,t}$ denotes the long difference of various concentration measures, namely the Herfindahl index (HHI) and the concentration ratio ($CR4$). Table 2.5 reports these results. Columns (1) to (3) look at the industry level HHI, in the first period the effect is negative, but not significant, while in the second period the effect is estimated to be positive and significant. When looking at the overall effect over the two periods the effect remains positive despite not being significant. These results are consistent with what we find in columns from (4) to (6) concerning the concentration ratio of the four largest firms in the sector. Despite the results being weakly significant, the signs of the coefficients are positive in the second period and over the whole sample, which is consistent with the idea that firms in relatively more exposed industries might take advantage from a more dominant position in the market and charge high-markup prices. This effect is therefore driven from firms at the top of the market share distribution.

Table 2.6: Industry-Level Chinese Import Competition, Concentration

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

Notes: The table reports the estimated coefficients for equation (8). The dependent variable is defined as the difference in the Chinese import share over the periods 2000-2008 and 2008-2015, and is windsorized at the 5%. Regressions are weighted by beginning-of-the-period sales. Standard errors, in parentheses, are cluster at the 3-digit NACE industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, † $p < 0.15$.

Productivity. On top concentration, an additional mechanism that might allow firms to gain market power is innovation. Aghion et al. (2005) propose a model where firms have the incentive to innovate in order to appropriate post-innovation rents, and this is particularly crucial to allow them to survive or escape competition. They show evidence for UK, where they find an inverted U-shaped relationship between industry-level innovation and competition. Hombert and Matray (2018) provide evidence for the U.S. and find that $R\&D$ intensive firms are affected relatively less in the sectors exposed to Chinese competition, which is due to the link between innovation and product differentiation. We test whether industries exposed relatively more to Chinese import adjust in terms of productivity by estimating the following model:

$$\Delta TFP_{j,t} = \beta_1 \Delta IS^{BECH}_{j,t} + \mathbf{X}'_{\mathbf{j,2000}}\beta + \gamma_j + \delta_t + \varepsilon_{j,t}, \tag{2.12}$$

where $\triangle TFP_{j,t}$ denotes the (log) difference of Total Factor Productivity retrieved from the production function estimation. Columns (1) to (3) of Table 2.7 reports results on productivity. The stacked difference suggests an overall positive effect non-significantly estimated, this result however hide variation between the first and the second period. In fact, column (1) reports a negative and weakly significant impact on TFP, on the contrary in the second period the effect turns positive and significant at the 1%. This is suggestive of the comovement of the aggregate markups and aggregate productivity levels, which might be in line with the escape competition hypothesis previously mentioned.

Table 2.7: Industry-Level Chinese Import Competition, TFP and Theil Index

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

Notes: The table reports the estimated coefficients for equation (8). The dependent variable is defined as the difference in the Chinese import share over the periods 2000-2008 and 2008-2015, and is windsorized at the 5%. Regressions are weighted by beginning-of-the-period sales. Standard errors, in parentheses, are cluster at the 3-digit NACE industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, † $p < 0.15$.

Misallocation. Finally, in columns (4) to (6) of Table 2.7 we report results concerning markup dispersion, and in particular the Theil index. We are particularly interested at measuring what happens to the second moment of the markup distribution across firms in order to understand the efficiency cost induced by the Chinese shock. To interpret the results, we should think of an increase in markup dispersion as a worsening of the aggregate efficiency of a sector, and this is due to the fact that greater variance implies the presence of firms charging disproportionately higher markups that have potentially stronger effects for misallocation. Firms charging positive markups employ less than the optimal level of inputs to produce because the imperfectly competitive equilibrium output falls below the perfectly competitive one. Once again, we test the impact of Chinese import exposure on our measure of markup dispersion, namely the Theil index, by estimating this regression:

$$\Delta \text{ Dispersion }_{j,t} = \beta_1 \Delta IS^{BECH}_{j,t} + \mathbf{X'_{j,2000}}\beta + \gamma_j + \delta_t + \varepsilon_{j,t}, \tag{2.13}$$

where $\triangle TFP_{j,t}$ denotes the (log) difference of the Theil index derived in equation (9). Results show that markup dispersion increases in the import-exposed industries during the second period, but it is substantially zero over the period. This might suggest the presence of a potential worsening of input allocation within industries and across firms.

2.6 Conclusion

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

To overcome the lack of price and quantity data, we exploit balance sheet to estimate firm-level markups and aggregate them at the industry-level. This allows to decompose the aggregate level of markups in various components and inquire the drivers behind its evolution over time. We complement the analysis by computing additional aggregate sector level measures of market power such as concentration indices, like the Herfindahl index (HHI) and the concentration ratio for the top largest firms (CR4).

Exploiting the exogenous surge in China as an international manufacturing power, we pin down the effect of an increase in domestic import competition for Belgian firms. We find that relatively more exposed sectors experience a higher degree of market power in the form of higher levels and dispersion of markups, higher concentration, and higher productivity growth. These changes are not driven by reallocation between firms but by adjustments taking place within incumbents and can be explained by an increasing concentration level that surviving firms can exploit to their advantage. Overall, we provide evidence that trade liberalization can have anti-competitive effects in the long run.

Chapter 3
Economic Linkages and the Urban-Rural Divide in France

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"*Regional inequality is proving too politically dangerous to ignore.*"

— *The Economist* (2016)

3.1 Introduction

The "Great Divergence" in terms of employment and wages between large metropolitan areas, on the one hand, and medium-sized and small cities, on the other, is seen as one of the causes of the spectacular recent manifestations of rising populism and political polarization.[53] This phenomenon is not circumscribed to a specific region or country, as the experiences of Brexit in the UK (Colantone and Stanig, 2018), the Yellow Vests movement in France (Algan et al., 2020), and the election of Donald Trump in the US (Autor et al., 2020) have recently shown.[54]

[53] A first characterization of the phenomenon is provided by Moretti (2012) for the United States: "I consider the Great Divergence to be one of the most important developments in the United States over the past thirty years [...] The success of a city fosters more success, as communities that can attract skilled workers and good jobs tend to attract even more. Communities that fail to attract skilled workers lose further ground." From The New Geography of Jobs, 2012.

[54] Among others, see Iammarino et al. (2019) and Gaubert et al. (2021) for a recent discussion about diverging regional trends respectively for Europe and the United States.

Using French administrative establishment-level data re-aggregated at the local labor market level, we first document three new stylized facts on the evolution of local employment over the period 1995-2015.[55] First, the employment in large urban areas (except Paris) grows faster than in rural and small-sized urban areas. While this premium is fully explained by local differences in sectoral specialization between 1995 and 2005, this is not the case between 2005 and 2015, the decade during which the divergence accelerates. Second, rural and small-sized urban areas benefit in terms of employment growth from being closely located to fast-growing large urban ones in the first decade. However, this proximity premium fades away during the 2005-2015 period.

Recent work has aimed at understanding the potential causes behind this spatial divergence. In particular, globalization (Autor et al., 2013), automation (Acemoglu and Restrepo, 2019), and skill-biased technical change (Eckert et al., 2022) have been under scrutiny and evidence suggest to have played an important role. However, a view circulating widely in the public debate is that these radical economic transformations might have severed pre-existing economic ties between regions, preventing the peripheral areas from benefiting from the economic growth of the centers and fueling social discontent. In this paper, we aim to provide empirical and quantitative evidence to test this hypothesis. In particular, we focus on the effect that breaking regional economic linkages exert on spatial inequality, by looking at two types of regional ties: the spatial network of multi-establishment firms and demand linkages stemming from consumers' demand and input-output relationships.

We show that our stylized facts are robust to a number of robustness checks. In particular, the rising employment growth premium of large urban areas and the fading proximity premium enjoyed by rural and medium-sized urban areas that are close to large, fast-growing ones are robust to controlling for the initial share of local employment belonging to firms: i) with more than 500 employees; *ii*) involved in international trade; iii) from multinational corporations. The two premia are not driven by local amenities either, as measured by average temperatures and proximity to seaside and mountains, or by geographic centrality, proxied by the internal market access. Moreover, the employment growth premium is robust to a shift-share instrumental variable strategy where US sectoral employment growth is aggregated to predict French local employment growth.

[55] We follow Combes et al. (2012) and exploit the concept of French zones d'emploi. These geographical units are defined by the French national statistical institute and are conceptually similar to U.S. commuting zones. French employment zones are on average smaller in size and less populated than the U.S. counterpart. Other works exploiting this notion of commuting zone for France are Bakker et al. (2021), Chen et al. (2023), and Bilal (2023).

To rationalize our findings, we build a quantitative multi-region and multi-sector model of France in an open economy, where the rest of the world is modeled as a single outside region. In each region and sector, establishments produce differentiated varieties combining labor and intermediate inputs in the same spirit of Caliendo and Parro (2015). Workers are able to relocate between regions and sectors within France but not internationally; moreover, sectors are interconnected through the input-output structure. Workers and establishments buy final consumption goods and inputs from all regions incurring bilateral trade costs. We allow the network of establishments to play a role by introducing heterogeneous firms owning establishments across regions (Giroud and Mueller, 2018). Each firm can enter a regional market by setting up an establishment with productivity equal to the one of the headquarters and discounted by a penalty that increases with distance to the latter. Combining these elements allows us to endogenize the structure of linkages between regions and quantify how fundamental productivity changes affect the spatial distribution of activities.

In equilibrium the model provides two channels through which spatial linkages can propagate economic shocks across locations. The first channel relates to the spatial network of multi-establishment firms.[56] The second channel goes through the input-output structure of the economy and the local demand generated by consumers and establishments purchases.[57] These demand linkages account for the internal gravity structure of France.[58] We calibrate the model based on values directly observable in our data and use estimates from the literature for those parameters for which data is not available. Finally, we provide a validation exercise of the model by replicating reduced-form estimates using theory-driven measures of employment growth and productivity shocks. The structural results are qualitatively and quantitatively in line with reduced-form evidence, suggesting that the ingredients of the model are able to replicate the main mechanisms at play.

Related Literature. Our paper contributes to several strands of the literature. First, we contribute to the recent literature on the "Great Divergence". As documented for the U.S. by Moretti (2012), cities specialized in innovative sectors have grown faster than the

[56] Firms' ownership plays an important role in propagating shocks across locations. Giroud and Mueller (2018) study how US multi-establishment firms generate a positive local employment sensitivity to shocks occurring in locations in which firms' establishments are located. Kleinert et al. (2015) provide evidence for the importance of multinational ownership in generating GDP co-movements between French regions and other countries.

[57] A growing literature studies the role of the input-output network in propagating shocks. See Acemoglu et al. (2012) for an application to the domestic economy and Caliendo and Parro (2015) for an application to international trade.

[58] An extensive literature has looked at the importance of gravity as a factor affecting the interdependence of regions and countries. For a classic discussion see Head and Mayer (2014).

others since the 1980s. This phenomenon induced both an employment and a wage gap between these cities and the old manufacturing regions.[59] Contemporaneous and subsequent research on this topic has mostly focused on the growing wage inequality between large and small cities, especially for the highly educated.[60] All these studies revolve around the notion of "urban wage premium". This wage premium finds its roots in agglomeration economies, and it holds even when the spatial sorting of workers (Combes et al., 2008; Baum-Snow and Pavan, 2012; Roca and Puga, 2017) and firms (Gaubert, 2018) is accounted for.[61] Various mechanisms have been proposed to account for the fact that the urban wage premium has been growing in the late XXth and early XXIst centuries, especially for high-skill workers. They all generally combine an increasingly skill-biased labor demand in large cities and/or endogenous amenity formation Diamond (2016). In particular, Eckert et al. (2022) and Eeckhout et al. (2021) emphasize the role of IT investment at large firms in big cities, Giannone (2022) focuses on the interaction between skill-biased technological change and agglomeration economies, and Eckert (2019) discusses the interplay between decreasing communication costs and the specialization of large cities in high-skilled business services. The analysis we provide here differs substantially as the divergence between large and small cities we document in France between 1995 and 2015 is a divergence in employment, not in terms of average wage. We thus abstract from any consideration regarding skills to focus on the determinants of overall local employment. Moreover, none of these works deals with economic linkages between regions. In this respect, we are closer to the papers that try to understand why cities and regions differ in terms of economic size.[62]

[59]This work builds on the regional economic literature studying the consequences of market potential on the long-run spatial distribution of output and employment. See Bartik (1991) and Blanchard and Katz (1992) among others.

[60]Moretti (2010) is an exception. He shows that local employment multipliers are higher for skilled jobs and jobs in high-skill industries.

[61]Several studies have provided evidence of agglomeration economies. Redding & Sturm (2008) exploit the division of Germany to quantify the importance of market access for the subsequent evolution of city size distribution in the country. They find that the institution of the new border negatively impacted neighboring cities' size. Brülhart et al. (2018) exploit the fall of the Iron Curtain to identify the overall employment and wage effects of increased market access for Austrian towns. They find the effect positive for towns nearby and welfare gains maximum for mid-size cities. See Combes and Gobillon (2015) for a comprehensive review.

[62]In the New Economic Geography (NEG) and urban economics literatures, spatial inequality generally happens as the outcome of agglomeration forces, mostly internal and external economies of scale at the industry level, and dispersion forces, such as trade costs, commuting costs and tensions on the input and the housing markets. The early contributions in these fields were based on models rich in predictions, especially due to agglomeration economies and multiple equilibria (Krugman, 1991; Krugman and Venables, 1995; and Helpman, 1998). At the same time, these models were too stylized to be directly brought to the data. For detailed reviews, see Fujita et al. (2001) and Fujita and Thisse (2013). Overman et al. (2003) and Head and Mayer (2004) provide reviews of the reduced-form empirical literature

The role of amenities in driving regional inequality has also been widely studied in frameworks à la Rosen (1979) and Roback (1982), with empirical applications combining data on local wages and local rents to infer the ranking of cities in terms of amenities (Albouy, 2016; Albouy and Stuart, 2020). Weather (Rappaport, 2007) and access to the mountains or the coast (Lee and Lin, 2018) are the dimensions most often considered when dealing with the role of natural amenities in local attractiveness. We control for them in our reduced-form empirical analysis. Also relevant to our work, a couple of papers on "urban shadows" show that the proximity to large urban areas may positively or negatively affect population growth in nearby locations depending on the relative evolution of commuting costs, within and across locations, and shipping costs. Cuberes et al. (2021) provide a long-run perspective on this issue for the US. They show that proximity to large urban areas was a curse for surrounding locations between 1840 and 1920 and then became a blessing. Partridge et al. (2008) also find a strong negative effect of distance to higher-tiered urban areas on population growth in the US between 1950 and 2000. Compared to these works, our approach is more short-run, which implies a smaller role for changes in trade costs between regions; moreover, it focuses on employment growth, rather than population growth, in areas that are designed to ensure a 70% of the local population to live and work inside the boundaries. We thus ignore commuting in our analysis.

Second, we contribute to a growing trade, urban, and macro literature studying the propagation of shocks within and between countries. Following the pioneering work on trade and output correlation by Frankel & Rose (1998), quantitative studies have highlighted the role of vertical production linkages (Di Giovanni & Levchenko, 2010), gravity (Clark & Van Wincoop, 2001; Baxter & Kouparitsas, 2005; Ng, 2010), multinational linkages (Kleinert et al., 2015; Di Giovanni et al., 2018; Cravino & Levchenko, 2017), production networks (Acemoglu et al., 2012), and financial linkages (Giroud and Mueller, 2019) in determining the geographic propagation of shocks.[63] Compared to this literature, we develop a spatial model of multi-establishment firms that endogenizes both domestic and

inspired by NEG models.

[63]The role of firms has been emphasized in recent studies. Di Giovanni et al. (2023) exploit French firm-level data to quantify the role of direct multinational linkages in explaining output co-movements between France and foreign countries. They find that such linkages account for one-third of the correlation. Cravino & Levchenko (2017) show that large multinational firms account for 10% in the transmission of productivity shocks for an average country, and eliminating barriers to multinational production would decrease cross-country standard deviation in output growth by 30%. Kleinert et al. (2015) look at output co-movements at a more disaggregated level. They exploit variation in multinational affiliates' presence across French regions and find a positive output correlation between the latter and the countries of origin of the affiliates.

international linkages and allows us to quantify their role in generating the urban-rural divide.

Finally, we broadly relate to research applying quantitative general equilibrium models to address questions in trade and spatial economics (Monte et al., 2018; Caliendo et al., 2018). Recent years have experienced a methodological shift in the analysis of spatial inequality by relying more and more on quantitative models.[64] Inspired by quantitative trade models à la Eaton and Kortum, 2002), this line of research is based on models featuring multiple sectors and locations that differ in terms of productivity and amenities. Compared to previously discussed literature, quantitative spatial models do not aim to explain economic activity's agglomeration *per se*. Rather, they provide a framework to replicate the observed spatial distribution of economic activity and run counterfactual analyses that account for general equilibrium effects. We directly build on this strand of the literature as our multi-region and multi-sector model features exogenous productivity differences between regions, inter-regional demand linkages through both final consumption and input-output relationships, and inter-regional labor mobility. One important distinctive feature of our model is that it incorporates inter-regional linkages through the network of multi-establishment firms. Indeed, several recent papers have shown that firms play a pivotal role in transmitting shocks across regions (Giroud and Mueller, 2018). We use our quantified model to assess the role of several inter-regional linkages in the disconnection between large and small local labor markets. To do so, we alternatively shut down each type of connection to study how counterfactual distributions of local employment growth rates match those measured in the data. This is close in spirit to Desmet and Rossi-Hansberg (2018) and Behrens et al. (2017), who also use quantified spatial models to assess the role of various types of fundamentals and spatial frictions in shaping the size distribution of cities.

Finally, several recent papers try to better understand the drivers of spatial inequality evolution in France over the past few decades. Davis et al. (2020) show that the Great Divergence is accompanied by greater job polarization in big cities in France. Chen et al. (2023) find that the shift from manufacturing to services has been more pronounced in large French cities and that this is mainly explained by the location of large firms, particularly large exporters. Bilal (2023) analyzes the role of the spatial sorting of employers across French local labor markets to explain spatial differences in unemployment rates. Charnoz et al. (2018) study how changes in communication costs induced by the

[64] For a review, see Redding and Rossi-Hansberg (2017).

high-speed rail have affected the allocation of managers and production workers across the establishments of multi-establishment firms. Kleinert et al. (2015) and Di Giovanni et al. (2023) focus on the role of multinational firms in transmitting foreign shocks to French regions and local labor markets. Nonetheless, it remains an open question whether and how the evolution of economic linkages between employment zones shapes spatial inequality.

Outline. The rest of the paper is organized as follows. Section 3.2 presents the data and the measure of urbanization. Section 3.3 presents the three stylized facts about the French economy. Section 3.4 develops the general equilibrium model. Section 3.5 discusses the impact of productivity shocks on the spatial distribution of employment. Section 3.6 discusses how to take the model to data. Section 3.7 presents the quantification exercises. Finally, Section 3.8 concludes.

3.2 Data

We combine several datasets provided by different French administrative sources. To document the spatial distribution of economic activities and constructing firms' linkages, we use information reported in the Social Security database, the *Déclaration Annuelle des Données Sociales* (DADS), produced by the National Institute of Statistics and Economic Studies (INSEE). The dataset contains establishment-level information on total employment, managerial employment, the wage bill, the location zip code, and the core industry of activity. Data covers the universe of firms active in the extraction, manufacturing, and service sectors between 1995 and 2015.

For the empirical analysis, we exclude the agriculture sector, reported only up to 2003, and restrict our attention to private employment.[65] Moreover, we focus on non-occasional jobs reported at the establishment level and exclude occasional jobs.[66] We also compute internal migration patterns using the 2006 population Census.

Establishments are identified by their SIRET code. Associated with each establishment, the SIREN code defines the boundaries of all multi-establishment firms. Using the SIREN

[65] The choice of excluding public employment addresses the change in reporting methodology for this category in 2009 as detailed in Appendix C.1

[66] The same worker might be employed in different occasional jobs across establishments in the same year. The choice of excluding them prevents incurring double counting. This aspect would be an issue in our context since it could artificially increase the correlation in employment growth between locations.

identifier, we trace the spatial distribution of these firms across locations. In addition, we combine information about managerial employment and the wage bill at the establishment level to predict the origin location of firms' headquarters (HQ).[67]

We complement this information with firm-level balance sheet data collected by the fiscal authority, the *Fichier de Comptabilité Unifié dans* SUSE (FICUS) and the *Fichier Approché des Résultats d'Esane* (FARE), with FARE replacing FICUS from 2008 onward. The two datasets contain information on domestic and export revenues, value added, total production, employment in full-time equivalent (FTE), capital, and intermediate inputs. Overall, the full merged dataset covers the period 1995-2015, with a yearly average of 1.4 million plants, 1.1 million firms, and 16 million workers across 220 different sectors classified at the level of 3-digit NAF Rev. 2 (*Nomenclature d'Activités Française*).

To identify proximity spillovers, we rely on US industry-level data from KLEMS on the wage bill and employment over the 1995-2015 period. We additionally construct different measures of exposure to global markets using information from the French Customs on firm-level exports and imports and from the *Liaison Financière* (LIFI) database on firms' multinational ownership. To allocate trade data, we apportion a firm's import and export volumes to its respective establishments using the employment share of the latter. Moreover, we use the regular and the symmetric input-output (IO) tables provided by INSEE for 2015 to retrieve aggregate economic measures for the French economy and construct within-France IO linkages.

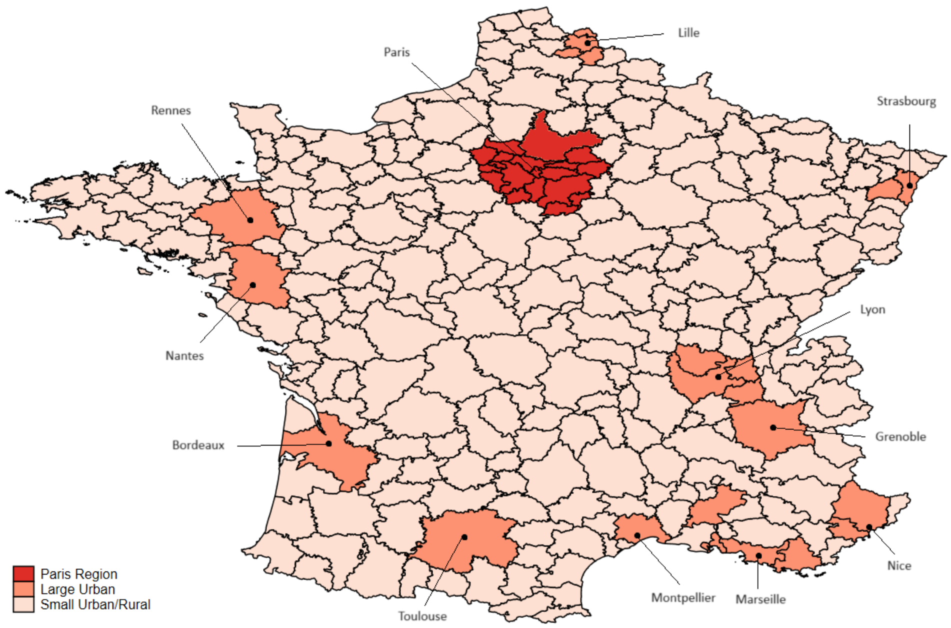
As the unit of our analysis, we focus on the employment zones (EZ) or *zones d'emploi* belonging to metropolitan France. Employment zones are geographical entities characterized by a larger fraction of the local population living and working within their boundaries. For our scope, we use the territorial division provided by INSEE for 2010. Employment zones are smaller than French regions and *départements* identifying 297 different territorial entities encompassing towns and cities of various densities and sizes.

3.2.1 Urbanization Index

Each employment zone defines a geographical area encompassing many cities and towns characterized by a different number of inhabitants, population densities, and boundary

[67]We cross-validate the predicted HQ location using firm-level information from FICUS-FARE, that covers a subsample of the universe of firms reported in the DADS. Our strategy allows us to match more than 80% of the reported HQ location.

Figure 3.1: Urbanization Index, EZ Level



Note: The figure reports the degree of urbanization for each of the 297 French employment zones. Employment zones are defined according to the INSEE definition in 2010.

structures. To assign an urbanization index to each EZ, we rely on the 2010 administrative geographic repartition of France in Urban Areas (UA), or *Aires Urbaines*, developed by INSEE, which assigns each municipality to an urban agglomerate following similar principles to those used for defining local labor markets.

