UNIVERSITÀ
DEGLI STUDI
FIRENZE

PhD in

Development Economics and Local Systems (DELoS)

CYCLE: XXXVII

COORDINATOR: Prof. Romano Donato

Three Essays on Local Industrial Growth

Academic Discipline (SSD): ECON-04/A

Doctoral Candidate

Dr. Berti Mecocci Filippo

Supervisor

Prof. Bellandi Marco

Coordinator

Prof. Romano Donato

Contents

I Introductory Part **11**

1 Key concepts and dissertation structure **13**

1.1 Key concepts 14

1.2 Dissertation structure 15

2 Introduction **17**

2.1 Manufacturing contributes to national and local growth 17

2.1.1 1st Stylized fact 19

2.1.2 2nd Stylized fact 20

2.1.3 Connecting the dots: localized external economies and increasing returns 21

2.2 The economics of localized increasing returns 25

2.2.1 Inequalities and the space of policies 28

2.3 The new Italian economic geography 32

2.3.1 Some empirical considerations 32

2.3.2 Theoretical foundation 34

2.3.3 Emerging challenges 35

II Original Contributions **39**

3 Firm size and local multipliers **41**

3.1 Introduction 43

3.2 An overview on local multipliers 47

3.3 Pecuniary externalities and the working mechanisms 50

3.3.1 Testable implications 52

3.4 Data and econometric design . . . 53
3.4.1 Identification strategy . . . 55
3.5 Main results . . . 56
3.5.1 Replication . . . 57
3.5.2 The impact of entry varies by firm size . . . 58
3.5.3 The effect of tradable firm entry on other tradables . . . 60
3.5.4 Territorial heterogeneity and firms size . . . 62
3.6 Summary and conclusive remarks . . . 65

Appendices **69**
A Tables of Statistics . . . 71
B Models of Local multipliers . . . 72
B.1 Moretti (2010) . . . 72
B.2 Moretti and Thulin (2013) . . . 73
B.3 Van Dijk (2018) . . . 73
B.4 Osman and Kemeny (2022) . . . 74

4 Local Competition and External Economies **75**
4.1 Introduction . . . 77
4.2 A tentative model of oligopsony in local industries . . . 80
4.2.1 Labor Supply . . . 81
4.2.2 Labor Demand . . . 82
4.2.3 Parametric external economies in the case of monopsony in the labor market 83
4.2.4 Intuition and testable predictions . . . 85
4.3 Model and identification . . . 86
4.3.1 First step: LITFP estimation . . . 86
4.3.2 Further endogeneity concerns . . . 88
4.3.3 Second step: Estimation on local and industrial characteristics . . . 91
4.4 Data . . . 92
4.5 Results . . . 93
4.5.1 Manufacturing as an industrial unit of analysis . . . 95
4.5.2 Fine tuning of the correct unit of analysis . . . 98
4.6 Conclusive remarks . . . 101

Appendices **105**

A Chipman external economies . . . 107

B Relevance of the soil productivity indices . . . 108

C Robustness tests for table 4.2 . . . 108

D Robustness tests for table 4.3 . . . 111

E Robustness tests for table 4.4 . . . 111

5 Global Shocks, Local Responses **115**

5.1 Motivation . . . 117

5.2 Regional Unemployment and Input-Output Linkages . . . 122

5.3 Data and context . . . 125

5.4 The model . . . 126

5.4.1 Local Input-Output Linkages . . . 128

5.4.2 Control variables . . . 129

5.4.3 Identification strategy: DiD estimator and parallel trends . . . 131

5.5 Results . . . 134

5.5.1 The effect of COVID-19 as a placebo treatment . . . 136

5.6 Conclusions and policy implications . . . 139

Appendices **141**

A Robustness Tests for Financial Crisis . . . 143

III Conclusive Part **145**

6 Conclusions **147**

6.1 Brief Summary and Main Contributions . . . 147

6.1.1 Employment . . . 149

6.1.2 Productivity . . . 150

6.1.3 Unemployment . . . 151

6.2 Policies implications . . . 152

6.2.1 Policies for Place-Based Jobs . . . 152

6.2.2 Place-Based Policies for Productivity . . . 154

6.2.3 Afterthought on Pro-cyclical Place-Based Policies . . . 158

7 Future Research Perspective **161**

7.1 Working papers 161

7.2 Research projects 162

List of Figures

2.1 **Italian LMAs according to Quintiles of Manufacturing Distribution** . . 22
2.2 **Empirical Regularities of Manufacturing Geographic Concentration** . . 22
2.3 **Italian Productive Geography** 34

3.1 **Business Demographics in Italian LMAs** 46
3.2 **Compensation of Employees** 51
3.3 **The heterogeneous effect of an increase in tradable jobs on non-tradable jobs** 59

4.1 **Competition and productivity in Italy** 78
4.2 **Effect of 3-digit industry specialization on LITFP** 95
4.3 **Effect of manufacturing specialization on 3-digit LITFP** 98
4.4 **Effect of skill relatedness on 3-digit LITFP** 100
5 **Marginal Effects of estimation in table A.2** 110
6 **Marginal Effects of estimation in table A.5** 113
7 **Marginal Effects of estimation in table 4.4** 114

5.1 **Structural and dynamic unemployment in Italy (2006-2022)** 118
5.2 **Treated and Non-Treated Italian Local Labor Market Areas** 130
5.3 **Test for parallel trends assumption** 133
5.4 **Vacancy and unemployment rates in Italy (2006-2022)** 134
5.5 **Input output and unemployment - Event Study** 136
5.6 **Input Output and Unemployment** 137
5.7 **Input output and unemployment during Covid-19** 138
5.8 **Input Output and Unemployment during Covid-19** 138

6.1 **Unemployment Change in Italian LMAs** 159

List of Tables

2.1 Decomposition of the Italian Manufacturing Output 18
2.2 Kaldor-Verdoorn Law in Italian LMAs 19
2.3 Ellison and Glaeser Agglomeration Index in the Case of Italy 21
2.4 Estimate of External and Internal scale economies 24
2.5 Main Empirical Regularities 33

3.1 The size of establishments in district and non-district areas 44
3.2 Baseline results of changes in tradable on non-tradable 58
3.3 Effect of changes in tradable heterogeneous firms size on non-tradable 60
3.4 Effect of tradable on other tradables 62
3.5 Effect of changes in tradable on non-tradable according to different territorial settings 63
3.6 Effect of changes in tradable heterogeneous firms size on non tradable according to different territorial settings 63
3.7 Summary of effects of changes in tradable heterogeneous firms size on non-tradable according to the degree of urbanization 64
1 Structural composition of Italian LMAs in 2012 71
2 Summary statistics and correlation matrix 71
3 Summary statistics and correlation matrix 72
4 Effect of changes in tradable on non-tradable according to different time spans 72

4.1 Metrics for TFP 89
4.2 Effect of 3-digit specialization, competition and their interaction on LITFP 94

4.3 **Effect of manufacturing specialization, competition and their interaction on LITFP** . . . 97
4.4 **Effect of skill relatedness, competition and their interaction on LITFP** 99
1 **Predicting specialization using soil and grassland productivity** . . . 108
2 **Effect of 3-digit manufacturing specialization, competition and their interaction on different measure of LITFP** . . . 108
3 **Effect of 3-digit manufacturing specialization, competition and their interaction on different measure of LITFP** . . . 109
4 **Effect of manufacturing specialization, competition and their interaction on LITFP** . . . 111
5 **Effect of manufacturing specialization, competition and their interaction on LITFP** . . . 112

5.1 **Unemployment rates in 2022 (highest and lowest)** . . . 119
5.2 **Trade between manufacturing and services in Italy (2010)** . . . 126
5.3 **Input Output and unemployment changes** . . . 135
1 **Input Output and Employment Changes** . . . 143
2 **Input Output and Unemployment Changes (subset of IDs)** . . . 143
3 **Input Output and Employment Changes (subset of IDs)** . . . 143
4 **Input Output and Uneployment Changes (Quartiles)** . . . 144