INSEE classifies urban units using different levels of employment threshold, particularly 10, 5, and 1.5 thousand workers, to distinguish between large and medium urban centers. These urban units need to be autonomous entities detached from larger urban agglomerates. All towns and rural areas in the outskirts of the urban unit are then incorporated into the latter as long as they employ at least 40% of their workforce in the urban unit. These municipalities can also be connected to multiple large urban units. Each urban unit along its adjacent economic zone of influence constitutes an Urban Area. This classification procedure excludes remote, low-populated towns and villages considered utterly rural. With all cities, towns, and villages assigned to a UA, INSEE provides an index, from zero to ten, defining the UA population size to which any municipality belongs.

Each municipality, whose boundaries fall within the geographic definition of employment zone, is assigned an index of urbanization, making it convenient for aggregations. We compute a population-weighted average of the urbanization degree for each municipality

Table 3.1: Summary Statistics by Urbanization Degree, 1995-2015

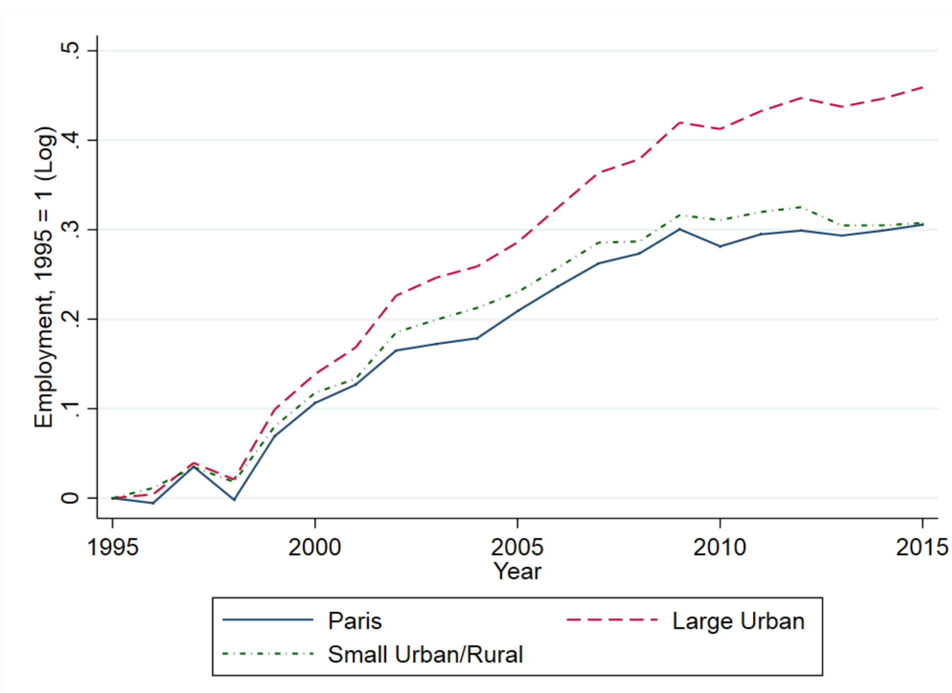
	Small Urban/Rural	**Large Urban**	**Paris**
Panel A: Levels in 1995			
Private Employment	25.588	127.674	179.102
Wage Bill (million EUR)	489	2.655	4.707
Average Wage	18.514	20.401	22.642
Exports per Employee	11.335	16.322	13.166
Share Exporters	0.10	0.13	0.14
Share Exporters, Manuf.	0.24	0.26	0.29
Share Manuf. Employment	0.34	0.27	0.27
Panel B: Changes 1995-2015			
Private Employment (%)	40	55	28
Wage Bill (%)	111	134	88
Average Wage (%)	51	51	46
Exports per Employee	5.440	6.705	5.646
Share Exporters	0	-0.02	-0.02
Share Exporters, Manuf.	-0.01	-0.02	-0.03
Share Manuf. Employment	-0.12	-0.11	-0.13

Note: Panel A provides summary statistics at the employment zone level in 1995. *Share Exporters* defines the average number of establishments involved in exporting activity across establishments at the EZ level. *Share Exporters, Manuf.* defines the average number of manufacturing establishments involved in exporting activity across manufacturing establishments at the EZ level. *Share Manuf. Employment* defines the average share of manufacturing employment over the total private employment at the EZ level. Panel B shows EZ-level changes over the sample period (1995-2015). Variables are reported in absolute values in Panel A, with the exception of those expressed in percentage changes and marked with *%*.

at the EZ level and define three different urbanization categories. Figure 3.1 shows the subdivision of France in the 297 EZs with their respective urbanization degrees: small urban/rural areas, large urban centers, and the region of Paris. Our methodology can capture the high urbanization degree of France's largest cities (in dark orange). Excluding the region of Paris (in red), in the North-East, we identify Lille and Strasbourg; in the South-East, we have Lyon and Grenoble in the inner side, and Nice, Cannes, Toulon, Marseille, Avignon, and Montpellier on the coast; in the SouthWest, we identify Toulouse and Bordeaux; finally, in the North-West, we have Nantes and Rennes.

Summary statistics by urbanization category are reported in Table 3.1. The evolution of private employment, in Panel B, is suggestive of diverging trends between the large urban areas and the rest of the country. Paris behaves differently from the other large urban areas, characterized by slow employment growth despite sharing similarities with the rest of the large urban areas. Figure 3.2 clarifies how this differential evolution has accrued over the studied period.

Figure 3.2: Evolution of Private Employment by Urbanization Degree



Note: The figure reports the evolution of French private employment over the 1995-2015 period for the three urban categories. For each of the latter categories, private employment is normalized to one in 1995.

The evolution of these average growth rates hides a high degree of heterogeneity. When looking at the EZ level, rural and medium urban areas can be found at the top and the bottom of the distribution. For example, the best performing EZ in terms of employment growth is Clermont-l'Hérault, a predominantly rural area in the southern part of France and neighboring Montpellier. The latter employment zones share the same fate as Clermont-l'Hérault, the fast-growing employment zone among the large urban areas. Tables C.2 and C.3 in Appendix C.2 report summary statistics for the top and bottom five employment zones by employment growth, respectively, for small urban and rural areas and large urban areas. Such a pattern highlights an important degree of heterogeneity, which becomes apparent across all 297 employment zones.[68]

In the next section, we will assess the determinants of the urban premium and economic proximity's role in generating the observed heterogeneity in employment growth across the small urban and rural employment zones.

3.3 Stylized Facts

This section documents three main stylized facts about the French economy and the evolution of the urban-rural divide. We first show the diverging employment trends between large urban areas and the rest of the country. We then provide evidence of the role of large urban areas as a pull factor for local employment growth of small and rural employment zones. Finally, we show how this pulling effect evolves. In each paragraph, we present the baseline empirical specifications and discuss the main explanatory variables and controls introduced in detail.

Stylized Fact 1. *Large urban employment zones are characterized by a greater employment growth over the period 1995-2015; we call this growth differential the Urban Employment Growth Premium.*

Table 3.2 presents the first empirical regularity: the relationship between employment growth and the degree of urbanization at the employment zone level. We estimate the following OLS specification:

$$\Delta_\tau \mathrm{Log}\left(L_{i,t}\right) = U_i + \beta_1 SS_{i,\tau} + \mathbf{X}'_{i,t}\gamma + \varepsilon_{i,t}, \tag{3.1}$$

[68] See Figure C.1 in Appendix C.4.

where $\Delta\text{Log}\left(L_{i,t}\right)$ defines the (private) employment growth in EZ i over the period $\tau \in \{1995-2015, 1995-2005, 2005-2015\}$, U_i the urbanization index as previously defined, $SS_{i,\tau}$ an industry-level shift-share, and $\mathbf{X}'_{i,t}$ a set of beginning-of-the-period EZ-level controls for local natural amenities. To account for the initial heterogeneity in size across employment zones and location centrality, we provide additional results in Appendix C.2.

The specification in equation (3.1) aims to test whether being a large urban employment zone affects the evolution of local employment growth, controlling for potential confounding factors. In particular, the inclusion of the shift-share controls for the initial industrial specialization at the local level. In recent decades, France experienced a strong decline in manufacturing employment with a structural shift towards services (Chen et al., 2022) that we want to account for in the specification. A steady decline of employment in the manufacturing sector is a common trend across Western economies, with different underlying explanations.[69] Malgouyres (2017) shows how the rise of Chinese import competition harmed manufacturing employment growth across local labor markets. Similar results are found in Acemoglu, Lelarge, and Restrepo (2020), looking at the effect of robot adoption on overall French manufacturing employment growth. Figure C.2 in Appendix C.2 reports the distribution of manufacturing employment shares across employment zones in 1995 and 2015.

To account for these long-run trends, we control for the predicted industry-level employment growth. As shares, we use the beginning-of-the-period industry-level employment level, while as shifts, the national industry-level employment growth rate between 1995 and 2015. Formally, defining by k an industry present in employment zone i, K_i, we construct the shift-share as:

$$\text{SS}_{i,\tau} = \sum_{k \in K_i} \frac{L_{ik,t}}{L_{i,t}} \Delta_\tau \text{Log}\left(L_{k,t}\right). \tag{3.2}$$

Finally, for the vector of beginning-of-the-period controls $\mathbf{X}'_{i,t}$, we include a set of local natural amenities such as a dummy for the presence of mountains chains, a dummy for the seaside, and a categorical variable for the average temperature deviation from the mean temperature of France. Natural amenities are described in Figures C.3, C.4, and C.5 in Appendix C.3.

[69]For the U.S. economy, see Autor et al. (2013) on the impact of Chinese import competition and Acemoglu and Restrepo (2019) on the impact robotization.

Table 3.2: Large Urban EZs' Employment Growth Premium, 1995-2015

	Dep. var.: Private Empl. Growth (%)								
	1995-2015			1995-2005			2005-2015		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Large Urban	0.12***	0.05	0.03	0.05**	0.01	-0.01	0.07***	0.03***	0.03**
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Paris	-0.04*	-0.15***	-0.14***	-0.04*	-0.10***	-0.08***	-0.00	-0.06***	-0.06***
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Empl. Growth Mean	0.40	0.40	0.40	0.29	0.29	0.29	0.08	0.08	0.08
Empl. Growth St. Dev.	0.28	0.28	0.28	0.17	0.17	0.17	0.10	0.10	0.10
Shift Share Industry		✓	✓		✓	✓		✓	✓
Natural Amenities			✓			✓			✓
Obs.	297	297	297	297	297	297	297	297	297
R^2	0.04	0.46	0.54	0.05	0.40	0.49	0.08	0.31	0.36

Note: The table reports the marginal coefficients for equation (1), standard errors are reported in brackets. Regressions are weighted using beginning-of-the-period levels of employment at the EZ level. The dependent variable is the growth rate of private employment at the employment zone level over the reported period. All independent variables in columns (1) to (6) are calculated in 1995, while those in (7) to (9) in 2005. "Large Urban" and "Paris" are dummies defining the urban status of the employment zone (see map). "Shift Share Industry" is the predicted growth of employment based on the industrial composition of the EZ at the beginning of the period. "Natural Amenities" is a set of variables about proximity to the seaside, proximity to mountain chains, and average temperature deviation from the annual French mean. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Columns (1) to (3) from Table 3.2 report the marginal coefficients for equation (3.1) over the full period. Coefficients for the Large Urban and Paris dummies should be interpreted as relative to the Small Urban and Rural EZs. The effect is positive and statistically significant in the baseline specification. However, the effect disappears once controlling for the shift-share. The diverging path in terms of employment growth can be mostly explained by the local sector composition in the initial year, which also emerges from the large contribution to the R-squared.

Looking at each sub-period separately, it emerges a different picture. While in the first half, from columns (4) to (6), there is no significant difference between employment growth in the large versus the rest, there exists an employment growth premium for large urban areas in the second half, from columns (7) to (9), even when conditioning for the predicted industrial employment growth. This result suggests that the employment divide that arose in the mid-2000 reported in Figure 3.2, cannot be solely accounted for by the difference in initial employment zone industrial specialization. Importantly, the positive and statistically significant effect in column (9) highlights that local amenities are not key in explaining the differential trend.

Appendix C.2 reports a series of robustness to the baseline specification. In particular, in Table C.5, we control for the initial level of employment to account for size heterogeneity. In Table C.6, we add some measures of spatial centrality, constructed as a proximity-weighted average of all French employment zone employment levels, and market potential, constructed using the same weighted average over employment growth across employment zones. Finally, in Table C.7, we introduce exposure to international trade proxied by the share of local employment belonging to firms that import or export, to multinational firms, and large firms with total employment above 500 units. Across specifications, results remain qualitatively unchanged.

An important consideration regarding this exercise concerns the interpretation of the coefficients. For example, across specifications, the region of Paris has a consistently negative coefficient that suggests a slower employment growth with respect to the average small urban or rural area. However, the average employment zone in Paris is seven times bigger than the former, which might mechanically result in smaller growth rates. At the same time, being France a large economy, we should expect the inflow of people from abroad to be relatively marginal to the entire domestic population; hence, most of the variation over time should be induced by either a reallocation of people between employment zones or the progressive change in the working age population dictated by the demographics.

Therefore, the regression identifies an employment zone's relative performance in attracting workers from other regions or inducing local new workers to remain.[70] It follows that even if the sheer size of employment in Paris has been increasing, the inflow of new workers was not at the expense of the rest of the country. On the contrary, the positive employment growth premium registered for the large urban employment zones provides evidence of a stronger attraction capacity that draws employees from the rest of the country. We now turn to understand whether the benefits of such an employment premium spill over to the neighboring areas.

[70] A decomposition exercise of the growth of the labor force is provided in Appendix C.5. We first show that the expansion of the labor force mainly drives employment growth, while the contribution of unemployment is marginal. This finding is also corroborated by the work of Bilal (2023), showing that unemployment in France is relatively stable for the 2002-2008 period. Second, we show that the growth in the labor force can be accounted for a 50% by demographic factors and a 50% by domestic migration.

Stylized Fact 2. *Small urban and rural employment zones that are relatively less distant from the large urban ones grow systematically more in terms of employment. We call this effect the Proximity Premium.*

Table 3.3 presents the second empirical regularity: the relationship between employment growth and proximity to large urban employment zones. We estimate the following OLS specification:

$$\Delta_\tau \text{Log}\left(L_{i,t}\right) = \beta_1 PROX_i + \beta_2 PtoP_i + \beta_3 SS_{i,\tau} + \mathbf{X}'_{i,t}\gamma + \varepsilon_{i,t}, \tag{3.3}$$

where $\Delta\text{Log}\left(L_{i,t}\right)$ defines the (private) employment growth in a small urban or rural EZ i over period $\tau \in \{1995-2015, 1995-2005, 2005-2015\}$, $PROX_i$ measures proximity in kms of EZ i to large urban areas, $PtoP_i$ measures proximity of EZ i to Paris, $SS_{i,t}$ the industry-level shift-share, and $\mathbf{X}'_{i,t}$ the set of beginning-of-the-period EZ-level controls for local natural amenities.

Specification in equation (3.3) aims to test geographic spillovers from large urban employment zones. We restrict the analysis to small urban and rural employment zones, and we condition our result for the same set of controls used in equation (3.1) but also on proximity to Paris. As already pointed out, Paris behaves differently from the rest of the large urban employment zones, experiencing relatively slower employment growth. However, its sheer size is such that even small growth rates are sufficient to hollow out the neighboring areas.

We additionally estimate spillovers using a measure of proximity that takes into account the performance of the large urban employment zones. We test three different specifications in this respect. First, we exploit variation in employment growth of the closest large urban area. Subsequently, we extend the measure to account for the impact of the five and ten closest large urban employment zones. To account for the role of gravity, we weigh employment growth by the inverse of bilateral distance, such as having relatively closer large urban areas to have a bigger role. Formally, we estimate:

$$\Delta_\tau \text{Log}\left(L_{i,t}\right) = \beta_1 WLG_{i,\tau} + \beta_2 PtoP_i + \beta_3 SS_{i,\tau} + \mathbf{X}'_{i,t}\gamma + \varepsilon_{i,t}, \tag{3.4}$$

where the employment growth weighted average over period τ across large urban EZs j is given by:

$$WLG_{i,\tau} = \sum_j \frac{1}{d_{ij}} \Delta_\tau \text{Log}\left(L_{j,t}\right). \tag{3.5}$$

Columns (1) to (12) in Table 3.3 report the estimated marginal effects of equations (3) and (4). We provide several ways to account for proximity to large urban employment zones. Columns (1), (5), and (9) report the coefficient for the logarithm of the inverse of distance to the closest large urban employment zone. The effect is positive and statistically significant when considering the whole, meaning that small urban and rural employment zones that are closer to large urban ones experience systematically higher employment growth rates. However, the effect ceases to be significant in the second half of the period, which also corresponds to the period in which the large urban areas experience a systematic employment growth premium.

Table 3.3: Proximity to Large Urban EZs Premium, 1995-2015

	Dep. var.: Private Empl. Growth (%)											
	1995-2015				1995-2005				2005-2015			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Proximity Large Urban (Log)	0.03**				0.02**				0.00			
	(0.01)				(0.01)				(0.01)			
Empl. Growth Large Urban		7.15***				7.97***				5.57		
		(2.51)				(2.52)				(3.81)		
Empl. Growth Large Urban, 5			2.57**				2.56**				2.05	
			(1.03)				(1.13)				(1.75)	
Empl. Growth Large Urban, 10				1.83**				1.56*				1.79
				(0.87)				(0.92)				(1.65)
Proximity Paris (Log)	-0.05***	-0.04***	-0.05***	-0.05***	-0.04***	-0.03***	-0.04***	-0.04***	-0.02*	-0.01	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Shift Share Industry	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Natural Amenities	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	256	256	256	256	256	256	256	256	256	256	256	256
R^2	0.57	0.59	0.58	0.57	0.50	0.51	0.50	0.49	0.36	0.37	0.37	0.37

Note: The table reports the estimated marginal coefficients for equations (3) and (4), standard errors are reported in brackets. The dependent variable is defined as the growth rate of private employment at the EZ level, over the reported period. All independent variables in columns (1) to (8) are calculated in 1995, while those in (9) to (12) in 2005. "Proximity Large Urban (Log)" is the inverse of distance to the closest Large Urban area in log. The "Empl. Growth Large Urban", "Empl. Growth Large Urban, 5", and "Empl. Growth Large Urban, 10" are respectively the employment growth rates of the 1/5/10 closest Large Urban areas weighted by their respective distance. "Shift Share Industry" is the predicted growth of employment based on the industrial composition of the EZ at the beginning of the period. The "Natural Amenities" control accounts for proximity to the seaside, mountain chains, and local average temperature. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Proximity might still correlate with other confounding factors not controlled for in the specification. As a robustness, we test whether the magnitude of the urban premium is associated with stronger spillover effects. In columns (2), (6), and (10), we estimate equation (3.3) by replacing the inverse of distance with the product between the latter and the actual employment growth of the closest large urban employment zone. Again, coefficients remain positive and significant across specifications, as we would expect in the case of positive spatial spillovers, with the exception of the second period.

As discussed, we provide additional results by looking at the effect generated by the presence of multiple large urban areas. Columns (3), (7), and (11) report results for the effect of the closest 5 large urban areas, confirming the sign and the magnitude of the previous specification. Results in columns (4), (8), and (12), for which the closest 10 large urban employment zones are considered, are substantially in line with the other results.

Another aspect emerging from this reduced-form exercise is that the Paris area generates negative spillover effects on the neighbors. To fix ideas concerning what may drive the sign of the effect, let's consider the potential mechanism at play. The spatial employment growth spillovers we are identifying should be thought of as the joint effect of two forces on the demand and supply of workers. On the one, the increasing demand for workers in the large urban areas has to be sustained with additional workers potentially arriving from neighboring areas. This effect would negatively impact the employment growth of neighboring employment zones by affecting the local supply. On the other hand, the positive local growth might generate gains for neighboring areas and increase the latter demand for workers if locations were linked through consumption or production linkages. A limitation of the exercise is that it does not allow thinking about the actual employment level. Being the coefficient informative only about the relative performance, we might have positive coefficients even if large urban areas were reducing employment growth everywhere else but relatively less so in their peripheral areas. However, this would not change the interpretation regarding the presence of geographically concentrated feedback induced by large urban areas.

Instrumental Variable Strategy. The empirical quantification of the spillover effects in the context of regional economics has been subject to criticism (Gibbons and Overman, 2012). The OLS identification of the elasticity of employment growth to proximity to large urban employment areas might suffer from an omitted variable bias induced by the effect of unobservables in generating higher employment growth across neighboring employment zones. Additionally, the OLS coefficient would be biased in the presence of feedback effects generated by the neighboring small urban or rural areas favoring the growth in employment of the large urban ones. Ideally, we want to capture variation in employment growth in large urban areas that is orthogonal to employment growth in the rest of the country.

To solve for the omitted variable and reverse causality biases, we exploit variation in the initial industrial composition across large urban employment zones by relying on an instrumental variable (IV) approach. We construct a Bartik shock exploiting sector-level specialization of large urban EZs at the beginning of the period interacted with the growth in U.S. sector-level employment from 1995 to 2015. The latter is computed from the U.S. KLEMS data on industry-level employment and wage bills. Formally:

$$WLG^{IV}_{i,\tau} = \sum_j \frac{1}{d_{ij}} \tilde{L}^{IV}_{j,\tau}, \tag{3.6}$$

where:

$$\tilde{L}^{IV}_{j,\tau} = \sum_k \frac{L_{jk,t}}{L_{j,t}} \Delta_\tau \mathrm{Log}(L^{US}_{k,t}), \tag{3.7}$$

represents the predicted aggregate employment growth at the EZ j level and $L^{US}_{k,t}$ the employment in U.S. industry k over period at time t. The instrument is constructed to predict large French urban areas' employment growth if these experience the same sector-level economic shocks as the United States. For this reason, the exclusion restriction requires U.S. underlying shocks for the sample period to be orthogonal to those affecting French small urban and rural employment zones. A potential threat to identification is the "China Shock", which impacted manufacturing at large and should be expected to increase the correlation between U.S. and French employment growth at the industry level. However, manufacturing constitutes a third of local employment on average in small urban and rural areas, making employment growth in services more salient for validating the instrument. Moreover, it is doubtful that the U.S. service sector and the small urban and rural French areas service sector are affected by similar shocks.

Moving to the results, columns (1) to (6) from Table 3.4 report the estimated marginal effects for the 2SLS regressions. First, the KP F-statistics is well above ten across specifications. This suggests that the instrument has enough power to predict urban EZs' employment growth. Estimated coefficients are positive, statistically significant, and bigger in magnitude with respect to the OLS ones. Table C.8 in Appendix C.2 reports comparable estimates for the same 2SLS specification for where the shift component of the Bartik was constructed using the growth of U.S. industry-level wage bill instead of employment. These results confirm that fast-growing urban employment zones are a pulling factor for the neighboring areas over the period considered.