6.1 **Jobs Multipliers** . . . 154
6.2 **Nonlinearities in Productivity Elasticities** . . . 156

Part I

Introductory Part

Chapter 1

Key concepts and dissertation structure

Firms, workers, and economic activities in general are unevenly distributed in space. Some are diffuse, such as services (non-tradable activities), while others are concentrated, such as extractive and manufacturing activities, due to the presence of natural resources, external economies, and favorable institutional frameworks. External economies due to geographical concentration arise according to the local industrial structure. Their presence modifies the economic outcomes of local firms, workers, and communities and leads to increasing spatial concentration; this is the main interest of the dissertation.

This dissertation focuses on the effect of *external economies* on *economic performance* resulting from the *geographic concentration* of *manufacturing activities*. In particular, I focus on several aspects of economic performance, such as unemployment fluctuations, productivity, and employment growth; on factors that facilitate external economies, such as competition and local structures; on a specific geographic unit of study, the local labor market area (divided into industrial districts and other areas); and on manufacturing as a variable that affects local growth (through basic to non-basic multipliers) as well as a variable that is affected by local characteristics. In what follows, I recall the key concepts on which the thesis elaborates.

1.1 Key concepts

External economies are unpaid side effects of one producer's output or inputs on other producers. *Technological external economies* (or externalities) in this sense imply that market prices do not reflect the marginal social cost of production, giving rise to a 'market failure', while *pecuniary external economies* are rather the price effects between or among industries and their firms (Bohm, 2017). In the dissertation I focus on both types of external economies. Pecuniary externalities are discussed and used in the framework of the chapter 3. Technological externalities are the focus of chapters 4 and 5. An important category of externalities are *external (dis-)economies of scale*. These arise when there is an extra input in the production function - not accounted for - from which external (dis-)economies of scale arise when, for example, inputs are doubled. If inputs are doubled and output is (less) more than doubled, then external (dis-)economies arise. Examples of these inputs are specific public goods such as health, education, and specific training of the labor pool (Silvestre, 2016).

Economic Performance refers to the ability of a place to generate a sustained path of growth. This is reflected in several economic indicators such as productivity, employment growth and unemployment. The elasticity of productivity with respect to external economies is one of the main indicators used in the literature to measure agglomeration (Henderson, 2003). In chapter 4, I focus on this relationship. Productivity shocks also increase either employment or wages according to the housing supply elasticity (Hsieh & Moretti, 2019). In chapter 3 I focus on employment growth according to non-basic multipliers. Chapter 5 focuses on unemployment fluctuations in business cycles.

Geographic Concentration here refers to the fact that some industries are more spatially concentrated than others[1]. The fact that some industries are more concentrated than others generates unequal regional growth paths (Sachs & McCord, 2016). The presence of specific local factors generate economic rationale for localization, and in the dissertation I focus on local industrial structures. Specifically, I focus on the case of Italy and my unit of investigation is the local labor market area (LMA, hereafter). LMAs are travel to work areas and are traditionally divided into *industrial districts* and other LMAs. The classification of industrial districts began after the seminal work of Sforzi et al. (1991), who developed the official procedure then used

[1]However, in the literature, geographic concentration also refers to the concentration of - among other things - human capital, population, and innovation.

by the Italian Statistical Office. Starting from the definition of a reference area in which the commuting flows are exhausted, industrial districts are defined as those in which there is manufacturing specialization. Not only specialization is required to be an industrial district, but a second necessary condition is that the majority of manufacturing employment is accounted for by small and medium firms. This makes it possible to distinguish between areas of large firms and industrial districts (Becattini & Coltorti, 2006).

Manufacturing activities involve the physical or chemical transformation of materials, substances, or components into new products. This process may include assembly, processing, fabrication, and packaging, and is typically characterized by the use of machinery, labor, and a systematic sequence of operations. According to Smith (1776), the division of labor achieved in manufacturing activities is the main reason for economic growth and progress, generating increasing returns at the aggregate level. Division of labor occurs in expanding industries and generates specialized skills to emerge. 'It is also practiced by small firms which all contribute to the production of parts (inputs) for the manufacturing of a complex output. [...] It is a geographical form of division of labour, developed from the notion of clustering related firms in a particular area or industrial district' (Groenewegen, 2017, p.2).

There is a link between manufacturing activities, geographical concentration and external economies. In the dissertation, I started from the grounded literature to expand the knowledge about this link. In particular, I focus on the ways this triadic relationship affects local economic performance. In the conclusions, I provide some insights about how differentials in economic performance affect national growth.

1.2 Dissertation structure

This thesis is divided into three main parts with a total of 7 chapters. Part I is the introductory part, and this chapter is included in that introductory part. Part II is the original part of the thesis including the three original chapters on which I worked during the three-years PhD program. Part III summarizes the main findings, provides some original policy implications in light of the framework presented in part I, and gives an overview of my future research perspective. Each part has two chapters, except for part II, which has three. In the next three paragraphs I briefly describe the structure of each part.

Part I is the introduction of the thesis. Chapter 1, the actual one, is preliminary, providing

some concepts necessary to gauge the ideas, mechanisms, and phenomena described in subsequent chapters. Chapter 2 is composed by three main sections. Section 2.1 shows empirically how manufacturing contributes to national and local growth and documents the existence of increasing returns to scale at the level of local manufacturing. It sketches two main stylized facts that suggest a relationship between geographic concentration and increasing returns to manufacturing. It also suggests that geographic concentration is associated with higher firm and worker performance. This provides a general perspective on the rationale for focusing on manufacturing in the three main original chapters of the dissertation, and offers reasons for place-based economic thinking. Section 2.2 reviews the economic rationales underlying localized increasing returns. In addition, the fact that manufacturing is a relevant engine of growth and that it tends to be concentrated creates an uneven growth path. It offers some insights from the perspective of public economics, which are elaborated in part III of the paper. However, these considerations are introductory. Finally, section 2.3 qualifies the places where the concentration of productive activities takes place in Italy. These places are Marshallian industrial districts. I briefly recall their theoretical foundations and the emerging challenges highlighted by the Italian economic geography literature. This is the starting point for the development of the original part of thesis.

Part II is the proper body of the thesis. Here I present the original contributions of the thesis, the result of the work of the three-year doctoral program. Part II is divided in three chapters. Chapter 3 uses pecuniary externalities to show that increasing the number of manufacturing (+ extraction activities) establishments generates additional jobs in non-tradable activities. Chapter 4 examines the role of local industrial structure in the generation of externalities from manufacturing specialization. That is, it examines the local factors (such as industrial specialization and competition) that allow productivity gains for localized firms. Chapter 5 is interested in understanding how places enjoying external economies due to manufacturing specialization react to global shocks. All three chapters provide empirical evidence for policy. However, policies are not included (sometimes only sketched) in each chapter. These are presented in the part III.

Part III represents the moment of meta-reflection. It is divided into two chapters. Chapter 6 is divided in two main sections. Section 6.1 summarizes the results of the original chapters and synthetically answers the main research questions of each of them as a way to give deliverables at hand. Section 6.2 uses the framework presented in section 2.2 and the main results from the econometrics of each original chapter in part II to provide a rationale for place-based economic policies. Chapter 7 provides a broad overview of my interests and related future research perspectives.

Chapter 2

Introduction

2.1 Manufacturing contributes to national and local growth

Are there still reasons to focus on tradable sectors in 2024, especially manufacturing? Why should some sectors receive more attention than others in an economy? There are a couple of answers. The first is short. The second is longer and requires a detailed presentation of theories and facts. In what follows, I focus on the empirics of Italy over the last 20 years.