Table 3.4: Proximity to Large Urban EZs Premium (2SLS), 1995-2015

	Dep. var.: Private Empl. Growth (%)								
	1995-2015			1995-2005			2005-2015		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Empl. Growth Large Urban	12.99**			10.36**			4.26		
	(4.79)			(5.11)			(4.56)		
Empl. Growth Large Urban, 5		4.55*			4.89*			1.03	
		(2.42)			(2.51)			(1.80)	
Empl. Growth Large Urban, 10			2.97**			3.83***			0.90
			(1.35)			(1.38)			(1.63)
Proximity Paris (Log)	-0.03	-0.03	-0.04**	-0.03**	-0.03	-0.03*	-0.01	-0.02*	-0.02*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Shift Share Industry	✓	✓	✓	✓	✓	✓	✓	✓	✓
Natural Amenities	✓	✓	✓	✓	✓	✓	✓	✓	✓
Empl. Growth Mean, Small Urban EZs	0.40	0.40	0.40	0.29	0.29	0.29	0.07	0.07	0.07
Empl. Growth St. Dev., Small Urban EZs	0.28	0.28	0.28	0.18	0.18	0.18	0.09	0.09	0.09
Empl. Growth Mean, Large Urban EZs	0.63	0.61	0.60	0.39	0.38	0.37	0.16	0.17	0.17
Empl. Growth St. Dev., Large Urban EZs	0.23	0.21	0.18	0.13	0.11	0.10	0.07	0.06	0.05
Obs.	256	256	256	256	256	256	256	256	256
KP F-Stat	24.61	28.09	160.05	22.45	35.85	206.79	89.88	237.65	495.73

Note: The table reports the estimated marginal coefficients for equations (3) and (4) instrumented for the growth of employment in the US, standard errors are reported in brackets. The dependent variable is defined as the growth rate of private employment at the EZ level over the reported period. All independent variables in columns (1) to (4) are calculated in 1995, while those in (5) and (6) in 2005. The "Empl. Growth Large Urban", "Empl. Growth Large Urban, 5", and "Empl. Growth Large Urban, 10" are respectively the employment growth rates of the 1/5/10 closest Large Urban areas weighted by their respective distance. "Shift Share Industry" is the predicted growth of employment based on the industrial composition of the EZ at the beginning of the period. The "Natural Amenities" control accounts for proximity to the seaside, mountain chains, and local average temperature. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Tables 3.3 and 3.4 also allow us to highlight a further empirical regularity: the persistence of the positive spillover effect throughout the two sub-periods. This constitutes our third empirical pattern.

Stylized Fact 3. *The Proximity Premium weakens over the period 1995-2015.*

This is an important finding to understand the role of transmission in explaining the long-run divergence in employment growth paths across locations. Intuitively, we might have diverging employment trends between two locations either through a change in their respective employment growth or fixing the latter through a change in the transmission of shocks between urban and rural employment zones.

The fact that large urban areas grow more in relative terms when spatial spillovers become weak is suggestive of the second channel playing a role. However, a reduced form test of the role of transmission is nontrivial, due to the strong non-linearities between the variables at play. To overcome this challenge, we provide a quantitative spatial model of regional trade, which has the advantage of imposing a structure to such relationships. Moreover, we make the model rich enough to allow linkages between regions to arise endogenously from the interaction of *i*) the spatial distribution of multi-establishment firms, *ii*) the domestic input-output structure of production, and *iii*) gravity. We turn to the presentation of the model in the next section.

3.4 A Spatial Model of Linkages, Trade, and Migration

We provide a general equilibrium model of the French economy that endogenizes the spatial distribution of firm linkages between locations and accounts for I-O linkages, domestic and international trade, and within-country migration. We consider an economy with R regions and S sectors. We identify a region by $r \in \{1, \ldots, R\}$ (or n) and a sector by $s \in \{1, \ldots, S\}$ (or g). A region corresponds to a competitive labor market that is endowed with a heterogeneous level of amenities z_r. Sectors can be tradable, in which case goods from that sector can be traded at a cost across regions or non-tradable.

The economy features an exogenous mass of firms (or headquarters) with heterogeneous productivity levels. Firms can open establishments across regions to produce and sell their differentiated varieties. An establishment' efficiency is a function of its headquarter's productivity and some geographical frictions. Production takes place under a Cobb-Douglas technology over two factors of production: labor, l, and a bundle of materials,

M_{rs}. Workers face a migration cost and an idiosyncratic preference shock that affects their relocation across regions, but can freely move between sectors.

3.4.1 Households

Consumers. In any region r, there is an endogenous mass L_r of individuals. Each individual supplies inelastically a unit of labor and receives a competitive wage, w_r. Consumption is allocated over a Cobb-Douglas bundle of local final goods coming from all sectors. Preferences take the following form:

$$C_r = \prod_{s=1}^{S} (C_{rs})^{\alpha_s}, \tag{3.8}$$

where C_{rs} denotes consumption of the composite good in sector s and region r at price P_{rs} and α_s the final consumption share, with $\sum_s \alpha_s = 1$. The overall spending in region r for sector s is given by $P_{rs}C_{rs} = \alpha_s I_r$, where I_r denotes the total income available in region r. In equilibrium, the real income is such to make any individual indifferent between remaining and migrating:

$$V_r = \frac{I_r}{P_r}, \tag{3.9}$$

where $P_r = \prod_{s=1}^{S} (P_{rs}/\alpha_s)^{\alpha_s}$ denotes the regional price index and P_{rs} the composite good price in sector s and region r.

Location Choice. Beyond consumption, individuals derive a utility from the presence of local amenities $z_r \geq 0$, and are allowed to relocate across regions at a migration cost, $t_{nr} \geq 0$.[71] Each individual experiences an additive idiosyncratic region-specific preference shock, ϵ_r, which is i.i.d. and Gumbel distributed.[72] Therefore, the utility of any individual h born in region n and residing in r is given by:

$$U^h_{nr} = \zeta \ln \left(V^h_r\right) + z_r - t_{nr} + \epsilon^h_{nr}. \tag{3.10}$$

[71] We assume the migration cost to be time-invariant, additive, and measured in terms of utility as in Caliendo et al. (2019).

[72] Gumbel or Type-I Extreme Value distribution has a long tradition in the economics literature since McFadden (1984), and has become standard in discrete choice models of migration. Some notable examples are Redding (2014), Diamond (2015), Monte et al. (2018), and Monras (2019).

There is an exogenous number $\bar{L}_n$ of individuals born in region n each choosing to reside in the region that gives them the highest utility level. Following McFadden (1984), we can write the probability of individual h born in region n to move to region r as:

$$\Pr\left[U_{nr}^{h} = \max_{\{r'\}} U_{nr'}^{h}\right] = \frac{L_{nr}}{\bar{L}_n} = \frac{\exp\left[\zeta \ln\left(V_r^h\right) + z_r - t_{nr}\right)\right]}{\sum_{r'} \exp\left[\zeta \ln\left(V_{r'}^h\right) + z_{r'} - t_{nr'}\right)\right]}. \tag{3.11}$$

Hence, the number of people choosing to live in region r is given by:

$$L_r = \sum_n \frac{\exp\left[\zeta \ln\left(V_r^h\right) + z_r - t_{nr}\right)\right]}{\sum_{r'} \exp\left[\zeta \ln\left(V_{r'}^h\right) + z_{r'} - t_{nr'}\right)\right]} \bar{L}_n. \tag{3.12}$$

3.4.2 Establishments and Production

Establishments. In region r and sector s there is an endogenous mass N_{rs} of establishments. Each establishment produces a differentiated variety with a certain productivity z_{rs} and incurs a fix cost in order to produce. The production technology features increasing returns to scale, hence the output of an establishment in region r and sector s is given by:

$$Q\left(z_{rs}\right) = z_{rs}\left[\left[l\left(z_{rs}\right)\right]^{\gamma_s} \prod_g \left[M_g\left(z_{rs}\right)\right]^{\gamma_g^s} - F\right], \tag{3.13}$$

where $l\left(z_{rs}\right)$ denotes labor and $M_g\left(z_{rs}\right)$ the intermediate inputs bundle from sector g used in the production of variety z_{rs}. The fixed cost of production, F, is defined in terms of the bundle of production factors, and $\gamma_s > 0$ and $\gamma_g^s \geq 0$ are respectively the technological parameters for labor and intermediate inputs, such that $\sum_g \gamma_g^s = 1 - \gamma_s$. We assume the intermediate inputs bundle, $M_{rg}\left(z_{rs}\right)$, to have a CES structure over all varieties accessible from region r.

Local Composite Goods. Varieties demanded in region r and sector s from all regions are aggregated into a local sectoral composite good, Q_{rs}, that can be either consumed locally or used as input in production:

$$Q_{rs} = \left[\sum_n \int q_r \left(z_{ns} \right)^{\frac{\sigma_s - 1}{\sigma_s}} dz_{ns} \right]^{\frac{\sigma_s}{\sigma_s - 1}}, \tag{3.14}$$

where $q_{rns}(z)$ denotes the demand from region r for variety z produced in region n and sector s and $\sigma_s > 1$ the elasticity of substitution between varieties within sector s.

Total expenditure in region r for sector s is given by:

$$E_{rs} = \alpha_r I_r + J_{rs}, \tag{3.15}$$

where $\alpha_r I_r$ denotes the share of income that local consumers in region r allocate to sector s and J_{rs} the total spending on the intermediate composite good in region r and sector s. Solving for the local composite good in region r and sector s, we obtain the following demand for variety z_{ns} :

$$q_{rs} \left(z_{ns} \right) = p_{rs} \left(z_{ns} \right)^{-\sigma_s} P_{rs}^{\sigma_s - 1} E_{rs}, \tag{3.16}$$

where $p_{rs} \left(z_{ns} \right)$ denotes the price of variety z_{ns} faced by consumers in region r in sector s and the region-sector specific price index is defined as:

$$P_{rs} = \left[\sum_n \int p_{rs} \left(z_{ns} \right)^{1 - \sigma_s} dz_{ns} \right]^{\frac{1}{1 - \sigma_s}}. \tag{3.17}$$

To simplify notation, we define the real expenditure in region r and sector s as $B_{rs} = P_{rs}^{\sigma_s - 1} E_{rs}$.

Prices, Costs, and Profits. A variety produced in a tradable sector in region r can be sold to any region n by incurring an iceberg transport cost $\tau_{rn} \geq 1$, with $\tau_{rr} = 1$. In the non-tradable sector $\tau_{rn} = \infty$. However, establishments do not need to incur any additional fixed cost to trade to other regions.[73] These assumptions together with the CES structure imply that all establishments will sell to each region in equilibrium.

Due to the CES demand structure, an establishment in region n and sector s with productivity z_{ns} maximizes its profits by charging a price on the destination region r equal

[73] Since we are focusing on the domestic French context, we consider this a convenient simplification. See Antras et al. (2023) for an application to a trade model.

to:

$$p_{rs}\left(z_{ns}\right)=\frac{\sigma_s}{\sigma_s-1}\frac{\tau_{rn}W_{ns}}{z_{ns}}, \tag{3.18}$$

where W_{ns} denotes the cost of the input bundle. In particular:

$$W_{ns}=\left[\gamma_s^{-\gamma_s}\prod_g\left(\gamma_g^s\right)^{-\gamma_g^s}\right]w_n^{\gamma_s}\prod_g P_{ng}^{\gamma_g^s}, \tag{3.19}$$

Note how all establishments in the same region-sector pair use factors of production in the same proportion. Total sales of variety z_{ns} across all regions are given by:

$$S\left(z_{ns}\right)=\sigma_s\Psi_s\Phi_{ns}z_{ns}^{\sigma_s-1}W_{ns}^{1-\sigma_s}, \tag{3.20}$$

where:

$$\Phi_{ns}=\sum_r B_{rs}\tau_{rn}^{1-\sigma_s}, \tag{3.21}$$

denotes the market potential in region r and sector s and Ψ_s is a constant.[74] The sales of an establishment, hence, depend negatively on its marginal costs and positively on the proximity to large markets. Finally, the establishment's total profits can be expressed as:

$$\Pi\left(z_{ns}\right)=\frac{S\left(z_{ns}\right)}{\sigma_s}-FW_{ns}. \tag{3.22}$$

The presence of an active establishment in sector s and region n depends on its relative efficiency compared to the local levels of competition and demand. Positive profits for such an establishment require its productivity z_{ns} to be higher than:

$$\underline{z}_{ns}=\left(\frac{FW_{ns}}{\Phi_{ns}\Psi_s}\right)^{\frac{1}{\sigma_s-1}}W_{ns}. \tag{3.23}$$

The productivity cutoff is higher in region-sector pairs featuring higher factors' costs and lower market potential.

[74]Specifically, $\Psi_s=\sigma_s^{-\sigma_s}\left(\sigma_s-1\right)^{\sigma_s-1}$

3.4.3 Firms, Ownership, and Productivity

Headquarters. There is an exogenous mass N_{os}^h of firms (or headquarters) originating from region o and active in sector s. Firms draw their productivity from a region-sector specific Pareto distribution:

$$g_{os}(z) = \kappa z_{os}^{\kappa} z^{-\kappa-1}, \tag{3.24}$$

where z_{os} represents the lower bound of the distribution and kappa > 0 the Pareto parameter. A headquarter originating from region o in sector s can open an establishment in any region r. Establishments produce a sector-region specific differentiated variety with productivity $z_{rs} = z_{os}/\beta_{or}$, where z_{os} defines the headquarter productivity and $\beta_{or} > 1$ any geographic friction between the establishment and its headquarter.[75] Establishments are thus less productive than the headquarters, with a productivity discount specific to the region pair.

We assume that the different varieties of the firm are exactly as substitutable as varieties across firms, ensuring that there is no "cannibalization" in our setup with many firms.[76] This simplification is akin to a firm-level Armington assumption: firms can produce an additional variety by opening an establishment in a region, but adding additional establishments in a region would not generate additional varieties. A variety is thus defined at the firm-region (or establishment) level.

Profits maximization implies that a firm with productivity z_{os} opens an establishment in all regions where it generates positive profits, hence in all regions where $z_{os} \geq \underline{z}_{rs}\beta_{or}$. This implies the number of establishments in region r and sector s to be given by:

$$N_{rs} = \underline{z}_{rs}^{-\kappa} Z_{rs}, \tag{3.25}$$

where Z_{rs} indexes the aggregate productivity level of all establishments in region r and sector s :

[75] This type of friction accounts for managerial and communications costs. Evidence of such organizational costs is studied by Gumbert et al. (2021) and Charnoz et al. (2018), respectively in the context of France and Germany.

[76] Relaxing this assumption would come at the cost of additional complexity without being instrumental to the results.

$$Z_{rs} = \sum_{o} N_{os}^{h} z_{os}^{\kappa} \beta_{or}^{-\kappa}. \tag{3.26}$$

It is worth noting that, conditional on selling in region r, the productivity distribution of establishments with a headquarter in the origin region o is independent of the one in region O.

3.4.4 Competitive Spatial Equilibrium

Expenditure Shares. Total sales in region r and sector s toward any destination region n is given by:

$$S_{rns} = \sum_{n} \int s_{ns}\left(z_{ns}\right) dz_{ns}, \tag{3.27}$$

where $s_{ns}\left(z_{ns}\right) \equiv q_{ns}\left(z_{ns}\right) p_{ns}\left(z_{ns}\right)$. Let denote with π_{rns} region n 's total expenditure share in sector s originating from region r :

$$\pi_{rns} \equiv \frac{S_{rns}}{E_{ns}} = \frac{S_{rs}\Phi_{rs}^{-1}\tau_{rn}^{1-\sigma_s}}{\sum_{r'} S_{r's}\Phi_{r's}^{-1}\tau_{r'n}^{1-\sigma_s}}. \tag{3.28}$$

Equation (3.28) takes the form of a standard gravity model of trade. The share of expenditure between any two regions depends on the relative efficiency of the producer, the real market potential of the destination, and the bilateral openness of the two regions.

In the same spirit, we can compute the share of total export from region r in sector s toward destination region n :

$$\frac{S_{rns}}{S_{rs}} = \frac{B_{ns}\tau_{rn}^{1-\sigma_s}}{\Phi_{rs}}. \tag{3.29}$$

Factor Payments and Welfare. Total sales of all establishments located in region r and sector s can be expressed as:

$$S_{rs} = \frac{\kappa\sigma_s}{\kappa+1-\sigma_s} FW_{rs}N_{rs} = \frac{\kappa\sigma_s}{\kappa+1-\sigma_s} \Psi_s^{\frac{\kappa}{\sigma_s-1}} Z_{rs} \Phi_{rs}^{\frac{\kappa}{\sigma_s-1}} W_{rs}^{-\kappa} \left(FW_{rs}\right)^{1-\frac{\kappa}{\sigma_s-1}}. \tag{3.30}$$

The combined sales of all establishments located in region r and active in sector s depend positively on their aggregate productivity level, Z_{rs} and the proximity to large markets, Φ_{rs}. Conversely, higher production, W_{rs}, and fixed costs, F, negatively affect sales.

The total payment to labor in region r directly depends on the sales:

$$w_r L_r = \sum_s \frac{\kappa\sigma_s + 1 - \sigma_s}{\kappa\sigma_s} \gamma_s S_{rs}, \tag{3.31}$$

and the total profits of all establishments located in region r are:

$$\pi_r = \sum_s \frac{\sigma_s - 1}{\kappa\sigma_s} S_{rs}. \tag{3.32}$$

For simplicity, we assume that all profits made by an establishment are redistributed locally, implying total income I_r to be:

$$I_r = w_r L_r + \pi_r + \Theta_r = \sum_s VA_{rs} + \Theta_r, \tag{3.33}$$

where $VA_{rs} = \left[\gamma_s + \frac{\sigma_s - 1}{\kappa\sigma_s}(1 - \gamma_s)\right] S_{rs}$ is the value added generate in region r and sector s and Θ_r a local net transfer, which can be positive or negative.

Equilibrium. The price index in sector s of region r is:

$$\begin{aligned} P_{rs} = \quad & \left[\sum_n N_{ns} \int p_{rs}(z_{ns})^{1-\sigma_s} \kappa z^{-\kappa-1} \underline{z}_{ns}^{\kappa} dz_{ns}\right]^{\frac{1}{1-\sigma_s}}, \\ = & \left[\frac{\kappa\sigma_s}{\kappa+1-\sigma_s}\left(\sum_n \frac{N_{ns}\tau_{nr}^{1-\sigma_s}}{\Phi_{ns}} F W_{ns}\right)\right]^{\frac{1}{1-\sigma_s}}, \end{aligned} \tag{3.34}$$

which can also be expressed as:

$$P_{rs} = \left[\sum_n \frac{\tau_{nr}^{1-\sigma_s} S_{ns}}{\Phi_{ns}}\right]^{\frac{1}{1-\sigma_s}}. \tag{3.35}$$

In equilibrium, total spending on sector s in region r is equal to the sum of spending for final consumption and for intermediate use:

$$E_{rs} = \alpha_s I_r + \sum_g \frac{\kappa\sigma_g + 1 - \sigma_g}{\kappa\sigma_g} \gamma_s^g S_{rg} = \sum_g A_{sg} S_{rg} + \alpha_s \Theta_r, \tag{3.36}$$

where $A_{sg} = \left[\alpha_s + \frac{\kappa\sigma_g+1-\sigma_g}{\kappa\sigma_g}\left(\alpha_s\left(\gamma_g - 1\right) + \gamma_s^g\right)\right]$ summarizes the exposure of sector g to sector s both through the final demand in s and the reliance of s on varieties coming from g. The real demand for sector s in region r is given by:

$$\Phi_{rs} = \sum_n \tau_{rn}^{1-\sigma} \left(\sum_m \tau_{mn}^{1-\sigma} \frac{S_{ms}}{\Phi_{ms}}\right)^{-1} \left(\sum_g A_{sg} S_{ng} + \alpha_s \Theta_n\right). \tag{3.37}$$

3.5 Shocks to Firms' Productivity

We now consider a shock to the vector of productivity parameters z_{os}. An increase in z_{os} raises the average productivity of headquarters in region o and sector s, and, everything else equal, the number of firms from region o opening an establishment in each region. This is akin to a positive productivity shock for other regions and as a consequence an increase in the connection of region o to the rest of the country. Formally, we have:

$$\hat{Z}_{rs} = \kappa \sum_o \frac{N_{rs}^o}{N_{rs}} \hat{z}_{os}, \tag{3.38}$$

where the ratio N_{rs}^o/N_{rs} is the share of establishments in region r and sector s belonging to a headquarter in region o. Using the equations for the cost of production bundle (3.19) and on total sales (3.30), we can express the change in the aggregate level of sales in region r and sector s induced by a change in productivity z_{os} as:

$$\hat{S}_{rs} = \hat{Z}_{rs} + \frac{\kappa}{\sigma_s - 1}\hat{\Phi}_{rs} - \frac{\kappa\sigma_s + 1 - \sigma_s}{\sigma_s - 1}\hat{W}_{rs}, \tag{3.39}$$

where the change in the aggregate cost of the production bundle is given by:

$$\hat{W}_{rs} = \left(\gamma_s \hat{w}_r + \sum_g \gamma_g^s \hat{P}_{rg}\right). \tag{3.40}$$

Equation (3.39) makes clear that a sector-region pair would sell more if it becomes more productive, $\hat{Z}_{rs}$, if demand conditions improve, $\hat{\Phi}_{rs}$ or if wages or input prices become cheaper $\hat{W}_{rs}$.

From the definition of the price index in equation (3.34) and from the payment to labor equation (3.31), we obtain:

$$\begin{aligned} \hat{P}_{rs} &= \frac{1}{1-\sigma_s} \sum_n \frac{S_{nrs}}{E_{rs}} \left(\hat{S}_{ns} - \hat{\Phi}_{ns} \right), \\ \hat{w}_r + \hat{L}_r &= \sum_s \frac{L_{rs}}{L_r} \hat{S}_{rs}, \end{aligned},$$

that can be replaced back to equation (3.39) to obtain:

$$\hat{\Phi}_{rs} = \sum_n \Gamma_{rns} \left(\hat{\Phi}_{ns} - \hat{S}_{ns} \right) + \sum_{n,g} \Lambda_{rnsg} \hat{S}_{ng} + \sum_n \Xi_{rns} \hat{\Theta}_n + \hat{\alpha}_s \varpi_{rns}, \tag{3.41}$$

Totally differentiating the real demand in equation (3.37) provides a connection between the vector of $\hat{\Phi}_{rs}$ and the vector of growth of sales $\hat{S}_{rs}$.

$$\hat{\Phi}_{rs} = \sum_n \Gamma_{rns} \left(\hat{\Phi}_{ns} - \hat{S}_{ns} \right) + \sum_{n,g} \Lambda_{rnsg} \left(\hat{S}_{ng} + \hat{A}_{sg} \right) + \sum_n \Xi_{rns} \left(\hat{\Theta}_n + \hat{\alpha}_s \right) \tag{3.42}$$

where:

$$\begin{aligned} \Gamma_{rns} &= \sum_m \frac{S_{rms}}{S_{rs}} \frac{S_{nms}}{E_{ms}}, \\ \Lambda_{rnsg} &= \frac{S_{rns}}{S_{rs}} \frac{A_{sg} S_{ng}}{E_{ns}}, \\ \Xi_{rns} &= \frac{S_{rns}}{S_{rs}} \frac{\alpha_s \Theta_n}{E_{ns}}, \\ \hat{A}_{sg} &= \hat{\alpha}_s \left(1 - \frac{\gamma_s^g}{A_{sg}} \right). \end{aligned} \tag{3.43}$$

and:

$$\hat{A}_{sg} = \hat{\alpha}_s \left(1 - \frac{\gamma_s^g}{A_{sg}}\right). \tag{3.44}$$

Expanding on the equation (3.44), we obtain:

$$\hat{\Phi}_{rs} = \sum_n \Gamma_{rns}\left(\hat{\Phi}_{ns} - \hat{S}_{ns}\right) + \sum_{n,g} \Lambda_{rnsg}\hat{S}_{ng} + \sum_n \Xi_{rns}\hat{\Theta}_n + \hat{\alpha}_s \varpi_{rns}, \tag{3.45}$$

with:

$$\varpi_{rns} = \sum_n \frac{S_{rns}}{S_{rs}}\left(1 - \frac{\sum_g \gamma_s^g S_{ng}}{E_{ns}}\right). \tag{3.46}$$

We now turn to a matrix notation to solve the system. Define $\hat{\boldsymbol{\Phi}}$ and $\hat{\boldsymbol{S}}$ as four column vectors of length $RS, \hat{\boldsymbol{\Theta}}$ a column vector of length R and $\hat{\boldsymbol{\alpha}}$ a column vector of length S. We also define the $RS \times RS$ matrices $\boldsymbol{\phi}, \boldsymbol{\varphi}$ as well as the $RS \times R$ matrix $\boldsymbol{\theta}$ and the $RS \times S$ matrix $\boldsymbol{a}$ defined by their elements (lines as subscripts, columns as superscripts): where the sum is taken over all partner regions, including Foreign and the corresponding $RS \times S$ matrices $\boldsymbol{a}$ by its elements: Finally, we can derive the change in L induced by the productivity shock:

$$\hat{L}_r = \zeta \sum_n \frac{L_{nr}}{L_r}\left(\hat{V}_r - \sum_{r'} \frac{L_{nr'}}{\bar{L}_n}\hat{V}_{r'}\right) = \zeta\left(\hat{V}_r - \sum_{r'}\left(\sum_n \frac{L_{nr}}{L_r}\frac{L_{nr'}}{\bar{L}_n}\right)\hat{V}_{r'}\right), \tag{3.47}$$

where L_{nr} is the number of people born in region n and residing in region r and where:

$$\begin{aligned} \hat{V}_r \quad & = \hat{I}_r - \hat{L}_r - \textstyle\sum_s \alpha_s \hat{P}_{rs} + \sum_s \left[1 + \ln(\alpha_s) - \ln(P_{rs})\right]\alpha_s\hat{\alpha}_s \\ & = \textstyle\sum_s \rho_{rs}\hat{S}_{rs} + \vartheta\hat{\Theta}_r - \sum_s \alpha_s \hat{P}_{rs} - \hat{L}_r + \sum_s \left[1 + \ln(\alpha_s) - \ln(P_{rs})\right]\alpha_s\hat{\alpha}_s \end{aligned} \tag{3.48}$$

where $\rho_{rs} = VA_{rs}/I_r$ is the share of the income in region r accounted for by the value added of sector s and $\vartheta_r = \Theta_r/I_r$ the share of transfers in the same sector. We can then express each $\hat{S}_{rs}$ as a linear combination of the productivity shocks to reconstruct the change in the indirect utility as a function of productivity shocks.

We are interested in the effect of a productivity shock on regional employment growth. We therefore plug $\hat{S}_{rs}$ as a function of $\hat{Z}_{rs}$ back into $\hat{V}_r$. To do so, we generate a $R \times RS$ matrix, $\boldsymbol{T_{LZ}}$, which maps a RS vector of productivity shock $\hat{Z}_{rs}$ into a vector of employment growth $\hat{L}_r$. We solve for matrix $\boldsymbol{T_{LZ}}$ in Appendix C.5.

3.6 Taking the Model to the Data

The model developed in the previous section provides two major advantages for studying employment growth in France. Its structure clarifies the specific mechanisms through which economic shocks propagate across employment zones and simultaneously allows the quantification of the magnitude of each of the different components on the aggregate outcomes. We need to parametrize the model to the French economy to generate quantitative meaningful estimates.

Solving the model requires information about regional sales $S_{rs,t}$, value added $VA_{rs,t}$, employment $L_{rs,t}$, the internal migration shares μ_{nr}, and the regional share of headquarters $n^o_{rs} = N^o_{rs}/N_{rs}$. We also need to compute the sectoral labor share γ_s, the Input-Output elasticity, γ^g_s, the Pareto parameter, κ, the sectoral expenditure share, α_s, the sectoral elasticity of substitution, σ_s, and set the marginal utility of consumption, ζ. We then use 2015 as our baseline and the model to project the evolution of our main variables of interest back to 1995.

Regions, Sectors, and Labor Markets. Our quantitative model features 297 French employment zones and a constructed rest of the world. Each employment zone constitutes a different labor market. We consider 36 sectors classified according to the European Statistical Nomenclature for Economic Activities (NACE). We include 13 manufacturing sectors, 15 service sectors, agriculture, construction, wholesale and retail, and five different public sectors. For the rest of the world, we assume a single labor market featuring the same set of sectors and parametrization as France.

Migration Flows. We construct migration flows across employment zones within France using information about the population census of 2006, the earliest year available. The Quetelet population census provides information on residential migration in France by reporting each individual's current zip code of residency and the past département of residency five years ahead. We first reallocate individuals' residency of origin to the employment zone using as weight the percentage of the département's population on the total EZ population to which it belongs. We then allocate each zip code to a unique employment zone so that to be able to construct the share of population residing in region r and coming from region n, μ_{rn}. We impose μ_{rn} to be constant over time and abstract from international migration flows.

Headquarters and Establishments. We compute the fraction of headquarters at the EZ-sector level from DADS, using the SIREN of each firm as a firm identifier and declaring all establishments with the same SIREN as part of the same firm. To identify the headquarter of the firm, we use information about the establishment number of managerial jobs and total wage bills. To double check, we use information from FICUS-FARE of the actual firms' headquarter for a subsample of manufacturing firms. Our methodology correctly identifies headquarters for more than 90% of observations.

Elasticities. We need to calibrate a total of five parameters, and we use information both from the Input-Output table in 2015 and the *symmetric* Input-Output table in the year 2015.[77] The symmetric Input-Output table splits the spending by each sector on each sector according to whether it is domestic spending or imported goods. However, it does not provide information on the wage bill. For the sector-level labor share, γ_s, we rely on the regular IO table and use only information about wage bills and intermediate input spending. We make this choice for consistency with the model that features only labor and intermediate inputs as production factors. In particular, we construct the labor share as:

$$\gamma_s = \frac{\text{Wage bill } s}{\text{Wage bill }_s + \text{ Intermediates }_s}, \tag{3.49}$$

where we use the total wage bill and the total spending on intermediate inputs in sector s. To compute the sector-level Input-Output elasticity, we rely on the symmetric IO table from which we obtain:

$$\gamma_s^g = (1-\gamma_s)\,\frac{\text{Intermediates }_{sg}^{sym}}{\sum_g \text{ Intermediates }_{sg}^{sym}}, \tag{3.50}$$

[77] 2015 is the earliest date for which INSEE provides a symmetric IO table, i.e. one where uses and production are expressed in the same unit.

where Intermediates $_{sg}^{sym}$ is the spending on domestic and foreign intermediate inputs from sector s on sector g coming from the symmetric tables. We assign the elasticity of substitution to be $\{\sigma_s\} = 4$. For the Pareto parameter, κ, we back it out using the structure of the model, in particular:

$$
\begin{aligned}
\frac{\kappa_s\sigma_s + 1 - \sigma_s}{\kappa_s\sigma_s} &= \frac{\text{Wage }_{\text{bill}}^{\text{sym}} + \text{ Intermediates }_s^{\text{sym}}}{\text{Sales }_s^{\text{sym}}}, \\
\kappa_s &= \frac{1-\sigma_s}{\sigma_s}\left(\frac{\text{Wage bill }_s^{\text{sym}} + \text{ Intermediates }_s^{\text{sym}}}{\text{Sales}_s^{\text{sym}}} - 1\right)^{-1},
\end{aligned}
$$

We take the sector-level expenditure information, Intermediates $_s^{\text{sym}}$ and Sales $_s^{\text{sym}}$, from the symmetric Input-Output table. Conversely, we reconstruct the wage bill using information about the labor share, γ_s, in the regular table and the intermediate input expenditures in the symmetric one. Formally:

$$
\text{Wage bill }_s^{\text{sym}} = \frac{\gamma_s}{1-\gamma_s}\text{ Intermediates }_s^{\text{sym}}. \tag{3.51}
$$

We construct the expenditure share, α_s, using information on domestic and foreign expenditure from the symmetric Input-Output table. In particular, we combine expenditure at the sector level from households and the public administration on goods and investment goods. This combines all the uses not made for intermediate purposes or for exports, which is closest to the final use in our model. Finally, we set the marginal utility of consumption, ζ, equal to two.

Reconciling IO and DADS. Our strategy relies on fitting our model to the 2015 aggregates of the symmetric IO table. However, for the time variation in employment distribution, we rely on employment data provided by the DADS. To ensure internal consistency, we need the total wage bill as reported by the IO table and the one of the DADS to match. The potential discrepancy between the two measures poses a practical issue of consistency.

To address the problem, we first define for each industry a coefficient ω_s stating how much underrepresented the wage bill in the DADS is compared to the one reported in the IO matrix in 2015. We thus define:

$$\omega_s = \frac{wb^{IO}_{s,2015}}{wb^{DADS}_{s,2015}}. \tag{3.52}$$

The national wage bill in sector s at time t is defined as:

$$wb_{s,t} = \omega_s wb^{DADS}_{s,t}, \tag{3.53}$$

while the one at the regional level as:

$$wb_{rs,t} = \omega_s wb^{DADS}_{rs,t}. \tag{3.54}$$

This implies, for example, that we obtain a wage bill at the employment zone level in the data we construct from:

$$wb_{r,t} = \sum_s wb_{rs,t} = \sum_s \omega_s wb^{DADS}_{rs,t}. \tag{3.55}$$

The wage bill growth per employment zone is different in our data compared to the growth from the DADS. The reporting in the DADS of agriculture/forestry, public administration, and education is inconsistent over the period. We fix the share of these sectors in the total DADS wage bill to their value in 2015 for all years. Note that this is not exactly equivalent to fixing their total sales to a given level, but it is very close.

From the wage bill above and using the calibrated parameters, we can compute for each year both sales and value added as:

$$\begin{aligned} S_{rs,t} &= \frac{wb_{rs,t}}{\gamma_s} \frac{\kappa_s \sigma_s}{\kappa_s \sigma_s + 1 - \sigma_s} \\ VA_{rs,t} &= \left(1 + \frac{1}{\gamma_s} \frac{\sigma_s - 1}{\kappa_s \sigma_s + 1 - \sigma_s}\right) wb_{rs,t} \end{aligned}$$

With this, we can notably compute the share of a region's value added accounted for by each sector (the matrix $\boldsymbol{\rho}$) as well as the share of employment accounted for by each sector ($\boldsymbol{\lambda}$ when using the assumption that wages in a region are constant across sectors. From (3.35), we also obtain the expenditure on each sector in each region E_{rs}.

Aggregate International Trade. Exports and imports are available from the symmetric IO table. Trade in services is included in the IO table, which solves one of the typical issues arising from using customs data. We assume the national current account to be balanced, employing that the actual imports and exports would not perfectly match those predicted by the model, given sales at the sector level. We use the model to recompute the yearly sector-level imports and exports to correct this discrepancy. In particular, we rely on the relationship between expenditures and sales:

$$E_{rs} = \sum_g A_{sg} S_{rg}. \tag{3.56}$$

Summing over all French regions:

$$E_s^{FR} = \sum_g A_{sg} S_g^{FR}. \tag{3.57}$$

Defining NX_s as the French net exports of s :

$$S_s^{FR} - NX_s = \sum_g A_{sg} S_g^{FR}. \tag{3.58}$$

We observe the vector of sales and can reconstruct a vector of net exports that is compatible with the model. It is very close to the observed one but differs because of the current account imbalance at the national level. To ensure that our recomputed exports and imports are not negative, we equate exports to actual imports plus the computed net exports if net exports are positive and equate imports to actual exports minus net exports if net exports are negative. In this process, we take out the re-exports included in the IO table (some imports in the IO table are used as exports).

International trade of EZs. When it comes to the international trade of each French ZE, we project national values onto regions using the region's share in the sector's national wage bill. This approach is similar to papers à la Autor et al. (2013). For each region $r \in FRA$ and sector $n \notin FRA$, we compute:

$$S_{rns} = \frac{w_r L_{rs}}{\sum_{m \in FRA} w_m L_{ms}} S_{Fns}, \tag{3.59}$$

where S_{Fns} are French exports to n in sector s. Since we assign exports and sales to French regions using the same proportions of the national value, this implies that: $\frac{S_{rns}}{S_{rs}} = \frac{S_{Fns}}{S_{Fs}}$. To compute imports per region, we compute the expenditure in each region-sector pair using (). We assign the national imports to each region as a fraction of the national expenditure accounted for by the EZ:

$$S_{nrs} = \frac{E_{rs}}{\sum_{m \in FRA} E_{ms}} S_{nFs}. \tag{3.60}$$

Trade between French Regions. We do not observe trade between French EZs, hence we recompute internal flows in a theory-consistent way using:

$$\frac{S_{rns}}{S_{rs}} = \frac{B_{ns} \tau_{rn}^{1-\sigma_s}}{\Phi_{rs}}, \tag{3.61}$$

where the denominator can be rewritten as:

$$\Phi_{rs} = \sum_{n \in FRA} B_{ns} \tau_{rn}^{1-\sigma_s} + \Phi_{rs} \sum_{n \notin FRA} \frac{S_{rns}}{S_{rs}}, \tag{3.62}$$

or:

$$\left(1 - \frac{X_{rs}}{S_{rs}}\right) \Phi_{rs} = \sum_{n \in FRA} B_{ns} \tau_{rn}^{1-\sigma_s}, \tag{3.63}$$

where X_{rs} are the exports of the region $r : \sum_{n \notin FRA} S_{rns}$. With the way we assign sales and exports to regions: $X_{rs}/S_{rs} = X_s/S_s$ and is the same for all regions. To compute B_{rs} for French regions, we use that $B_{rs} = P_{rs}^{\sigma_s - 1} E_{rs}$ and that:

$$P_{rs}^{1-\sigma_s} = \sum_{n} \frac{\tau_{nr}^{1-\sigma_s} S_{ns}}{\Phi_{ns}} = \sum_{n \in FRA} \frac{\tau_{nr}^{1-\sigma_s} S_{ns}}{\Phi_{ns}} + \sum_{n \notin FRA} \frac{S_{nrs}}{B_{rs}}, \tag{3.64}$$

where the second equality uses (3.52). Using the definition of B_{rs}, this can be rewritten as:

$$\left(1 - \sum_{n \notin FRA} \frac{S_{nrs}}{E_{rs}}\right) P_{rs}^{1-\sigma_s} = \sum_{n \in FRA} \frac{\tau_{nr}^{1-\sigma_s} S_{ns}}{\Phi_{ns}}. \tag{3.65}$$

This gives:

$$P_{rs}^{1-\sigma_s} = \frac{1 - \frac{X_{rs}}{S_{rs}}}{1 - \frac{M_{rs}}{E_{rs}}} \sum_{n \in FRA} \frac{\tau_{nr}^{1-\sigma_s} S_{ns}}{\sum_{n' \in FRA} P_{n's}^{\sigma_s - 1} E_{n's} \tau_{nn'}^{1-\sigma_s}}, \tag{3.66}$$

which is a non-linear system of price indices. For each French region, we observe S_{rs}, the total sales of region r in sector s. For the matrix τ_{nr}, we use the great circle distance between the centroid of the EZs. [81] We follow Nitsch (2000) and measure internal distance within an employment zone as $\sqrt{\frac{\text{Area in km}^2}{3.14}}$. We compute E_{rs} to reach rs pair as their theoretical equivalent $E_{rs} = \sum_g A_{sg} S_{rg}$. Once we obtain P_{rs} for each ZE-sector pair, we compute $B_{rs} = P_{rs}^{\sigma_s - 1} E_{rs}$ and Φ_{rs} using (3.54). This allows to compute S_{rns} using (3.52).

3.7 Quantifying the Effect of Productivity Shocks

The model we developed allows us to calculate the regional elasticity of employment with respect to a productivity change in any sector and in any region. This section provides a goodness-of-fit exercise to prove the model's ability to reproduce our stylized fact of interest. We then illustrate the magnitude and the scope of each of the different mechanisms at play. Subsequently, we will look at the aggregate effect of a common productivity shock across sectors. To clarify the interpretation of the different mechanisms, we weight our linkages measures by the share of EZs' value added, allowing us to visualize EZ-specific outcomes from underlying region-sector variables. Formally, we will look at how a productivity shock $\hat{Z}_{rs}$ that is common to all sectors within an employment zone maps into a regional vector of employment growth, $\hat{L}_r$.

Structural IV Regression. The richness of the model allows to account for various transmission mechanisms between French employment zones. In order to test the ability of the model to replicate our stylized facts, we provide a structural 2SLS regression of equation (3.3), where the employment growth of small urban and rural areas and the instrument, in equation (3.6), are constructed using the predicted employment growth from the model.

We perform this exercise in two stages. In the first stage, we compute the predicted employment growth in the large French urban areas for the period 1995-2015 using the

Bartik structure as in equation (3.7):

$$\hat{L}_{urb} = \sum_k \frac{L_{urb,k}}{L_{urb}} \Delta \text{Log}(L_k^{US}). \tag{3.67}$$

From here we use the model to retrieve the vector of industry-level productivity shocks $\hat{Z}_k$ predicting employment growth in the large French urban areas as in equation (3.67). This supply-side shock is the one captured by the instrument in the reduced form exercise and which variation allows to pin down the causal effect of employment growth in the large urban areas to employment growth in the rest of the country.

Table 3.5: Proximity to Large Urban EZs Premium (Structural 2SLS), 1995-2015

	Dep. var.: Theory-predicted Empl. Growth (%) 1995-2015	
	(1)	(2)
Empl. Growth Large Urban	4.86***	5.65***
	(3.19)	(4.11)
Proximity Paris (Log)	-0.01***	-0.01***
	(0.02)	(0.02)
Shift Share Industry		✓
Natural Amenities		✓
Obs.	256	256
R^2	0.29	0.33

Note: The table reports the estimated marginal coefficients for equations (3.36). The dependent variable is the predicted growth rate of employment in small urban and rural employment zones from 1995 to 2015. All independent variables are calculated in 1995. "Shift Share Industry" is the predicted growth of employment based on the industrial composition of the EZ at the beginning of the period. The "Natural Amenities" control accounts for proximity to the seaside, to mountain chains, and local average temperature. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

In the second stage, we plug back the vector of productivity shocks, $\hat{Z}_k$, to the matrix of linkages to predict employment growth across small urban and rural areas, $\hat{L}_r$. It is now possible to test the magnitude of such linkages by estimating the following OLS specification:

$$\hat{L}_r = \beta_1 \text{PROX}_r + \beta_2 PtoP_i + \beta_3 SS_{i,\tau} + \mathbf{X}'_{i,t}\gamma + \varepsilon_{i,t}, \tag{3.68}$$

where PROX_r defines the employment growth of the closest large urban areas, $PtoP_i$ the proximity to Paris, $SS_{i,t}$ the industry-level shift-share, and $\mathbf{X}'_{i,t}$ the standard set of beginning-of-the-period controls.

Table 3.5 reports the estimated coefficients for equation (3.68). Reassuringly, the estimated β_1 has the correct sign and magnitude of the coefficient estimated by 2SLS. This exercise validates the model in terms of the ability to capture the magnitude of the transmission mechanisms highlighted in Section 3.3. We now turn to the quantification of each mechanism at play.

Linkages by Employment Zone. We start from the more disaggregated level: the employment zone. The model allows capturing the propagation of productivity shocks through three main mechanisms. These constitute the building blocks of the structure of linkages. Let's consider a shock to productivity in a region-sector pair, z_{rs}, as discussed in Section 3.6. The first block is related to the role of firms' ownership:

$$\sum_s \frac{VA_{rs}}{VA_r} \frac{N^o_{rs}}{N_{rs}}, \tag{3.69}$$

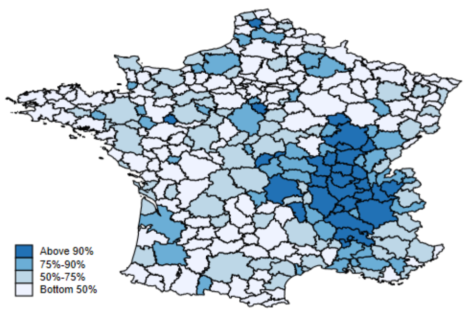
where VA_{rs}/VA_r denotes the share of value added generated by sector s in region r and N^o_{rs}/N_r the share of headquarters originating in region o and having establishments in region r and sector s.

Figure 3.3 shows the spatial propagation of a productivity shock affecting Lyon through the HQs in 1995 (left) and 2015 (right). The differential effect is driven by the presence of establishments directly linked to headquarters in Lyon. The map clarifies the role of distance, which generates aggregation around Lyon itself, and the role of market access, which pushes headquarters in Lyon to open establishments around the large urban areas.

The second block is related to the role of competition:

$$\sum_s \frac{VA_{rs}}{VA_r} \left(\sum_m \frac{S_{rms}}{S_{rs}} \frac{S_{nms}}{E_{ms}} \right), \tag{3.70}$$

Figure 3.3: Productivity Shock through HQ Linkages with Lyon as Source, 1995-2015



Note: The figure reports the relative degree of exposure in terms of employment growth in 1995 and 2015 across employment zones to an industry-wide 1% productivity shock in Lyon. The shock propagates only through linkages between establishments across employment zones and the headquarters located in Lyon.

where the term in brackets denotes the propensity of region r to satisfy demand from region m in sector s compared to the aggregate demand in the same sector in region m from another competitor in region n.

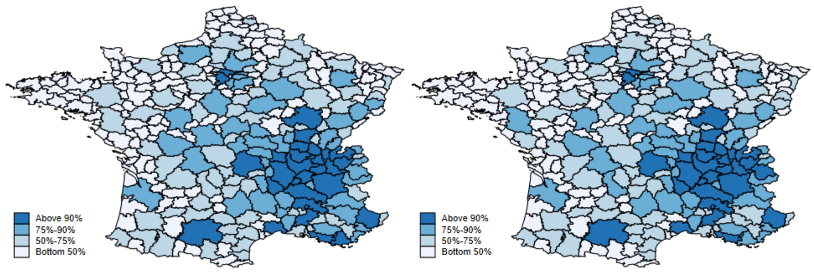
Figure 3.4 shows the spatial propagation of a productivity shock affecting Lyon through competition in 1995 (left) and 2015 (right). The differential effect is driven by the gain in efficiency of establishments in Lyon that push competition in the destination markets.

Finally, the third block is related to the role of input-output linkages:

$$\sum_s \frac{VA_{rs}}{VA_r} \left(\sum_g \frac{\gamma_g^s}{\sigma_g - 1} \frac{S_{nrg}}{E_{rg}} \right), \tag{3.71}$$

where the term in brackets denotes the propensity of region r in satisfying its demand for sector g from region n through the input-output demand of sector s from g.

Figure 3.4: Productivity Shock through Competition Linkages with Lyon as Source, 1995-2015



Note: The figure reports the relative degree of exposure in terms of employment growth in 1995 and 2015 across employment zones to an industry-wide 1% productivity shock in Lyon. The shock propagates only through the final demand of consumers located in Lyon.

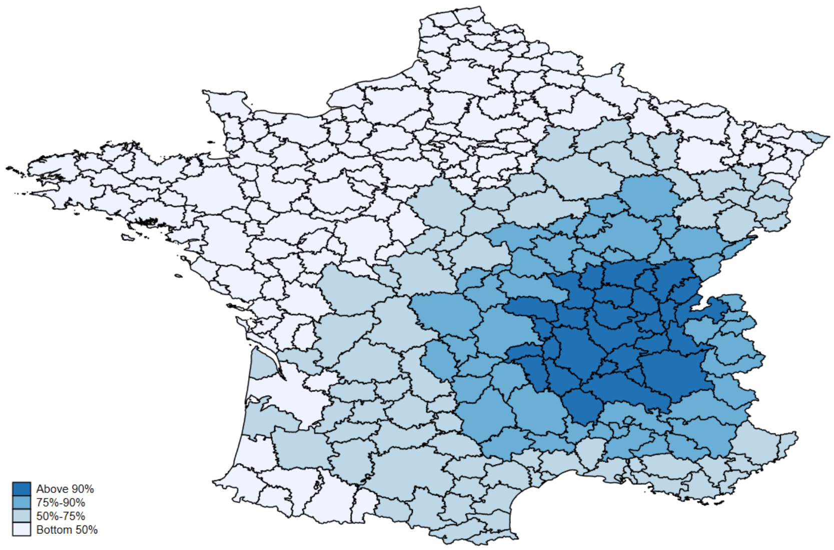
Figure 3.5 shows the spatial propagation of a productivity shock affecting Lyon through input-output in 2015. The differential effect is driven by the gain in efficiency of establishments in Lyon that push competition in the destination markets.

We conclude by showing the overall effect of the three channels. Figure 3.6 shows the spatial propagation of a productivity shock affecting Lyon through HQ linkages, the degree of competition, and the input-output between 1995 and 2015. The differential effect is driven by the gain in efficiency of establishments in Lyon that push competition in the destination markets.

Linkages by Urban Status. We are interested in measuring the evolution of linkages of large urban employment zones over time. In Figure 3.7, we depict the evolution of average linkages from large employment zones to small ones as well as to other large ones over the sample period. In the graph, all large urban EZs and all small EZs in France are considered as destinations.