The first answer is based on the basic to non-basic multiplier (Moretti, 2010; Malizia et al., 2020). In general, tradable sectors are those that allow the development of places because they push the flow of financial resources from outside to the local market. Tradable sectors are those that have as their core activity the export of their production. The table 2.1 shows the difference in terms of the decomposition of output between manufacturing and service activities[1] The manufacturing sector exports about a third of its total output, while the services sector exports only 3%. The main idea behind the theory is that when a tradable sector locates in a place, it generates a flow of income through its exports. The income generated is then used to pay for factors of production, some of which are strictly local, such as labor and land. In turn, this distributed income is spent by workers and landowners according to a parameter (the propensity to spend locally), generating further rounds of multipliers. Non-tradable activities flourish as a consequence of the growth process of tradable activities. I focused on this process

[1]Manufacturing output is calculated as the output sum of two-digit industries from 10 to 33. Some industries are grouped together, such as 10, 11 and 12; 13, 14 and 15; and 31 and 32. Intermediate goods are calculated as the ratio of output sold for intermediate goods to total manufacturing output. Final consumption is the ratio of output sold to government, households and NPISHs to total manufacturing output. Exports is the ratio of exports to total manufacturing output. The sum of the three components does not equal 100 because I exclude the variation of investment and reserves from the calculation.

in chapter 3.

Table 2.1: **Decomposition of the Italian Manufacturing Output**

	2010	2020
Non-Manufacturing		
Intermediate	0.46	0.45
Final Consumption	0.43	0.43
Export	0.03	0.04
Manufacturing		
Intermediate	0.49	0.46
Final Consumption	0.17	0.16
Export	0.25	0.32

Notes. Data sources: Istat freely available input-output tables. Sources: Authors' calculations.

The local growth of tradable activities depends on: 1) technological externalities, 2) pecuniary externalities and 3) internal-to-firms economies. While pecuniary externalities are transmitted in markets through price adjustments, technological externalities refer to uncompensated benefits received by economic agents. For example, when a new firm enters the local market, it may generate both pecuniary and technological externalities. The former operates through the generation of additional demand when the new equilibrium employment is not offset by competition (Ottaviano & Thisse, 2001). The latter refers to learning processes that allow local firms to enjoy productivity gains in the form of knowledge spillovers (Moretti, 2021). As a result, goods that generate technological externalities are often underprovided. This is the case for human capital externalities (Heckman, 2000; Moretti, 2004). Consequently, when there is an under-supply of a good that generates uncompensated externalities, the market failure must be corrected by optimal and efficient policies. On the other hand, according to the traditional theory, goods and transactions that produce pecuniary externalities do not require any further policies to be implemented. In Chapter 3, I use pecuniary externalities to develop the causal mechanism. In Chapter 4, I use technological externalities (especially those that arise in the labor market) to develop a theoretical model and an econometric test for *localization economies*[2].

The answer to the second question concerns technological externalities. Such externalities tend to operate more in manufacturing than in agriculture and services. Overall, their presence generates the aggregate increasing returns that are the very engine of self-sustaining growth.

[2]Localization economies are defined as those economies that arise from the co-location of activities and are internalized by firms operating in the same industry. They are usually compared to *urbanization economies*, which still arise from co-location but across different industries (Frenken et al., 2007).

They arise from both internal and external - to the firm - economies, and when they are external, they tend to be highly localized (Rosenthal & Strange, 2004). This is because external economies, which arise from transportation cost savings as well as technological externalities, have a spatial decay (Dekle & Eaton, 1999). The existence of localized increasing returns has implications for inequality and, in the context of technological externalities, provides room for policy action (Glaeser and Gottlieb, 2008; Austin et al., 2018).

2.1.1 1st Stylized fact

There are several ways to show that there is a positive relationship between the size of a (manufacturing) industry and its productivity. In the following, I use the *Kaldor-Verdoorn* law (Kaldor, 1966). This law postulates that as sectoral output increases, sectoral productivity also increases. The main equation identified by the *Kaldor-Verdoorn* law is:

$$Productivity_r = \alpha + \eta \cdot Output_r + \epsilon_r \tag{2.1}$$

The subscripts r here can be thought of as regional values. Productivity refers to labor productivity, while output refers to gross output.