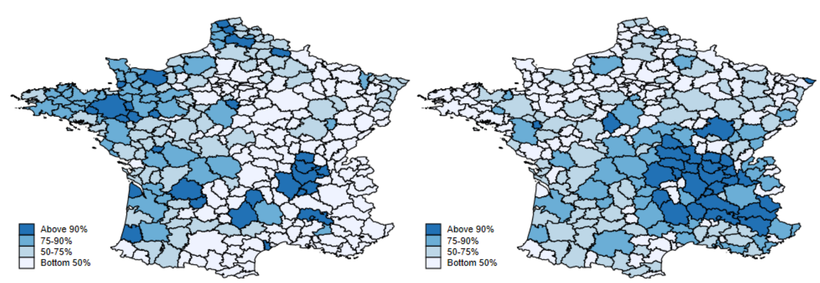
The first striking pattern that arises from the figure is the persistence over time of

Figure 3.5: Productivity Shock through Input-Output Linkages with Lyon as Buyer, 2015



Note: The figure reports the relative degree of exposure in terms of employment growth in 2015 across employment zones to an industry-wide 1% productivity shock in Lyon. The shock propagates only through input-output relationships established with buyers located in Lyon.

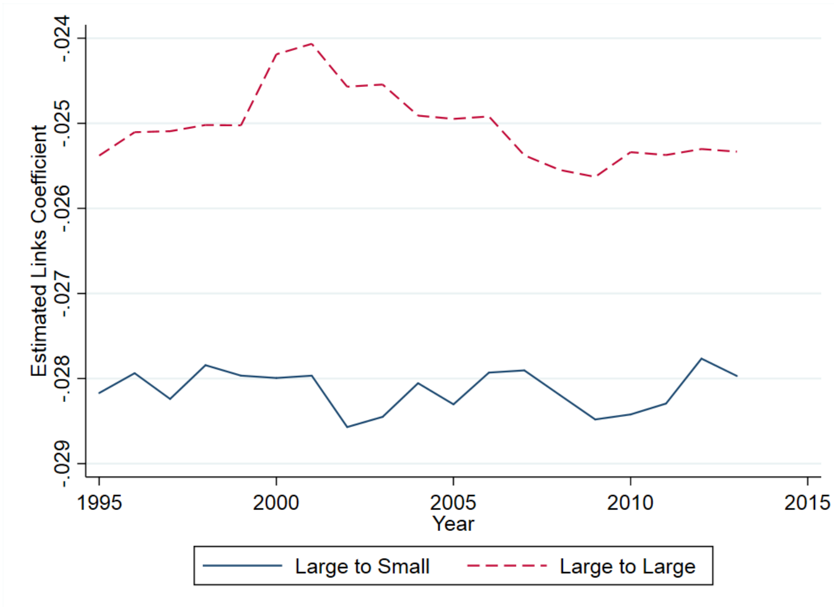
Figure 3.6: Aggregate Productivity Shock with Lyon as Source, 1995-2015



Note: The figure reports the relative degree of exposure in terms of employment growth in 2015 across employment zones to an industry-wide 1% productivity shock in Lyon.

the average aggregate effect going through linkages. As highlighted in Section 3.3, a weakening in the urban-to-rural areas' transmission is an aspect characterizing the French economy over the period considered. However, the model implies that the propagation of shocks between large urban employment zones and from large to small urban ones has remained intact.

Figure 3.7: Evolution Average Linkages 1995-2015, All EZs



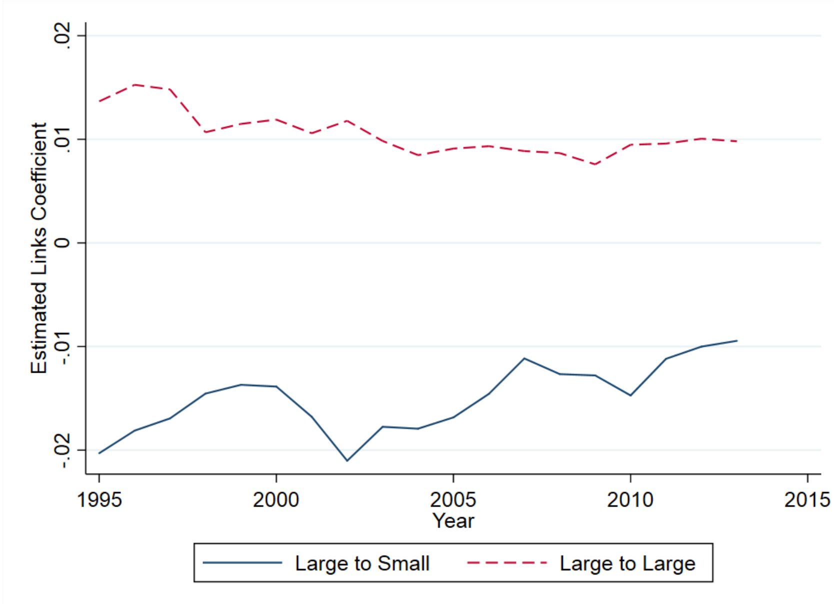
Note: The figure reports the average degree of exposure through linkages between large urban and small urban or rural employment zones (dashed red), and between large urban employment zones (in solid blue) over the period 1995-2015.

The second aspect of interest is that the sign of the coefficient is negative for both groups. This is unexpected and surprising in light of the reduced form findings but might be due to a problem relating to the *ad hoc* calibration of the model. For example, elasticities for the service sector are all equal to four, or the homogeneity across locations of the marginal utility of consumption. Other aspects of large urban employment zones might reduce or dissipate the local effect of productivity shocks. As an example, the model abstracts from fixed capital, which is a source of local congestion and which introduction should induce lower linkages and disproportionately more for large urban areas. Another aspect to consider is the dynamism of the urban labor market, which might prevent productivity shocks from generating large local gains.[78]

Figures 3.8 and 3.9 restrict the perimeter of the effect to employment zones located within 100 km or 200 km of distance from the large urban ones. Results are not sensitive to dis-

[78]See Bilal (2022) for a discussion about the persistence of unemployment across French local labor markets.

Figure 3.8: Evolution Average Linkages 1995-2015, EZs < 100km



Note: The figure reports the average degree of exposure through linkages between large urban and small urban or rural employment zones (dashed red), and between large urban employment zones (in solid blue) at a distance of maximum 100 km over the period 1995-2015.

tance as transmission mechanisms have been hardly diverging over time. If anything, they seem to have converged, which might suggest the actual employment growth divergence to be the result of changes in the economic fundamentals of urban areas. Conversely to the baseline, large-to-large linkages are estimated to generate positive spillovers.

3.8 Conclusion

In this paper, we shed light on the role that economic linkages play in shaping the spatial distribution of employment between urban and rural areas. We use a rich set of administrative micro-level data for France over the period 1995-2015 to document three empirical regularities regarding the spatial distribution of French employment growth. First, we show that employment in large urban areas grows on average faster than in the rest of the country. Second, we find evidence of positive employment spillovers generated by proximity to large urban areas. Third, we show that such proximity premium remains stable over the period considered.

Motivated by these findings, we construct a spatial general equilibrium model of trade

Figure 3.9: Evolution Average Linkages 1995-2015, EZs < 200km

Note: The figure reports the average degree of exposure through linkages between large urban and small urban or rural employment zones (dashed red), and between large urban employment zones (in solid blue) at a distance of maximum 200 km over the period 1995-2015.

and migration to retrieve theory-consistent measures of domestic economic linkages. In equilibrium, the model provides three channels through which spatial linkages can propagate economic shocks from urban locations to the rest of the country. The first channel relates to the ownership linkages of establishments located in different employment zones and belonging to the same firm. The second channel goes through the effect of gravity. The third channel affects the spatial distribution of employment through regional trade and the input-output structure of the economy.

The model clarifies the specific mechanisms through which economic shocks propagate across employment zones, but has also the advantage of being taken directly to the data for quantification exercises. To generate meaningful estimates, we parametrize the model to the French economy by computing part of the observable variables from data and retrieving the unobservable from the structure of the model. We match our variable of interest to 2015, which we assume is our baseline year. We finally project the evolution of the same main variables back to the year 1995.

Results provided by the model contrast the reduced form evidence: the structure of linkages between urban and rural areas has not been drifting apart over the period 1995-2015.

This result might suggest that changes in the fundamentals of large urban employment zones might be the driver of employment growth divergence. Our contribution is twofold: on the one hand, we provide new evidence of the role of transmission mechanisms in explaining the urban-rural divide. On the other, we develop a general equilibrium model that can be used to study the spatial distribution of activity and account for the role of firm linkages on top of input-output linkages and gravity.

Concluding Remarks

This study presents three distinct chapters, each contributing to our understanding of various aspects of international economics. While these findings may not revolutionize the field, they offer opportunities for future research and exploration.

The first chapter introduces the concept of dynamic external economies of scale into a quantitative Ricardian model. This novel addition provides insights into potential productivity gains from scaling up industry-level production. Future research may delve further into how economies of scale can be harnessed for growth and explore specific conditions under which such policies are effective. Additionally, the identification strategy outlined in this chapter for estimating scale elasticity using aggregate trade and production data, rather than relying on micro-level data, opens up possibilities for broader application. Subsequent studies could investigate the applicability of this approach to different sectors and countries, potentially uncovering sector-specific nuances that inform more tailored policy decisions.

The second chapter examines the implications of international trade competition, focusing on China's impact on the Belgian manufacturing sector. While the findings hint at the long-term anti-competitive effects of trade liberalization, they raise questions about the broader implications for other industries and nations. Future research could explore the complexities of this relationship, considering various factors that influence market power dynamics. Furthermore, this chapter underscores the significance of monitoring concentration indices and firm-level markups to assess industry health. Subsequent studies may delve into the effectiveness of diverse regulatory measures and antitrust policies in addressing market power concentration issues arising from international trade.

The third chapter provides insights into the spatial distribution of employment and the role of economic linkages, particularly in France. While the study documents empirical regularities within this specific context, there is potential for expanding this research to encompass other regions and periods. Future avenues of research might involve comparative analyses, examining how economic linkages impact employment patterns under various economic conditions and in different geographical areas. The spatial general equilibrium model introduced in this chapter offers a framework for understanding the propagation of economic shocks. Researchers could utilize this model to explore a range of scenarios, including the effects of regional policies, infrastructure investments, and shifts in trade patterns on employment distribution. These investigations can inform policymakers about potential outcomes and consequences associated with regional development strategies.

In conclusion, while not claiming revolutionary findings, this study provides valuable insights into international economics. It suggests several avenues for future research, which, if pursued, may enhance our understanding of international trade dynamics, market power concentration, and regional employment patterns. These endeavors can potentially contribute to more nuanced and well-informed policy decisions in the field of international economics.

Appendix to Chapter 1

A.1 Solving the Model

This section covers the steps required to solve the model. As explained in Section 1.2, 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_{iodt} represents the consumption of variety o in sector i from country d, β_{iodt} is an idiosyncratic demand shifter incorporating both quality and consumer tastes, μ_{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 μ_{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.[79] Therefore, the profit maximization reads:

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

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:

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

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

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.

A.2 Reduced Form Estimation

This section describes an alternative identification strategy for the dynamic scale parameter, ψ_i. As discussed in Section 1.3, estimating the dynamic gravity equation requires constructing the dynamic scale measure, z_{iot-n}. However, the industry-level productivity level, A_{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_{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:

$$k_{ot} = (\sigma - 1) \ln \left(A_{ot}/w_{ot} \right), \tag{A.19}$$

where σ 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):

$$\ln \left(X_{iot} \right) = (\sigma_i - 1) \ln \left(A_{iot}/w_{ot} \right) + \ln \left(\Lambda_{iot} \right) + \sum_{n=1}^{t} \psi_i^n z_{iot-n}, \tag{A.20}$$

where:

$$\Lambda_{iot} = \sum_{d=1}^{N} \frac{\beta_{iodt} \tau_{odt}^{1-\sigma_i} \mu_{idt} Y_{dt}}{\sum_{\zeta=1}^{N} \beta_{i\zeta dt} \tau_{i\zeta dt}^{1-\sigma_i} \Phi_{i\zeta t}^{1-\sigma_i}}, \tag{A.21}$$

and:

$$z_{iot-n} = (\sigma_i - 1) \ln \left[\frac{A_{iot-n}}{w_{ot-n}} X_{iot-n} \right]. \tag{A.22}$$

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

$$\ln (X_{iot}) = \delta_{ot} + \delta_{is} + \delta_{it} + \varepsilon_{iot}, \tag{A.23}$$

where δ_{ot} is the source country-year fixed effect capturing the role played by A_{ot}/w_{ot}, δ_{is} and δ_{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 δ_{ot} as long as ϵ_{iot} and δ_{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:

$$\delta_{ot} = (\sigma - 1) \frac{\ln (A_{ot}/w_{ot})}{\ln (A_{USt^{init}}/w_{USt^{init}})}. \tag{A.24}$$

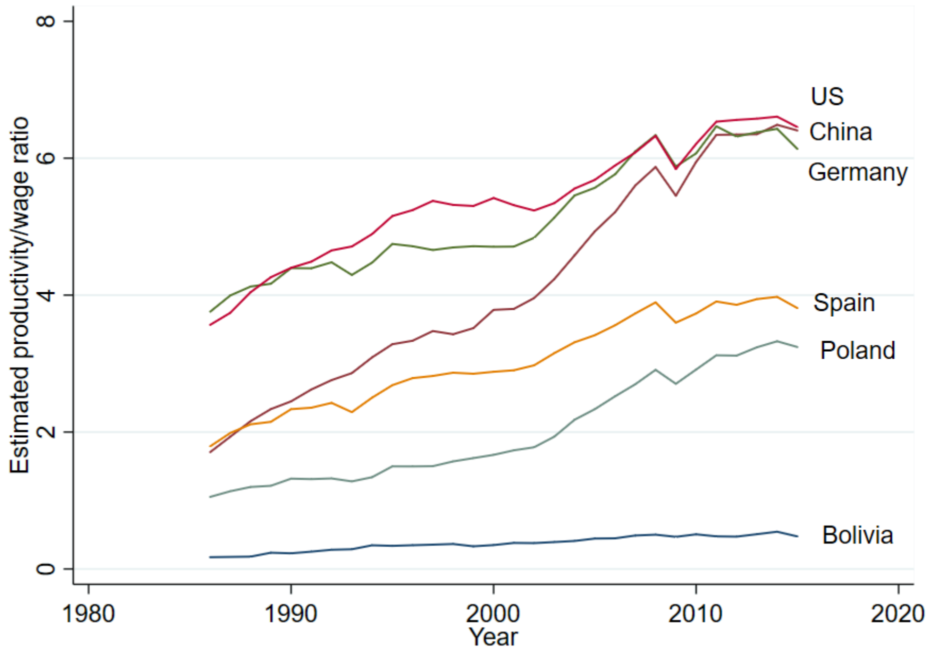
This is very convenient since it is simply possible to correct for the adjusted average elasticity of substitution $(\sigma - 1)$ and the observable term $\ln (w_{USt^{\text{init}}} / A_{USt^{\text{init}}})$ to retrieve $\ln (A_{ot}/w_{ot})$.[80] With the estimates of A_{ot} and w_{ot} at hand, it is possible to construct the dynamic scale measure Z_{iot-n}, for different lagged periods and use it to estimate ψ_i.

Figure 1 and Figure 2 report the estimates of $\ln (A_{ot}/w_{ot})$ 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.

Introducing Z_{iot-n} for the estimation requires three additional assumptions. First, it requires β_{iodt} to be uncorrelated with the industry-destination-time fixed effect. This is

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

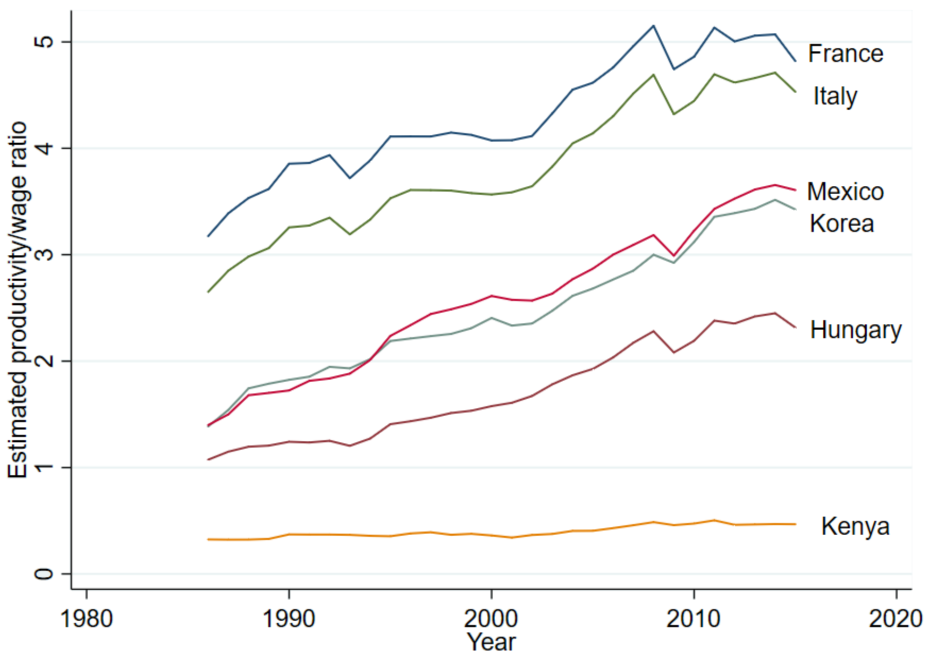
Figure A.1: Estimated Productivity/Wage Ratios I, 1986-2015



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.

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 holding. Second, it is also necessary to assume orthogonality between A_{iot} and w_{ot} with Λ_{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 A.1 and A.2 show.

Figure A.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.

A.3 Additional Robustness

Table A.1: 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 (1.18) using CEPII bilateral controls. Estimation relies on the Stata command **reghdfe** developed by Correia (2016). Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

A.4 Tables

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

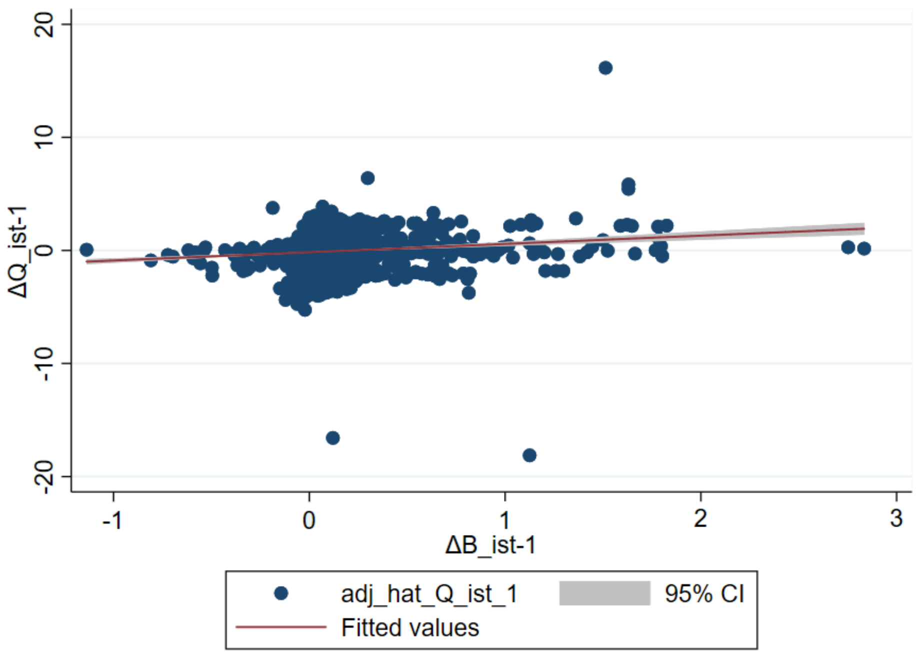
Industry (SITC Rev.2)	
Dairy products and birds' eggs (02)	Leather, leather manufactures, nes, and dressed furskins (61)
Fish, crustacean and molluscs, and preparations thereof (03)	Rubber Manufactures, nes (62)
Cereals and cereal preparations (04)	Cork and wood, cork manufactures (63)
Vegetables and 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 A.3: 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

A.5 Figures

Figure A.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%.

Appendix to Chapter 2

B.1 Product-Industry Concordance

As explained in Section 2.2, UN Comtrade data are reported at the 6-digit HS product classification. Over our sample period, the HS classification is reported in four different versions: H1 in 1996, H2 in 2002, H3 in 2007, and H4 in 2012. Specifically from 2007 onward, the H3 classification is made available for all the subsequent batches of trade data. The core activity of our Belgian manufacturing firms is defined at the 4-digit NACE Rev. 2 industry classification.

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

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

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

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

B.2 Data Cleaning

As discussed in Section 2.2, we merge various firm-level datasets from the Belgian federal institutes and the National Bank of Belgium. From each source, we extract all active firms over the 1996-2015 period. To select the sample, we keep firms that over the period meet the following requirements:

1. report positive values of sales and value added;

2. report positive employment, in full-time equivalent (FTE), at least once;

3. report a minimum of 100 euro of physical capital stock at least once;

4. report positive assets, at least once.

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

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

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

1. to report at least one employee, which excludes individual entrepreneurs;

2. to be active for at least two consecutive years, to ensure the possibility of constructing one-period lag variables as instruments in the GMM estimation.

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

B.3 Firm's Cost Minimization

In this section, we provide the mathematical derivation for the representative firm's optimization problem used in Section 2.3. As highlighted by De Loecker and Warzynski (2012), this approach has the advantage of nesting various price-setting models that are common to the international trade and industrial organization literature.

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

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

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

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

with the associated Lagrangian reading:

$$\mathcal{L}\left(L_{it}, K_{it}, M_{it}, \lambda_{it}\right) = w_{it}L_{it} + r_{it}K_{it} + p_{it}^{M}M_{it} + \lambda_{it}\left(Q_{it} - F_{it}(\cdot)\right), \tag{B.3}$$

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

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

$$\frac{\partial \mathcal{L}_{it}}{\partial M_{it}} = p_{it}^{M} - \lambda_{it}\frac{\partial F_{it}(\cdot)}{\partial M_{it}} = 0 \tag{B.4}$$

The shadow price λ_{it} represents the marginal cost of production for any given level of total production Q_{it}. Rearranging equation (B.3), and multiplying both sides by $\frac{M_{it}}{Q_{it}}$, we obtain:

$$\frac{\partial F_{it}(\cdot)}{\partial M_{it}} \frac{M_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{p_{it}^{M} M_{it}}{Q_{it}} \tag{B.5}$$

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

$$\mu_{it} = \theta_{it}^{M} \left(\alpha_{it}^{M}\right)^{-1} \tag{B.6}$$

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

B.4 Productivity Estimation

In this section, we provide assumptions and the identification strategy used in order to estimate the production function. We also provide details for the limitations of the methodology discussed in Section 2.3. As discussed, we follow the 2-step strategy proposed by Ackerberg et al. (2015) and we tailor it to make it amenable for estimation in the Belgian manufacturing context.

Consider the following generic production function:

$$Q_{it} = F_{it}\left(L_{it}, K_{it}, M_{it}, \Omega_{it}\right) \tag{B.7}$$

Assumptions. We make the assumption that productivity is Hicks neutral with respect to production inputs and that $F_{it}(\cdot)$ is translog in its arguments. Production function estimation is performed for each aggregate manufacturing sector, but we omit the industry subscript to keep the notation simple. Hence, we can rewrite a log-linearized version of equation (B.7) as follows:

$$q_{it} = f_{it}\left(l_{it}, k_{it}, m_{it}; \beta\right) + \omega_{it} + \varepsilon_{it}, \tag{B.8}$$

Assumptions. We make the assumption that productivity is Hicks neutral with respect to production inputs and that $F_{it}(\cdot)$ is translog in its arguments. Production function estimation is performed for each aggregate manufacturing sector, but we omit the industry subscript to keep the notation simple. Hence, we can rewrite a log-linearized version of equation (B.7) as follows:

$$q_{it} = f_{it}\left(l_{it}, k_{it}, m_{it}; \beta\right) + \omega_{it} + \varepsilon_{it}, \tag{B.9}$$

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

$$q_{it} = \beta_l l_{it} \quad +\beta_k k_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2$$
$$+\beta_{lk} l_{it} + \beta_{km} k_{it} + \beta_{km} l_{it} + \beta_{lmk} l_{it} k_{it} m_{it}. \tag{B.10}$$

In order to have consistent estimates of the parameters we need two conditions. First, output and inputs need to be expressed in physical quantities, however, since we only have access to their counterparts in values, we use industry-level deflators to correct for prices.[81] Since such deflators capture only partially the price level, the left-hand side of equation (B.9) captures only a proxy for the quantity produced, which is given by $\tilde{Q}_{it} = R_{it}/P_{jt}$, with R_{it} being the firm's revenue and P_{jt} the industry-level deflator. This implies that the unobserved output price difference, $p_{it} - p_{jt}$, will end up in the residual, $\tilde{\varepsilon}_{it}$ determining an output price bias. Despite being unable to measure and correct the bias in the estimate, recent evidence from De Ridder et al. (2022) suggests that this bias is attenuated when studying the distribution of markup changes over time, which is the focus of our empirical exercise.

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

$$m_{it} = m_t \left(l_{it}, k_{it}, \omega_{it}, \mathbf{z_{it}}\right) \tag{B.11}$$

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

$$\omega_{it} = h_t \left(l_{it}, k_{it}, m_{it}, \mathbf{z_{it}}\right). \tag{B.12}$$

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

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

$$\tilde{q}_{it} = \phi_{it} + \tilde{\varepsilon}_{it} \tag{B.13}$$

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

$$\phi_{it} = f_{it}\left(\tilde{l}_{it}, \tilde{k}_{it}, \tilde{m}_{it}; \beta\right) + \omega_{it}. \tag{B.14}$$

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

$$\omega_{it} = g_t\left(\omega_{it-1}\right) + \xi_{it}, \tag{B.15}$$

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

$$\omega_{it}(\beta) = \hat{\phi}_{it}\left(\tilde{l}_{it}, \tilde{k}_{it}, \tilde{m}_{it}; \beta\right) - f_{it}\left(\tilde{l}_{it}, \tilde{k}_{it}, \tilde{m}_{it}; \beta\right). \tag{B.16}$$

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

$$\mathbb{E}\left(\xi_{it}(\beta)\left(\mathbf{X}_{it}\right)\right) = 0 \tag{B.17}$$

Estimation is performed using a standard GMM procedure and we separately run regressions at a higher aggregate industry level in order to generate sufficient within variation to identify the parameters. With the vector of estimated parameters, $\hat{\beta} = \Big\{\hat{\beta}_l, \hat{\beta}_k, \hat{\beta}_m, \hat{\beta}_{ll},$

$\hat{\beta}_{kk}, \hat{\beta}_{mm}, \hat{\beta}_{lk}, \hat{\beta}_{km}, \hat{\beta}_{km}, \hat{\beta}_{lmk}\}$ it is possible to retrieve the output elasticity of the intermediate input as follow:

$$\hat{\theta}_{it}^{m} = \hat{\beta}_m + 2\hat{\beta}_{mm}m_{it} + \hat{\beta}_{lm}l_{it} + \hat{\beta}_{km}k_{it} + \hat{\beta}_{lkm}l_{it}k_{it} \tag{B.18}$$

B.5 Melitz-Polanec Decomposition

In this section, we provide the mathematical derivation of the dynamic decomposition strategy developed by Melitz and Polanec (2015). The decomposition was originally applied to understand the aggregate productivity margins of adjustment over time; however, the formula is general enough to be also applied to other types of firm-level variables, such as markups, as in our setting.

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

$$M_{G,jt} = \sum_{i \in G} s_{ijt} \mu_{ijt} \tag{B.19}$$

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

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

$$\begin{aligned} M_{j1} &= s_{c,j1} M_{c,j1} + s_{x,j1} M_{x,j1} = M_{c,j1} + s_{x,j1} \left(M_{x,j1} - M_{c,j1} \right), \\ M_{j2} &= s_{c,j2} M_{c,j2} + s_{e,j2} M_{e,j2} = M_{c,j2} + s_{e,j2} \left(M_{e,j2} - M_{c,j2} \right), \end{aligned} \tag{B.20}$$

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

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

$$\Delta M = M_{c,j2} - M_{c,j1} + s_{e,j2}\left(M_{e,j2} - M_{c,j2}\right) - s_{x,j1}\left(M_{x,j1} - M_{c,j1}\right). \tag{B.21}$$

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

$$M_{G,jt} = \sum_{i \in G} \left(\bar{s}_{G,jt} - \Delta s_{ijt}\right)\left(\bar{\mu}_{G,jt} - \Delta\mu_{ijt}\right), \tag{B.22}$$

from which it follows:

$$\begin{aligned} M_{G,jt} &= G_{jt}\bar{s}_{G,jt}\bar{\mu}_{G,jt} + \sum_{i \in G} \Delta s_{ijt}\Delta\mu_{ijt} \\ &= \bar{M}_{G,jt} + \operatorname{cov}_{G,jt}, \end{aligned} \tag{B.23}$$

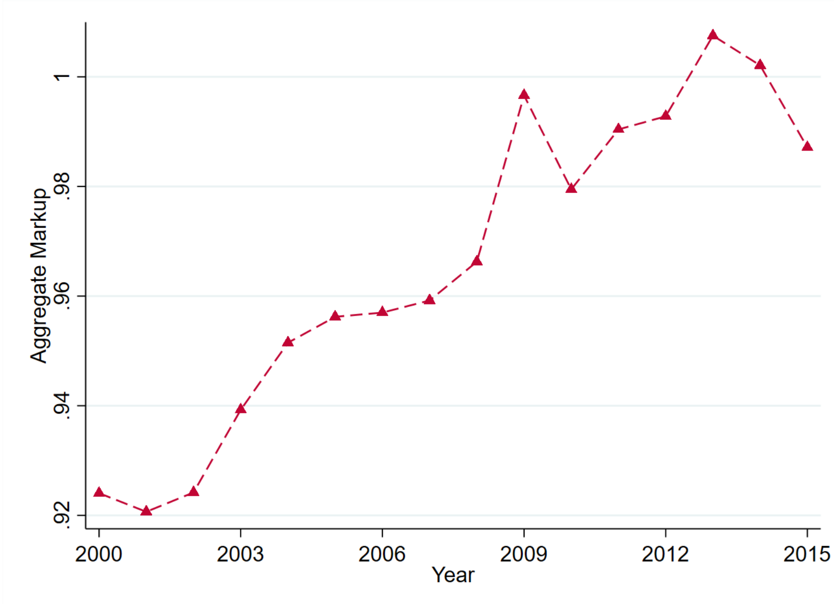
with $\bar{M}_{G,jt}$ being the average sector-level markup of incumbents, defining the within component, and $\operatorname{cov}_{G,jt}$ being the covariance between the change in firm-level markup and the respective change in market share, hence the between component. Therefore, it is possible to express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

$$\Delta M_j = \Delta\bar{M}_{c,jt} + \Delta\operatorname{cov}_{c,jt} + s_{e,j2}\left(M_{e,j2} - M_{c,j2}\right) + s_{x,j1}\left(M_{c,j1} - M_{x,j1}\right), \tag{B.24}$$

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

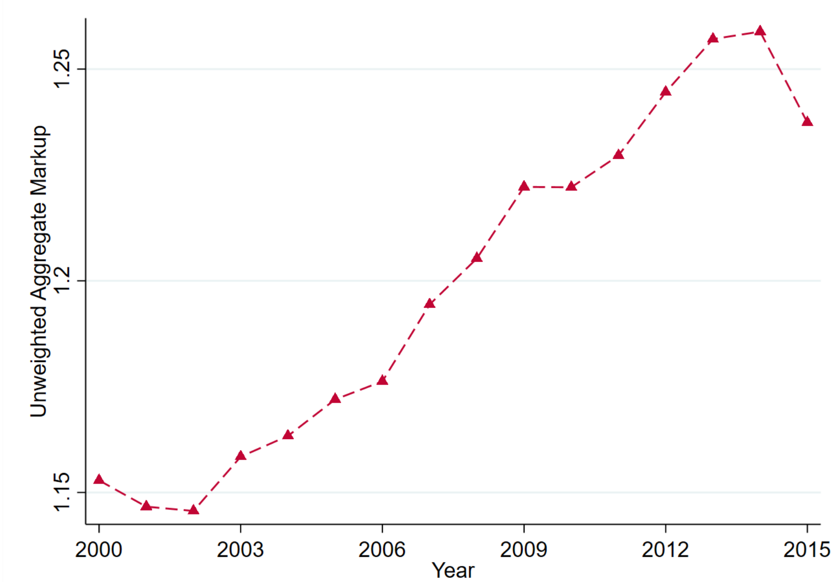
B.6 Figures

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



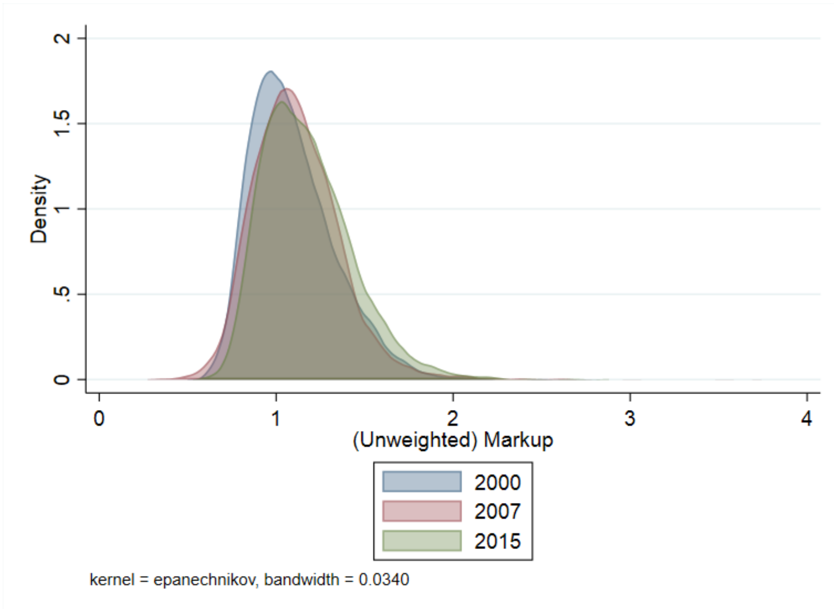
Notes: The figure shows the evolution of the revenue-weighted aggregate markup for the entire manufacturing sector.

Figure B.2: Evolution of the Unweighted Aggregate Markup



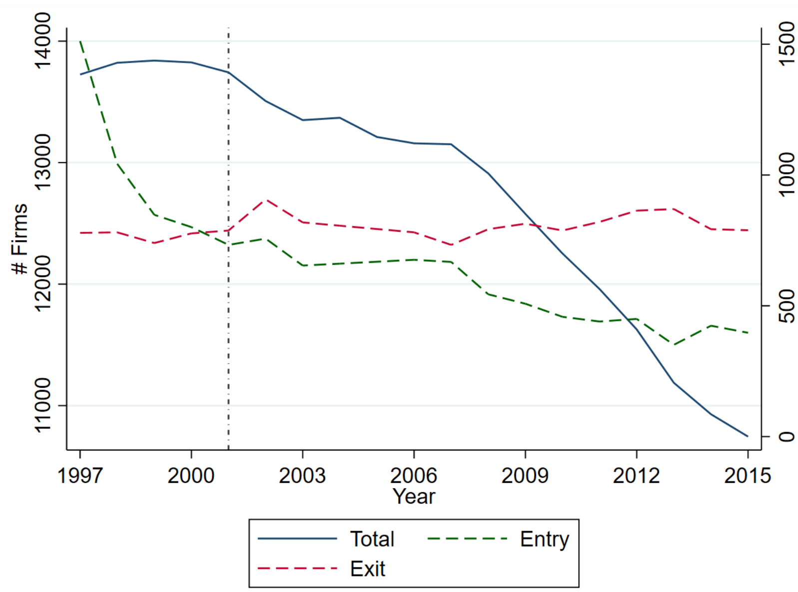
Notes: The figure shows the evolution of the unweighted aggregate markup for the entire manufacturing sector.

Figure B.3: Distribution of Firm-Level Markups



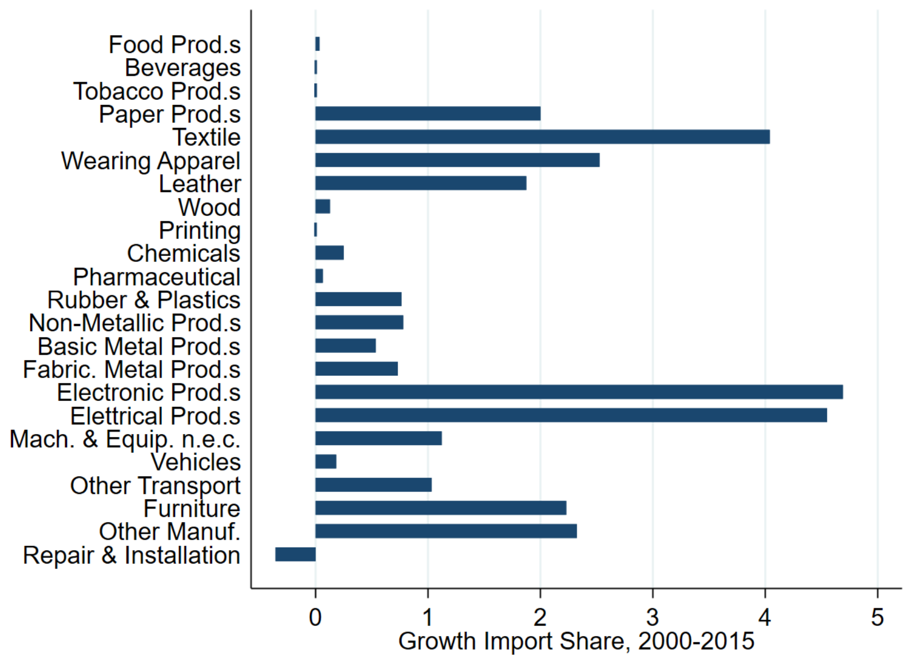
Notes: The figure shows the kernel distribution of firm-level markups for the entire manufacturing sector in the years 2000, 2008, and 2015.

Figure B.4: Firms' Entry and Exit



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

Figure B.5: Cross-Industry Growth in Chinese Import Share, 2000-2015



Notes: The figure shows the growth in Chinese Import Share across 2-digit NACE sectors over the period 2000-2015.

Appendix to Chapter 3

C.1 Data Cleaning

DADS. As discussed in Section 3.2, we merge establishment-level datasets from various French administrative sources. Data cleaning and harmonization required several steps that we discuss at length in this section.

From the DADS, we extract all active establishments for the 1995-2015 period. To select the sample, we require establishments to report information about employment and the wage bill, the commune or zip code in which the establishment is located, and the 3-digit NAF industry of activity. If an establishment reports a missing in one or more of these characteristics in a specific year, we fill in the gap using information from the previous and subsequent years. Whenever this is not possible, the observation is discarded.

We further need to provide correspondence between NAF industry classifications over the sample period to ensure consistency. This is due to a change in the NAF nomenclature in the years 2003 and 2009. Correspondence tables from NAF Rev. 1 to NAF Rev 1.1, for 2003, and from NAF Rev. 1.1 to NAF Rev 2, for 2009, are available, but their use comes at the cost of introducing systematic bias due to their many-to-many structure. Therefore, instead of assuming any type of proportionality for multiple matching, we use information for establishments active between the years featuring the change in nomenclature.

For example, consider the change in nomenclature in 2008. We assign to an establishment active in 2008 the reported 3-digit NAF industry code of the same establishment in 2009. We follow this procedure for all establishments present in the two years, while we use a proportionality rule for all other establishments active up to 2008. In particular, we reassign the new industry code with the highest likelihood to correspond to the old one.

Concerning aggregate industry-level information, DADS has limited coverage of establishments in the agriculture sector only up to 2003. For this lack of data availability, we exclude agriculture from the analysis in the empirical section. Moreover, public employment is reported using two different accounting methodologies before and after 2009.

We identify any public firm reported as a private firm at least once before 2009 and consider them as such for the whole period. Most likely, these firms went through a process of privation over the years and consistently reported our variables of interest. All the remaining establishments that belong to public firms are then discarded. The full sample covers an average of 1.4 million establishments, 1.1 million firms, and 16 million workers.

LIFI. Establishment information is merged with ownership data from LIFI, a dataset covering the ownership and nationality of the parent company of firms located in France. This dataset provides detailed information on the ownership of groups, the financial link between domestic and foreign affiliates, and information on shareholders. Ownership information is recorded only for firms meeting one of the following requirements in a financial year:

1. reporting at least 500 employees;
2. reporting at least 30 million euros of turnover;
3. reporting at least 1.2 million euros of shares in other firms.

Notice that even if relatively large firms are surveyed, financial links are reported with all their affiliates irrespective of their size.

French Custom. We merge establishment information with bilateral imports and exports from the French Customs. For each firm, this database reports the bilateral free-on-board value, the quantity of exports, the cost-insurance-freight value, and the quantity of imports. Extra-EU shipments threshold is set at 1,000 euros, and such transactions are therefore not reported. Concerning intra-EU shipments, the reporting threshold has increased from 1,000 to 150,000 euros. We select the most stringent threshold over the period to avoid introducing a bias.[82] We further need to allocate firm-level trade data to

[82]See Bergounhon et al. (2018) for a discussion.

establishments; hence, we apportion the share of import and export flows at the establishment level using the latter employment shares over the firm's total employment.

C.2 Tables

Table C.1: Urban Area (UA) Population Size Index Provided by INSEE

Population Threshold	**UA Index**
Rural Area	00
Urban Area ($<$ 15.000 inhabitants)	01
Urban Area (15.000-19.999 inhabitants)	02
Urban Area (20.000-24.999 inhabitants)	03
Urban Area (25.000-34.999 inhabitants)	04
Urban Area (35.000-49.999 inhabitants)	05
Urban Area (50.000-99.999 inhabitants)	06
Urban Area (100.000-199.999 inhabitants)	07
Urban Area (200.000-499.999 inhabitants)	08
Urban Area (500.000-9.999.999 inhabitants)	09
Urban Area of Paris	10

Note: The table reports the population threshold used by INSEE to classify French Urban Areas.

Table C.2: Top and Bottom 5 Employment Zones (EZ) Summary Statistics, Large Urban Only

	Empl. Growth	**Urban.**	**Sh. Manuf.**	**Sh. Exp.s**	**Exp./Empl. Growth**	**Imp./Empl. Growth**
Panel A: Top 5						
Montpellier	1.00	Large	0.10	0.10	-0.30	0.83
Toulouse	0.96	Large	0.23	0.13	1.52	3.22
Rennes	.86	Large	0.27	0.11	-0.31	0.56
Cannes-Antibes	0.81	Large	0.18	0.12	0.46	0.38
Nantes	0.79	Large	0.08	0.24	1.02	0.85
Panel B: Bottom 5						
Douai	0.36	Large	0.39	0.10	0.25	0.79
Istres-Martigues	0.43	Large	0.11	1.11	4.55	5.26
Strasbourg	0.30	Large	0.21	0.15	0.57	0.79
Molsheim-Obernai	0.28	Large	0.53	0.16	-0.03	-0.16
Roubaix-Tourcoing	0.10	Large	0.33	0.17	-0.30	0.01

Note: The table reports the ranking of the top and bottom 5 EZs by employment growth over the period 1995-2015. Only large urban areas are considered. *textbf* Sh. Manuf. refers to the share of employment working in the manufacturing sector in 1995, *Sh. Exp.s* to the share of establishments reporting positive trade values in 1995, *Exp./Empl. Growth* and *Imp./Empl. Growth* respectively to the export and import exposure per worker growth over the period.

Table C.3: Top and Bottom 5 Employment Zones (EZ) Summary Statistics, Small Urban and Rural Only

	Empl. Growth	**Sh. Manuf.**	**Sh. Exp.s**	**Exp./Empl. Growth**	**Imp./Empl. Growth**
Panel A: Top 5					
Clermont-l'Hérault	1.13	0.25	0.06	1.51	1.94
Aix-en-Provence	1.13	0.17	0.11	-0.19	0.50
Salon-de-Provence	1.06	0.15	0.09	0.87	-0.36
La Tarentaise	1.02	0.22	0.05	-0.05	0.75
Pauillac	1.00	0.08	0.08	-.035	-0.75
Panel B: Bottom 5					
Chatillon	-0.07	0.37	0.12	0.41	2.20
Neufchâteau	-0.10	0.11	0.06	4.55	3.89
Longwy	-0.11	0.40	0.11	-0.51	-0.31
Thiers	-0.12	0.70	0.20	1.22	3.09
Sante Claude	-0.23	0.22	0.06	0.78	2.52

Note: The table reports the ranking of the top and bottom 5 EZs by employment growth over the period 1995-2015. Only small urban and rural areas are considered. *textbf* Sh. Manuf. refers to the share of employment working in the manufacturing sector in 1995, *Sh. Exp.s* to the share of establishments reporting positive trade values in 1995, *Exp./Empl. Growth* and *Imp./Empl. Growth* respectively to the export and import exposure per worker growth over the period.

Table C.4: Large Urban EZs' Employment Growth Premium, 1995-2015 (Beta Coefficients)

	Dep. var.: Private Empl. Growth (%)								
	1995-2015			1995-2005			2005-2015		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Large Urban	0.18***	0.08	0.05	0.11**	0.01	-0.02	0.24***	0.15***	0.12**
	(3.37)	(2.01)	(1.09)	(2.16)	(0.25)	(-0.38)	(6.01)	(3.80)	(2.88)
Paris	-0.06*	-0.16***	-0.14***	-0.06*	-0.18***	-0.15***	-0.04	-0.12***	-0.12***
	(-1.22)	(-4.45)	(-3.63)	(-1.21)	(-5.02)	(-3.76)	(-0.79)	(-2.38)	(-2.28)
Empl. Growth Mean	0.40	0.40	0.40	0.29	0.29	0.29	0.08	0.08	0.08
Empl. Growth St. Dev.	0.28	0.28	0.28	0.17	0.17	0.17	0.10	0.10	0.10
Shift Share Industry		✓	✓		✓	✓		✓	✓
Natural Amenities			✓			✓			✓
Obs.	297	297	297	297	297	297	297	297	297
R^2	0.04	0.46	0.54	0.05	0.40	0.49	0.08	0.31	0.36

Note: The table reports the beta coefficients for equation (1), t-statistics are reported in brackets. Regressions are weighted using beginning-of-the-period levels of employment at the EZ level. The dependent variable is the growth rate of private employment at the employment zone level over the reported period. All independent variables in columns (1) to (6) are calculated in 1995, while those in (7) to (9) in 2005. "Large Urban" and "Paris" are dummies defining the urban status of the employment zone (see map). "Shift Share Industry" is the predicted growth of employment based on the industrial composition of the EZ at the beginning of the period. "Natural Amenities" is a set of variables about proximity to the seaside, proximity to mountain chains, and average temperature deviation from the annual French mean. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table C.5: Large Urban EZs' Employment Growth Premium Weighted Regression, 1995-2015

	Dep. var.: Private Empl. Growth (%)								
	1995-2015			1995-2005			2005-2015		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Large Urban	0.17***	0.09**	0.05*	0.08***	0.03	0.00	0.09***	0.05***	0.04***
	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Paris	0.04**	-0.10***	-0.08**	0.00	-0.10***	-0.07**	-0.02**	-0.03***	-0.03***
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Empl. Growth Mean	0.40	0.40	0.40	0.29	0.29	0.29	0.08	0.08	0.08
Empl. Growth St. Dev.	0.28	0.28	0.28	0.17	0.17	0.17	0.10	0.10	0.10
Shift Share Industry		✓	✓		✓	✓		✓	✓
Natural Amenities			✓			✓			✓
Obs.	297	297	297	297	297	297	297	297	297
R^2	0.04	0.46	0.54	0.05	0.40	0.49	0.08	0.31	0.36

Note: The table reports the marginal coefficients for equation (1), standard errors are reported in brackets, and regressions are weighted by beginning-of-the-period employment level. Regressions are weighted using beginning-of-the-period levels of employment at the EZ level. The dependent variable is the growth rate of private employment at the employment zone level over the reported period. All independent variables in columns (1) to (6) are calculated in 1995, while those in (7) to (9) in 2005. "Large Urban" and "Paris" are dummies defining the urban status of the employment zone (see map). "Shift Share Industry" is the predicted growth of employment based on the industrial composition of the EZ at the beginning of the period. "Natural Amenities" is a set of variables about proximity to the seaside, proximity to mountain chains, and average temperature deviation from the annual French mean. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table C.6: Large Urban EZs' Employment Growth Premium, 1995-2015 (Centrality Measures)

	Dep. var.: Private Empl. Growth (%)								
	1995-2015			1995-2005			2005-2015		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Large Urban	0.04	0.06*	0.07**	-0.01	0.02	0.03	0.04***	0.03*	0.03**
	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Paris	-0.11***	-0.09***	-0.14***	-0.08***	-0.06***	-0.09***	-0.04**	-0.05**	-0.05**
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Empl. Growth Mean	0.40	0.40	0.40	0.29	0.29	0.29	0.08	0.08	0.08
Empl. Growth St. Dev.	0.28	0.28	0.28	0.17	0.17	0.17	0.10	0.10	0.10
Shift Share Industry	✓	✓	✓	✓	✓	✓	✓	✓	✓
Natural Amenities	✓	✓	✓	✓	✓	✓	✓	✓	✓
Economic Centrality		✓	✓		✓	✓		✓	✓
Market Potential			✓			✓			✓
Obs.	297	297	297	297	297	297	297	297	297
R^2	0.04	0.46	0.54	0.05	0.43	0.50	0.08	0.43	0.44

Note: The table reports the marginal coefficients for equation (1), standard errors are reported in brackets. Regressions are weighted using beginning-of-the-period levels of employment at the EZ level. The dependent variable is the growth rate of private employment at the employment zone level over the reported period. All independent variables in columns (1) to (6) are calculated in 1995, while those in (7) to (9) in 2005. "Large Urban" and "Paris" are dummies defining the urban status of the employment zone (see map). "Shift Share Industry" is the predicted growth of employment based on the industrial composition of the EZ at the beginning of the period. "Natural Amenities" is a set of variables about proximity to the seaside, proximity to mountain chains, and average temperature deviation from the annual French mean. "Economic Centrality" is a measure of proximity to large economic areas constructed as the sum across EZs of the product between the inverse of distance and the latter initial employment level. "Market Potential" is similar in spirit to the previous measure of economic centrality where employment growth replaces the employment level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table C.7: Large Urban EZs' Employment Growth Premium Weighted Regression, 1995-2015 (Globalization Measures)

	Dep. var.: Private Empl. Growth (%)								
	1995-2015			1995-2005			2005-2015		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Large Urban	0.04	0.06*	0.08**	-0.01	0.01	0.03	0.04***	0.04***	0.05***
	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Paris	-0.11***	-0.06*	-0.05	-0.08***	-0.04	-0.03	-0.04**	-0.03*	-0.03*
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Empl. Growth Mean	0.40	0.40	0.40	0.29	0.29	0.29	0.08	0.08	0.08
Empl. Growth St. Dev.	0.28	0.28	0.28	0.17	0.17	0.17	0.10	0.10	0.10
Shift Share Industry	✓	✓	✓	✓	✓	✓	✓	✓	✓
Natural Amenities	✓	✓	✓	✓	✓	✓	✓	✓	✓
Empl. Share Trading Firms		✓	✓		✓	✓		✓	✓
Empl. Share Domestic MNE		✓	✓		✓	✓		✓	✓
Empl. Share Foreign MNE		✓	✓		✓	✓		✓	✓
Empl. Share 500+ Firms			✓			✓			✓
Obs.	297	297	297	297	297	297	297	297	297
R^2	0.50	0.52	0.54	0.49	0.52	0.52	0.38	0.41	0.41

Note: The table reports the marginal coefficients for equation (1), standard errors are reported in brackets. Regressions are weighted using beginning-of-the-period levels of employment at the EZ level. The dependent variable is the employment growth rate at the employment zone level over the reported period. All independent variables in columns (1) to (6) are calculated in 1995, while those in (7) to (9) in 2005. “Large Urban” and ”Paris” are dummies defining the urban status of the employment zone (see map). “Shift Share Industry” is the predicted growth of employment based on the industrial composition of the EZ at the beginning of the period. “Natural Amenities” is a set of variables about proximity to the seaside, proximity to mountain chains, and average temperature deviation from the annual French mean. “Empl. Share Trading Firms”, “Empl. Share Domestic MNE”, and “Empl. Share Foreign MNE” are the share of EZ-level employment in firms involved in trade, domestic multinational firms, and foreign multinational firms, respectively. “Empl. Share 500+ Firms” is the share of EZ-level employment in firms with over 500 employees. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table C.8: Proximity to Large Urban EZs Premium (2SLS), 1995-2015 (Wage Bill)

	Dep. var.: Private Empl. Growth (%)								
	1995-2015			1995-2005			2005-2015		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Empl. Growth Large Urban	9.28***			11.11***			3.71		
	(3.19)			(3.36)			(4.11)		
Empl. Growth Large Urban, 5		2.23*			2.41*			1.03	
		(1.25)			(1.26)			(1.71)	
Empl. Growth Large Urban, 10			1.63*			1.70*			0.93
			(0.94)			(0.95)			(1.59)
Proximity Paris (Log)	-0.04**	-0.05***	-0.05***	-0.03**	-0.04***	-0.04***	-0.01	-0.02*	-0.02*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Shift Share Industry	✓	✓	✓	✓	✓	✓	✓	✓	✓
Natural Amenities	✓	✓	✓	✓	✓	✓	✓	✓	✓
Empl. Growth Mean, Small Urban EZs	0.40	0.40	0.40	0.29	0.29	0.29	0.07	0.07	0.07
Empl. Growth St. Dev., Small Urban EZs	0.28	0.28	0.28	0.18	0.18	0.18	0.09	0.09	0.09
Empl. Growth Mean, Large Urban EZs	0.63	0.61	0.60	0.39	0.38	0.37	0.16	0.17	0.17
Empl. Growth St. Dev., Large Urban EZs	0.23	0.21	0.18	0.13	0.11	0.10	0.07	0.06	0.05
Obs.	256	256	256	256	256	256	256	256	256
KP F-Stat	99.02	93.02	90.58	148.58	143.45	141.45	60.21	68.65	68.25

Note: The table reports the estimated marginal coefficients for equations (3) and (4) instrumented for the growth of wage bill in the U.S., standard errors are reported in brackets. The dependent variable is the growth rate of private employment at the EZ level over the reported period. All independent variables in columns (1) to (4) are calculated in 1995, while those in (5) and (6) in 2005. The "Empl. Growth Large Urban", "Empl. Growth Large Urban, 5", and "Empl. Growth Large Urban, 10" are respectively the employment growth rates of the 1/5/10 closest Large Urban areas weighted by their respective distance. "Shift Share Industry" is the predicted growth of employment based on the industrial composition of the EZ at the beginning of the period. The "Natural Amenities" control accounts for proximity to the seaside, to mountain chains, and local average temperature. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table C.9: Input-Output Industry Classification and Elasticities of Substitution

Industry	Code	σ_s	Industry	Code	σ_s
Agriculture, Forestry, and Fishing	AZ	4	Commerce and Reparations	GZ	4
Mining and Quarrying	BZ	4	Transportation and Logistic	HZ	4
Food, Beverage, and Tobacco	CA	6.15	Accommodation and Food Service	IZ	4
Textile, Apparel, Leather	CB	7.28	Audio/Radio Broadcasting	JA	4
Wood, Paper, Printings	CC	4.69	Telecommunication	JB	4
Petroleum and Coal	CD	5.71	IT and Information Service	JC	4
Chemical	CE	5.49	Finance and Insurance	KZ	4
Pharmaceutical	CF	6.33	Real Estate	LZ	4
Rubber, Plastic, Non-Metallic	CG	5.34	Professional Activities	MA	4
Primary and Fabricated Metal	CH	4.68	Research and Development	MB	4
Informatics, Electronics, Optics	CI	10.82	Technical Activities	MC	4
Electric Equipment	CJ	5.99	Administrative and Support Services	NZ	4
Machinery	CK	5.95	Public Administration and Defence	OZ	4
Transport	CL	8.12	Education	PZ	4
Miscellaneous	CM	4.89	Human Health Activities	QA	4
Electricity, Gas, Steam	HZ	4	Social Works Activities	QB	4
Water Supply and Waste Management	EZ	4	Art and Recreational Activities	RZ	4
Construction	FZ	4	Other Services	SZ	4

Note: The table reports the Input-Output table industry classification. Elasticities of substitution, σ_s, for the manufacturing sector are taken from Imbs and Méjean (2018). For the other industries, we fix the elasticity to the average value of four.

Table C.10: Proximity to Large Urban EZs Premium (2SLS), 1995-2015

	Dep. var.: Private Empl. Growth (%)								
	1995-2015			1995-2005			2005-2015		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Empl. Growth Large Urban	8.31**			6.69*			3.88		
	(3.91)			(4.02)			(4.47)		
Empl. Growth Large Urban, 5		4.55*			4.89*			1.03	
		(2.42)			(2.51)			(1.80)	
Empl. Growth Large Urban, 10			2.97**			3.83***			0.90
			(1.35)			(1.38)			(1.63)
Proximity Paris (Log)	-0.04**	-0.03	-0.04**	-0.04**	-0.03	-0.03*	-0.01	-0.02*	-0.02*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Shift Share Industry	✓	✓	✓	✓	✓	✓	✓	✓	✓
Natural Amenities	✓	✓	✓	✓	✓	✓	✓	✓	✓
Empl. Growth Mean, Small Urban EZs	0.40	0.40	0.40	0.29	0.29	0.29	0.07	0.07	0.07
Empl. Growth St. Dev., Small Urban EZs	0.28	0.28	0.28	0.18	0.18	0.18	0.09	0.09	0.09
Empl. Growth Mean, Large Urban EZs	0.63	0.61	0.60	0.39	0.38	0.37	0.16	0.17	0.17
Empl. Growth St. Dev., Large Urban EZs	0.23	0.21	0.18	0.13	0.11	0.10	0.07	0.06	0.05
Obs.	256	256	256	256	256	256	256	256	256
KP F-Stat	30.02	30.02	19.58	19.58	47.45	47.45	99.21	30.65	9.25

Note: The table reports the estimated marginal coefficients for equations (3) and (4) instrumented for the growth of employment in the US, standard errors are reported in brackets.. The dependent variable is defined as the growth rate of private employment at the EZ level, over the reported period. All independent variables in columns (1) to (4) are calculated in 1995, while those in (5) and (6) in 2005. The "Empl. Growth Large Urban", "Empl. Growth Large Urban, 5", and "Empl. Growth Large Urban, 10" are the employment growth rates of the 1/5/10 closest Large Urban areas weighted by their respective distance. "Shift Share Industry" is the predicted growth of employment based on the industrial composition of the EZ at the beginning of the period. The "Natural Amenities" control accounts for proximity to the seaside, to mountain chains, and local average temperature. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

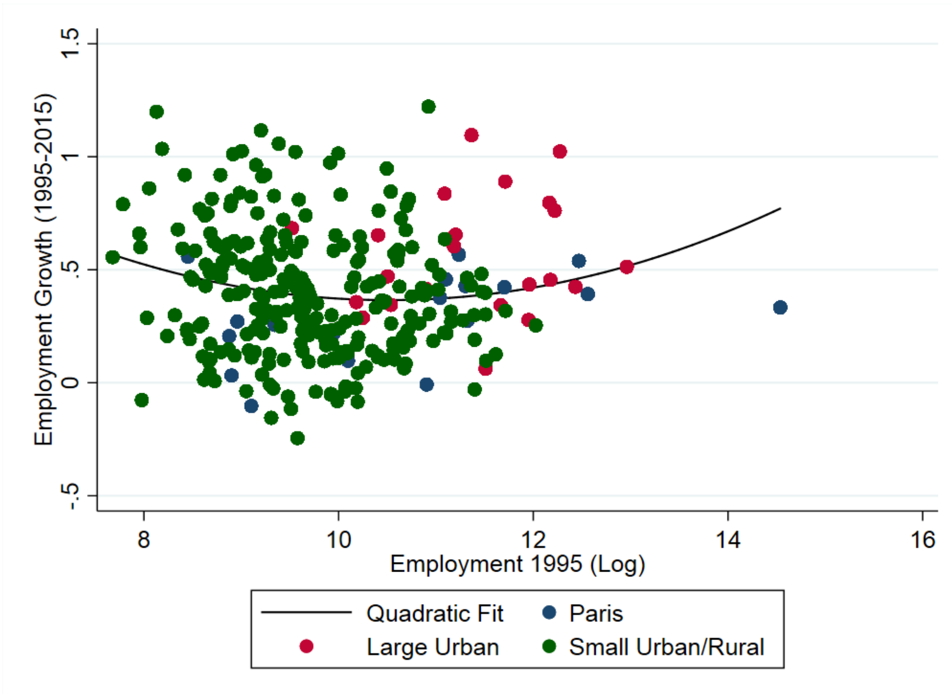
Table C.11: Proximity to Large Urban EZs Premium (2SLS), 1995-2015

	Dep. var.: Private Empl. Growth (%)								
	1995-2015			1995-2005			2005-2015		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Empl. Growth Large Urban	9.28***			11.11***			3.71		
	(3.19)			(3.36)			(4.11)		
Empl. Growth Large Urban, 5		2.23*			2.41*			1.03	
		(1.25)			(1.26)			(1.71)	
Empl. Growth Large Urban, 10			1.63*			1.70*			0.93
			(0.94)			(0.95)			(1.59)
Proximity Paris (Log)	-0.04**	-0.05***	-0.05***	-0.03**	-0.04***	-0.04***	-0.01	-0.02*	-0.02*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Shift Share Industry	✓	✓	✓	✓	✓	✓	✓	✓	✓
Natural Amenities	✓	✓	✓	✓	✓	✓	✓	✓	✓
Empl. Growth Mean, Small Urban EZs	0.40	0.40	0.40	0.29	0.29	0.29	0.07	0.07	0.07
Empl. Growth St. Dev., Small Urban EZs	0.28	0.28	0.28	0.18	0.18	0.18	0.09	0.09	0.09
Empl. Growth Mean, Large Urban EZs	0.63	0.61	0.60	0.39	0.38	0.37	0.16	0.17	0.17
Empl. Growth St. Dev., Large Urban EZs	0.23	0.21	0.18	0.13	0.11	0.10	0.07	0.06	0.05
Obs.	256	256	256	256	256	256	256	256	256
KP F-Stat	81.24	311.06	654.63	127.70	826.37	940.09	96.10	347.85	591.99

Note: The table reports the estimated marginal coefficients for equations (3) and (4) instrumented for the growth of employment in the US, standard errors are reported in brackets. The dependent variable is the growth rate of private employment at the EZ level over the reported period. All independent variables in columns (1) to (4) are calculated in 1995, while those in (5) and (6) in 2005. The "Empl. Growth Large Urban", "Empl. Growth Large Urban, 5", and "Empl. Growth Large Urban, 10" are respectively the employment growth rates of the 1/5/10 closest Large Urban areas weighted by their respective distance. "Shift Share Industry" is the predicted growth of employment based on the industrial composition of the EZ at the beginning of the period. The "Natural Amenities" control accounts for proximity to the seaside, to mountain chains, and to the local average temperature. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

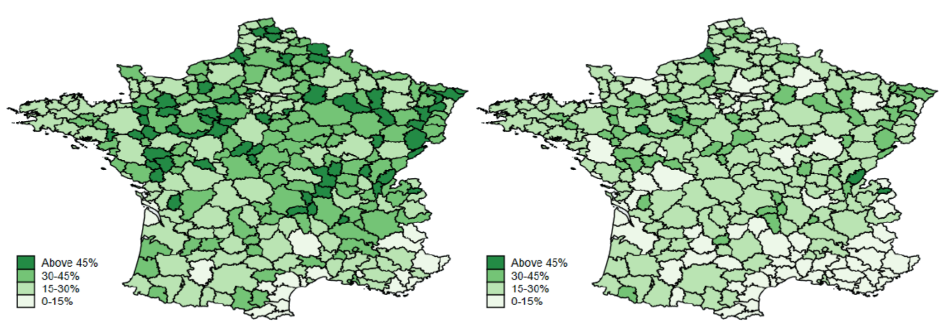
C.3 Figures

Figure C.1: Employment Growth vs the Initial Employment Level, EZ Level



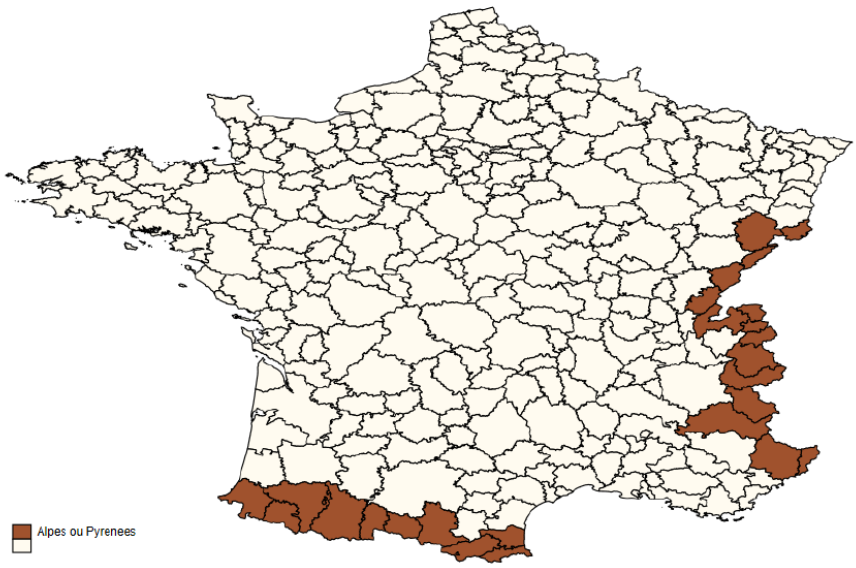
Note: The figure plots the employment growth over the 1995-2015 period as a function of the initial employment level in 1995 for each of the 297 employment zones.

Figure C.2: Manufacturing Share across EZs, 1995-2015



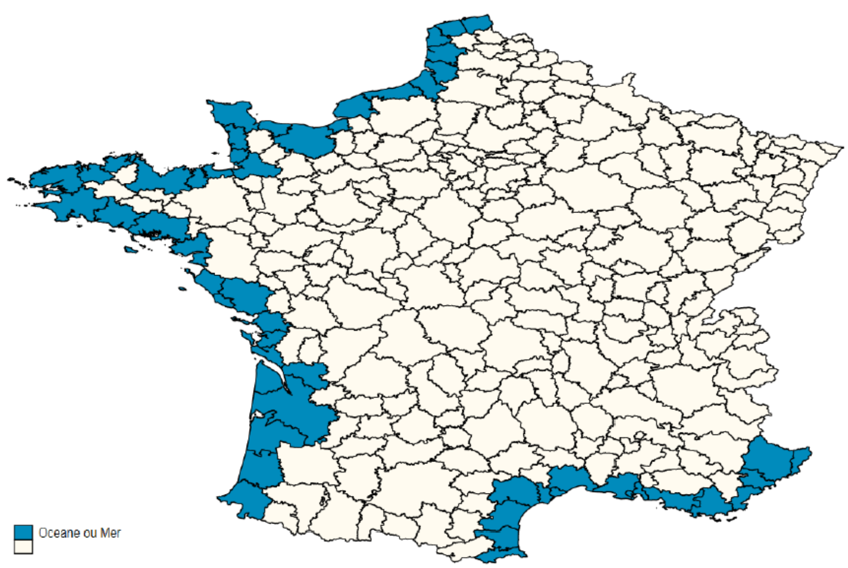
Note: The figure reports the distribution of manufacturing shares across French employment zones for 1995 and 2015.

Figure C.3: Presence of Mountain Chains, EZ level



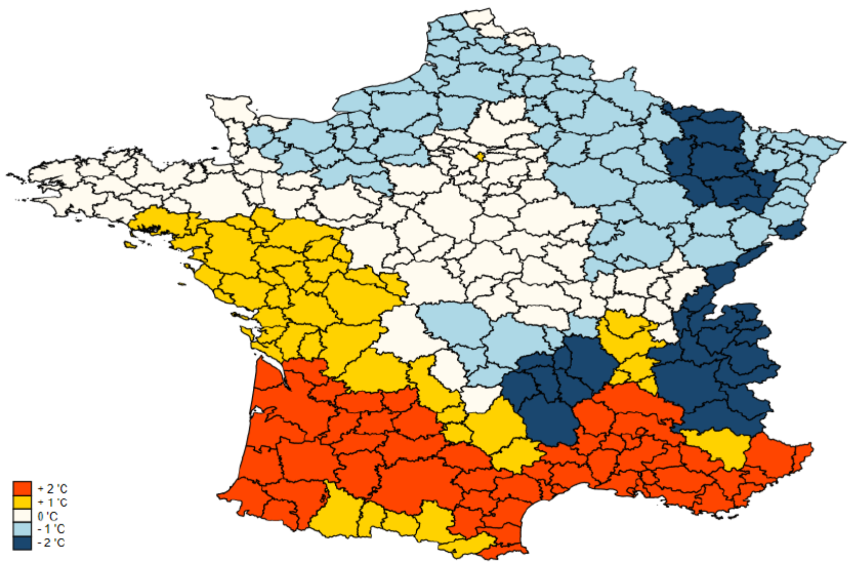
Note: The figure reports the presence of mountain chains (brown) for each of the 297 employment zones.

Figure C.4: Presence of Seasides, EZ level



Note: The figure reports the presence of a seaside (turquoise) for each of the 297 employment zones.

Figure C.5: Average Annual Temperature Deviation, EZ level



Note: The figure reports the deviation between the average temperature at the employment zone level and the average national temperature for each of the 297 employment zones.

C.4 Decomposition of the Labor Force

As discussed in Section 3.3, the growth in employment at the employment zone level might be driven by different underlying mechanisms. In order to have an estimate of the different channels, we propose two decomposition exercises. In the first decomposition, we focus on employment growth and we quantify the relative contribution of local population growth versus the local reduction in unemployment. In the second decomposition, we zoom out to study the evolution of the local working-age population and we assess the relative contribution of the local net inflow of new workers due to the evolution of demographics versus the net inflow of migrants from other locations.

Employment Growth Decomposition. To fix ideas, consider a generic region r, its population at time t, $\mathrm{P}_{r,t}$, can be decomposed as follows:

$$\mathrm{P}_{r,t} = \mathrm{LF}_{r,t} + \mathrm{I}_{r,t}, \tag{C.1}$$

where $\mathrm{LF}_{r,t}$ represents the labor force and $\mathrm{I}_{r,t}$ the inactive population. The labor force is only composed of working-age people, therefore the 15-65 population, while among the inactive we have people from any age cohort.

The labor force is in turn composed by people employed $\mathrm{E}_{r,t}$ and unemployed $\mathrm{U}_{r,t}$, such that:

$$\mathrm{P}_{r,t} = \mathrm{E}_{r,t} + \mathrm{U}_{r,t} + \mathrm{I}_{r,t}. \tag{C.2}$$

It is possible to define the change in employment between period t and $t+1$ as:

$$\Delta\mathrm{E}_{r,t+1} = \Delta\mathrm{P}_{r,t+1} - \Delta\mathrm{U}_{r,t+1} - \Delta\mathrm{I}_{r,t+1}. \tag{C.3}$$

We can divide everything by $\mathrm{E}_{r,t}$:

$$\frac{\Delta \mathrm{E}_{r,t+1}}{\mathrm{E}_{r,t}} = \frac{\Delta \mathrm{POP}_{r,t+1}}{\mathrm{E}_{r,t}} - \frac{\Delta \mathrm{U}_{r,t+1}}{\mathrm{E}_{r,t}} - \frac{\Delta \mathrm{I}_{r,t+1}}{\mathrm{E}_{r,t}}. \tag{C.4}$$

We can further simplify by:

$$\begin{aligned} \frac{\Delta \mathrm{E}_{r,t+1}}{\mathrm{E}_{r,t}} = \frac{\Delta \mathrm{P}_{r,t+1}}{\mathrm{E}_{r,t}}\frac{\mathrm{P}_{r,t}}{\mathrm{P}_{r,t}} - \frac{\Delta \mathrm{U}_{r,t+1}}{\mathrm{E}_{r,t}}\frac{\mathrm{U}_{r,t}}{\mathrm{U}_{r,t}} - \frac{\Delta \mathrm{I}_{r,t+1}}{\mathrm{E}_{r,t}}\frac{\mathrm{I}_{r,t}}{\mathrm{I}_{r,t}}, \\ \gamma_E = \gamma_P \frac{\mathrm{P}_{r,t}}{\mathrm{E}_{r,t}} - \gamma_U \frac{\mathrm{U}_{r,t}}{\mathrm{E}_{r,t}} - \gamma_I \frac{\mathrm{I}_{r,t}}{\mathrm{E}_{r,t}}. \end{aligned} \tag{C.5}$$

By defining $S_X^E = X_{r,t}/\mathrm{E}_{r,t}$ the relative size of X in total employment of region r at time t, we can write the previous formula as:

$$\gamma_E = S_P^E \gamma_P - S_U^E \gamma_U - S_I^E \gamma_I. \tag{C.6}$$

We regress each component on the growth of employment, γ_E, to quantify their relative impact over the period considered and we obtain that population growth accounts for 115% of the overall increase of employment, unemployment growth for -20%, and the growth of the inactive population for a 5%. Overall, this is suggestive evidence pointing against the idea that a reduction in unemployment over time can justify the employment growth rates documented in the paper.

Working-Age Population Growth Decomposition. Let's now define the working age population, $\mathrm{W}_{r,t}$, as the fraction of the 25-54 years people. This is a refinement of the concept of the labor force, $\mathrm{LF}_{r,t}$, nonetheless, long time series at the municipality level are available only according to this definition. In the age span 25-54, inactive people are mainly so because of a choice (e.g., NEETs, homemakers, students) and a tiny fraction of the population. The decomposition reads:

$$\mathrm{W}_{r,t} = \mathrm{E}_{r,t} + \mathrm{U}_{r,t} + \mathrm{I}_{r,t}. \tag{C.7}$$

For simplicity, we abstract from adding the superscript $(25 - 54)$. Following the same reasoning of the previous decomposition, we can rewrite the evolution of employment as:

$$\gamma_E = S_W^E \gamma_W - S_U^E \gamma_U - S_I^E \gamma_I. \tag{C.8}$$

The evolution of the working-age population is determined as follows:

$$\mathrm{W}_{r,t+1} = \mathrm{W}_{r,t} + \mathrm{W}^{Entry}_{r,t+1} - \mathrm{W}^{Exit}_{r,t+1} + \mathrm{M}^{In}_{r,t+1} - \mathrm{M}^{Out}_{r,t+1}, \tag{C.9}$$

where $\mathrm{W}^{Entry}_{r,t+1}$ is the part of local population turning 25, $\mathrm{W}^{Exit}_{r,t+1}$ the part of local population turning 55, $\mathrm{M}^{In}_{r,t+1}$ the 25-54 age population migrating to region r, and $\mathrm{M}^{Out}_{r,t+1}$ the same-age population leaving region r. We can rearrange the terms and divide everything by $\mathrm{W}_{r,t}$ to get:

$$\begin{aligned}
\frac{\mathrm{W}_{r,t+1} - \mathrm{W}_{r,t}}{\mathrm{W}_{r,t}} &= \frac{\mathrm{W}^{Entry}_{r,t+1} - \mathrm{W}^{Exit}_{r,t+1}}{\mathrm{W}_{r,t}} + \frac{\mathrm{M}^{In}_{r,t+1} - \mathrm{M}^{Out}_{r,t+1}}{\mathrm{W}_{r,t}}, \\
\gamma_W &= \frac{\mathrm{W}^{Entry}_{r,t+1} - \mathrm{W}^{Exit}_{r,t+1}}{\mathrm{W}_{r,t}} + \frac{\mathrm{M}^{In}_{r,t+1} - \mathrm{M}^{Out}_{r,t+1}}{\mathrm{W}_{r,t}}, \\
&\gamma_W = \tilde{\gamma}_L + \tilde{\gamma}_M.
\end{aligned}$$

We can use this identity to retrieve the net flow of migrants in region r, $\mathrm{M}^{In}_{r,t+1} - \mathrm{M}^{Out}_{r,t+1}$, which is not directly observable from the data. Plugging the working population growth back, we obtain:

$$\gamma_E = S^E_W \tilde{\gamma}_L + S^E_W \tilde{\gamma}_M - S^E_U \gamma_U - S_{I^E} \gamma_I. \tag{C.10}$$

We again regress each component on the growth of employment, γ_E. Results show that demographics account for one-half of population growth and migration for the other half. Meaning that both account for roughly 60% of the overall employment variation over the period 1995-2015.

C.5 Solving the Model

This section covers the steps required to close and solve the model.

Introduce the Rest of the World. We think of a very large foreign country compared to Home. Foreign essentially acts as a closed economy. This implies that:

$$E_{Fs} = S_{Fs} = \sum_g A_{sg} S_{Fg} \tag{C.11}$$

where subscript F stands for the foreign country. The equation pins down the relative S_{Fs}. We normalize the wage in Foreign, which gives the sum of sales in Foreign:

$$w_F L_F = \sum_s \kappa_s^4 \gamma_s S_{Fs} \tag{C.12}$$

and implies:

$$\hat{S}_{Fs} = \sum_g \frac{A_{sg} S_{Fg}}{S_{Fs}} \left(\hat{A}_{sg} + \hat{S}_{Fg} \right) = \sum_g \frac{A_{sg} S_{Fg}}{S_{Fs}} \hat{S}_{Fg} + \hat{\alpha}_s \left(1 - \sum_g \kappa_g^4 \frac{\gamma_s^g S_{Fg}}{S_{Fs}} \right) \tag{C.13}$$

Define the $S \times S$ matrix $\boldsymbol{A_F}$ by its elements:

$$A_{Fs}^g = A_{sg} \frac{S_{Fg}}{S_{Fs}} \tag{C.14}$$

The problem is that the vector $\boldsymbol{S_F}$ cannot be fully pinned down by the above equation since $\boldsymbol{I} - \boldsymbol{A_F}$ is not full rank. What the above equation allows to do is to pin down:

$$\hat{S}_{Fs} - \hat{S}_{F1} = \sum_g \frac{A_{sg} S_{Fg}}{S_{Fs}} \left(\hat{S}_{Fg} - \hat{S}_{F1} \right) + \hat{\alpha}_s \left(1 - \sum_g \kappa_g^4 \frac{\gamma_s^g S_{Fg}}{S_{Fs}} \right) \tag{C.15}$$

if $s = 1$:

$$0 = \sum_g \frac{A_{1g} S_{Fg}}{S_{F1}} \left(\hat{S}_{Fg} - \hat{S}_{F1} \right) + \hat{\alpha}_1 \left(1 - \sum_g \kappa_g^4 \frac{\gamma_1^g S_{Fg}}{S_{F1}} \right) \tag{C.16}$$

Taking the difference:

$$\underbrace{\hat{S}_{Fs} - \hat{S}_{F1}}_{\Delta \hat{S}_{Fs}} = \sum_g \underbrace{\left(A_{Fs}^g - A_{F1}^g \right)}_{\Delta A_{Fs}^g} \left(\hat{S}_{Fg} - \hat{S}_{F1} \right) + \hat{\alpha}_s \left(1 - \sum_g \kappa_g^4 \frac{\gamma_s^g S_{Fg}}{S_{Fs}} \right) - \hat{\alpha}_1 \left(1 - \sum_g \kappa_g^4 \frac{\gamma_1^g S_{Fg}}{S_{F1}} \right) \tag{C.17}$$

Using that $\hat{\alpha}_1 = -\frac{1}{\alpha_1} \sum_{s' \neq 1} \alpha_{s'} \hat{\alpha}_{s'}$, we get that for $s > 1$:

$$\Delta \hat{S}_{Fs} = \sum_g \Delta A_{Fs}^g \Delta \hat{S}_{Fg} + \hat{\alpha}_s \left(1 - \sum_g \kappa_g^4 \frac{\gamma_s^g S_{Fg}}{S_{Fs}} \right) + \sum_{s' \neq 1} \alpha_{s'} \hat{\alpha}_{s'} \frac{1 - \sum_g \kappa_g^4 \frac{\gamma_1^g S_{Fg}}{S_{F1}}}{\alpha_1} \tag{C.18}$$

We define $\hat{\boldsymbol{\alpha}}$ as the $S-1$ column vector with elements $\hat{\alpha}_2$ to $\hat{\alpha}_S$ and the $S-1 \times S-1$ matrix $\boldsymbol{a_F}$ by: We can define the $S-1 \times 1$ normalized vector $\boldsymbol{\Delta \hat{S}_F}$ as the vector of $\hat{S}_{Fs} - \hat{S}_{F1}$, the $S-1 \times S-1$ matrix $\boldsymbol{\Delta A_F}$

$$\Delta \hat{S}_F = \left(I - \Delta A_F \right)^{-1} a_F \hat{\alpha} \tag{C.19}$$

The weighted average of the changes in $\hat{S}_{Fs}$ is determined by the normalization of w_F :

$$\frac{\sum_s \kappa_s^4 \gamma_s S_{Fs}}{\sum_{s'} \kappa_{s'}^4 \gamma_{s'} S_{Fs'}} \hat{S}_{Fs} = 0 \tag{C.20}$$

This implies that:

$$\hat{S}_{Fs} = \Delta \hat{S}_{Fs} - \sum_g \frac{\kappa_g^4 \gamma_g S_{Fg}}{\sum_{s'} \kappa_{s'}^4 \gamma_{s'} S_{Fs'}} \Delta \hat{S}_{Fg}, \quad \text{with } \Delta \hat{S}_{Fs} = 0 \text{ for } s = 1 \tag{C.21}$$

To implement that, we compute a $S \times S-1$ matrix $\boldsymbol{J}$ with elements: This allows to pin down the $S \times 1$ vector of changes in foreign sales:

$$\hat{S}_F = \underbrace{J\left(I - \Delta A_F\right)^{-1} a_F}_{S_{F\alpha}} \hat{\alpha} \tag{C.22}$$

Since Foreign is a closed economy, we have:

$$\hat{\Phi}_{Fs} - \hat{S}_{Fs} = \left(\sigma_s - 1\right) \hat{P}_{Fs} \tag{C.23}$$

From the definition of the price index:

$$P_{Fs}^{1-\sigma_s} = \frac{\kappa_s \sigma_s}{\kappa_s + 1 - \sigma_s} \Psi_s^{\frac{\kappa_s}{\sigma_s - 1}} \left(\frac{F}{\Phi_{Fs}}\right)^{1 - \frac{\kappa_s}{\sigma_s - 1}} Z_{Fs}^{\kappa_s} W_{Fs}^{1 - \kappa_s - \frac{\kappa_s}{\sigma_s - 1}} \tag{C.24}$$

which, using the definition of $\Phi_{Fs} = P_{Fs}^{\sigma_s - 1} E_{Fs}$ and rearranging, gives:

$$P_{Fs} = \left(\frac{\kappa_s \sigma_s}{\kappa_s + 1 - \sigma_s} \Psi_s^{\frac{\kappa_s}{\sigma_s - 1}}\right)^{-\frac{1}{\kappa_s}} \left(\frac{F}{E_{Fs}}\right)^{\frac{1}{\sigma_s - 1} - \frac{1}{\kappa_s}} Z_{Fs}^{-1} W_{Fs}^{1 - \frac{1}{\kappa_s} + \frac{1}{\sigma_s - 1}} \tag{C.25}$$

In hat algebra:

$$\hat{P}_{Fs} = \kappa_s^3 \hat{S}_{Fs} - \hat{Z}_{Fs} + \left(1 - \kappa_s^3\right) \left(\gamma_s \hat{w}_F + \sum_g \gamma_g^s \hat{P}_{Fg}\right) \tag{C.26}$$

To proceed with matrix notation, we define $\mathbf{\Gamma}$ as the $S \times S$ matrix with elements γ_g^s (s refers to line, g to column) and derive the $S \times 1$ vector of changes in foreign prices:

$$\hat{P}_F = \underbrace{\left[I - \left(I - \kappa_3\right) \Gamma\right]^{-1}}_{P_{FZ}} \left(\kappa_3 \hat{S}_F - \hat{Z}_F\right) \tag{C.27}$$

Use Foreign Results in Domestic Equations. We now rewrite our main equations explicitly splitting domestic and foreign quantities: The price index in different region-sector pairs is:

$$\hat{P}_{rs} = \sum_{n \in FRA} \frac{1}{\sigma_s - 1} \frac{S_{nrs}}{E_{rs}} \left(\hat{\Phi}_{ns} - \hat{S}_{ns}\right) + \frac{S_{Frs}}{E_{rs}} \hat{P}_{Fs} \tag{C.28}$$

We obtain:

$$\hat{S}_{rs} = \kappa_s \hat{Z}_{rs} + \frac{\kappa_s}{\sigma_s - 1}\hat{\Phi}_{rs} - \frac{\kappa_s\sigma_s + 1 - \sigma_s}{\sigma_s - 1}\hat{W}_{rs} \tag{C.29}$$

Solving for the Distribution of Labor. We define all main vectors of interest as being $SR \times 1$ with the first line being sector 1 region 1, the second line sector 1 region 2, and the R + 1 line being sector 2 region 1, etc. We refer to the number of French regions as R.

We define the matrix that translates productivity shocks to headquarters in os into shocks to Z_{rs} as the matrix $\boldsymbol{H}$, which is $SR \times SR$ with elements H_{rs}^{ng} defined as: We can rewrite the expression for growth in sales (C.4) in matrix form as:

$$\hat{S} = \kappa \hat{Z} + \kappa_1 \hat{\Phi} - \kappa_2 \hat{W} \tag{C.30}$$

We also define the $R \times 1$ matrix of changes in population $\hat{L}_r$ as $\hat{\boldsymbol{L}}$, the $S \times 1$ vector of γ_s (labor share) as $\boldsymbol{\gamma}$. We also define $\tilde{\boldsymbol{\Omega}}$ and $\boldsymbol{\Omega}$ as two $RS \times RS$ matrix defined by their elements (rs: line, ng: column): and $\tilde{\Omega}_{\boldsymbol{F}}$ and $\boldsymbol{\Omega_F}$ as the $RS \times S$ matrices with elements: If we assume that all regions are exposed to Foreign in the same way: We also define the $RS \times RS$ matrix $\boldsymbol{\lambda}$ by its elements: and:

$$\boldsymbol{G} = \boldsymbol{I}_R \otimes \gamma \tag{C.31}$$

as a $RS \times R$ matrix where γ is the $S \times 1$ vector of γ_s. We obtain:

$$\left(\boldsymbol{\kappa}_1 - \boldsymbol{\kappa}_2 \tilde{\boldsymbol{\Omega}}\right) \hat{\boldsymbol{\Phi}} = -\hat{\boldsymbol{Z}} + \left(\boldsymbol{I} + \boldsymbol{\kappa}_2(\boldsymbol{\lambda} - \tilde{\boldsymbol{\Omega}})\right) \hat{\boldsymbol{S}} + \boldsymbol{\kappa}_2 \tilde{\boldsymbol{\Omega}}_F \hat{\boldsymbol{P}}_{\boldsymbol{F}} - \boldsymbol{\kappa}_2 \boldsymbol{G} \hat{\boldsymbol{L}} \tag{C.32}$$

We obtain:

$$(\boldsymbol{I} - \phi)\hat{\boldsymbol{\Phi}} = (\varphi - \phi)\hat{\boldsymbol{S}} + \boldsymbol{a}\hat{\boldsymbol{\alpha}} + \boldsymbol{\theta}\hat{\boldsymbol{\Theta}} + \boldsymbol{T}\hat{\boldsymbol{P}}_F + \boldsymbol{X}\hat{\boldsymbol{S}}_{\boldsymbol{F}} \tag{C.33}$$

To cut notation, we define:

$$\begin{aligned} \boldsymbol{N_1} \quad &= (\boldsymbol{I} - \boldsymbol{\phi}) \left(\boldsymbol{\kappa_1} - \boldsymbol{\kappa_2}\tilde{\boldsymbol{\Omega}}\right)^{-1} \\ \boldsymbol{N} \quad &= \boldsymbol{N_1} \left(\boldsymbol{I} + \boldsymbol{\kappa_2}(\boldsymbol{\lambda} - \tilde{\Omega})\right) - \boldsymbol{\varphi} + \boldsymbol{\phi} \end{aligned}$$

Combining (C.5) and (C.6) gives:

$$N\hat{S} = N_1 \left(\hat{Z} + \kappa_2 G\hat{L}\right) + \theta\hat{\Theta} + a\hat{\alpha} + X\hat{S}_F + \left[T - N_1\kappa_2\tilde{\Omega}_F\right] \hat{P}_F \tag{C.34}$$

which, with the expressions for $\hat{\boldsymbol{P}}_{\boldsymbol{F}}$ and $\hat{\boldsymbol{S}}_{\boldsymbol{F}}$ in (C.1) and (C.2) would be sufficient to determine the change in the vector of S if there was no labor mobility.

Introducing Labor Mobility. We finally need to complement the analysis with the matrix $\boldsymbol{\rho}$ with dimension $R \times RS$, defined by its elements: as well as $\boldsymbol{A}$, the $R \times RS$ matrix with elements $A_r^{ng} = \alpha_g$, computed as:

$$\boldsymbol{A} = \boldsymbol{I}_R \otimes \boldsymbol{\alpha}' \tag{C.35}$$

where $\boldsymbol{\alpha}$ is the $S \times 1$ vector of α 's.

$$\tilde{a}_r^s = 1 + \ln(\alpha_s) - \ln(P_{rs})\,\alpha_s \tag{C.36}$$

From the definition of prices:

$$\hat{\boldsymbol{P}} = \Omega(\hat{\boldsymbol{\Phi}} - \hat{\boldsymbol{S}}) + \Omega_F \hat{\boldsymbol{P}}_F \tag{C.37}$$

and from (3.47), we obtain:

$$\begin{aligned} \hat{\boldsymbol{V}} \quad &= \boldsymbol{\rho}\hat{\boldsymbol{S}} + \tilde{\boldsymbol{\theta}}\hat{\Theta} - \boldsymbol{A}\hat{\boldsymbol{P}} - \hat{\boldsymbol{L}} + \tilde{\boldsymbol{a}}\hat{\boldsymbol{\alpha}} \\ &= (\boldsymbol{\rho} + \boldsymbol{A}\Omega)\hat{\boldsymbol{S}} - \boldsymbol{A}\Omega\hat{\boldsymbol{\Phi}} - \boldsymbol{A}\Omega_F\hat{\boldsymbol{P}}_F - \hat{\boldsymbol{L}} + \tilde{\boldsymbol{a}}\hat{\boldsymbol{\alpha}} + \tilde{\boldsymbol{\theta}}\hat{\Theta} \end{aligned}$$

Plugging in $\hat{\boldsymbol{\Phi}}$:

$$\hat{V} = \underbrace{\left[\rho + A\Omega\left(I - \left(\kappa_1 - \kappa_2\tilde{\Omega}\right)^{-1}\left(I + \kappa_2(\lambda - \tilde{\Omega})\right)\right)\right]}_{V_S}\hat{S} + \underbrace{\left[A\Omega\left(\kappa_1 - \kappa_2\tilde{\Omega}\right)^{-1}\kappa_2 G - I\right]}_{V_L}\hat{L}$$
$$+A\Omega\left(\kappa_1 - \kappa_2\tilde{\Omega}\right)^{-1}\hat{Z} - A\left[\Omega\left(\kappa_1 - \kappa_2\tilde{\Omega}\right)^{-1}\kappa_2\tilde{\Omega}_F + \Omega_F\right]\hat{P}_F + \tilde{\boldsymbol{a}}\hat{\boldsymbol{\alpha}} + \tilde{\boldsymbol{\theta}}\hat{\Theta} \quad \text{(C.38)}$$

We finally define the matrix Λ as the $R \times R$ matrix with elements $L_r^n = \sum_{r'} \frac{L_{r'}}{L_r}\frac{L_{r'n}}{L_{r'}}$(r in rows, n in columns) so that (3.45) becomes:

$$\hat{\boldsymbol{L}} = \zeta(\boldsymbol{I} - \boldsymbol{\Lambda})\hat{\boldsymbol{V}} \quad \text{(C.39)}$$

Defining:

$$\boldsymbol{N}_2 = I - \zeta(I - \Lambda)\left(V_L + V_S N^{-1} N_1 \kappa_2 G\right)$$
$$N_3 = \zeta(I - \Lambda)V_S N^{-1}$$
$$N_4 = N_3\left(T - N_1\kappa_2\tilde{\Omega}_F\right) - A\left(\Omega\left(\kappa_1 - \kappa_2\tilde{\Omega}\right)^{-1}\kappa_2\tilde{\Omega}_F + \Omega_F\right)$$

gives:

$$\boldsymbol{N}_2\hat{\boldsymbol{L}} = \left[\boldsymbol{N}_3\boldsymbol{N}_1 + \boldsymbol{A}\Omega\left(\kappa_1 - \kappa_2\tilde{\Omega}\right)^{-1}\right]\hat{Z} + \left(\boldsymbol{N}_3\boldsymbol{\theta} + \tilde{\boldsymbol{\Theta}}\right)\hat{\boldsymbol{\Theta}} + \left[\boldsymbol{N}_3\boldsymbol{a} + \tilde{\boldsymbol{a}}\right]\hat{\boldsymbol{\alpha}} + \boldsymbol{N}_3\boldsymbol{X}\hat{\boldsymbol{S}}_F + \boldsymbol{N}_4\hat{\boldsymbol{P}}_{\boldsymbol{F}}$$

This yields:

$$\hat{L} = \underbrace{N_2^{-1}\left[N_3 N_1 + A\Omega\left(\kappa_1 - \kappa_2\tilde{\Omega}\right)^{-1}\right]}_{T_{LZ}}\hat{Z} + \underbrace{N_2^{-1}\left(N_3\theta + \tilde{\Theta}\right)}_{T_{L\Theta}}\hat{\Theta} - \underbrace{N_2^{-1}N_4 P_{FZ}}_{T_{LZF}}\hat{Z}_F$$
$$+ \underbrace{N_2^{-1}\left[N_3 a + \tilde{a} + N_3 X S_{F\alpha} + N_4 P_{FZ}\kappa_3 S_{F\alpha}\right]}_{T_{L\alpha}}\hat{\alpha}$$

Plugging back in $\hat{\boldsymbol{S}}$:

$$\hat{S} = \underbrace{N^{-1}N_1\left(I + \kappa_2 G T_{LZ}\right)}_{T_{SZ}}\hat{Z} + \underbrace{N^{-1}\left(\theta + N_1\kappa_2 G T_{L\Theta}\right)}_{T_{S\Theta}}\hat{\Theta} - \underbrace{N^{-1}\left(\left(T - N_1\kappa_2\tilde{\Omega}_F\right)P_{FZ} + \kappa_2 G T_{LZ}\right.}_{T_{SZF}}$$
$$+ \underbrace{N^{-1}\left(a + XS_{F\alpha} + \left(T - N_1\kappa_2\tilde{\Omega}_F\right)P_{FZ}\kappa_3 S_{F\alpha} + \kappa_2 G T_{L\alpha}\right)}_{T_{S\alpha}}\hat{\alpha}$$

We then turn to express the change in L_{rs}, the national change of employment for each industry at time t, as: in matrix form, we compute the $RS \times RS$ matrix $\tilde{\boldsymbol{G}}$ defined by its elements: and $\boldsymbol{E}$ a $RS \times R$ matrix that transforms $R \times 1$ vectors into $RS \times 1$ vectors.

$$\boldsymbol{E} = \mathbf{1}_S \otimes \boldsymbol{I}_R \tag{C.40}$$

which gives:

$$\hat{\boldsymbol{\mathcal{L}}} = (\boldsymbol{I} - \tilde{\boldsymbol{G}})\hat{\boldsymbol{S}} + \boldsymbol{E}\hat{\boldsymbol{L}} \tag{C.41}$$

where $\hat{\boldsymbol{\mathcal{L}}}$ is $RS \times 1$. To obtain changes at the national level for each sector, we use:

$$\hat{L}_s = \sum_r \frac{L_{rs}}{L_s}\hat{L}_{rs} \tag{C.42}$$

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