Table 2.2: **Kaldor-Verdoorn Law in Italian LMAs**

	(1)	(2)	(3)	(4)
Gross Output	0.152***	0.151***	0.337***	0.285***
	(0.005)	(0.005)	(0.062)	(0.061)
Year FE		✓		✓
LMA FE			✓	✓
Observations	3,043	3,043	3,043	3,043
N. LMAs	609	609	609	609
R2-within	.567	.571	.173	.133

Notes. Data sources: Istat data on LMAs All variables are in logarithmic form. Productivity is labor productivity. The estimation include LMA and year fixed effects, and no control variables. Errors are clustered at the LMA level.
*** p<.01, ** p<.05, * p<.1

Although the Kaldor-Verdoorn law has traditionally been estimated in cross-country regressions, there have been some attempts to estimate it in cross-regional regressions and, more recently, using panel data regressions (McCombie & Roberts, 2007). With panel data, the structure of the regression changes to include the LMA fixed effect in the error term and year fixed

effects as dummies for each year[3]. Including two-way fixed effects in the estimation helps deal with the source of bias that comes from spatial aggregation bias, a particular form of ecological fallacy (see McCombie and Roberts (2007) for further explanation). The traditional value of η is 0.5 and represents the elasticity of productivity with respect to output. I replicate the exercise using Istat available data[4]. Findings show a value of η equal to 0.285, which means that for every 1 p.p. increase in output, productivity increases by 0.285 p.p. (see column (4) of the table 2.2). Even if this is a pure correlation between variables and does not correct for other possible distortions due to the endogenous *quantity* and *quality* of labor (which I will deal with in Chapter 4), it gives us an idea of the extent of the Kaldor-Verdoorn law in the Italian local economy. Yet, I am not able to distinguish between internal and external to the firms source of increasing returns.

2.1.2 2nd Stylized fact

The 2nd stylized fact concern the geographical dimension of production. Table 2.3 shows trends in the Ellison and Glaeser (1997) agglomeration index (EGI)[5] using data on 5-digit industries in LMAs in Italy. To compute the averages across sectors, I followed Kolko (2010) and computed the weighted average, where the weight is the national employment. The first result that stands out is that manufacturing is the most concentrated sector in Italy. This partially differs from previous results, such as those of De Dominicis et al. (2013), where services are found to be more concentrated than manufacturing. The sample I use differs from theirs in that I use data on 5-digit industries, while they use 2-digit industries. Table 2.3 also shows that there is an increasing trend in geographical agglomeration. Also, it is possible to see that the largest manufacturing LMAs (fifth quintile of the distribution) accounts for 77% in 2011 to 80% in 2020 of total manufacturing activity[6]. This means that around 120 LMAs account for almost all manufacturing activity in Italy. As it is shown in figure 2.1, most of these areas are concentrated in the central north of the country. Some of these areas are industrial districts, in the next sections I will focus on this topic.

[3] This produces an equation such as $Productivity_{rt} = \eta \cdot Output_{rt} + \tau_t + \varepsilon_{rt}$ where t is time and $\varepsilon_{rt} = \epsilon_{rt} + \mu_r$.

[4] Data are available here:
https://www.istat.it/statistiche-per-temi/focus/informazioni-territoriali-e-cartografiche/statistiche-sul-territorio/sistemi-locali-del-lavoro-e-distretti-industriali/

[5] The index is computed as

$$\widehat{\gamma_{EG}} = \frac{\sum_i (s_i - x_i)^2 - (1 - \sum_i x_i^2) \cdot H}{(1 - \sum_i x_i^2) \cdot (1 - H)}$$

where s_i is the share of 5-digit industry employment in area i, x_i is the share of national employment in area i, and H is the Herfindhal-Hirschman index of competition computed using establishments for each 5-digit industry.

[6] Results are obtained by exploiting the plant level confidential dataset obtained in Laboratorio Adele Istat.

Table 2.3: **Ellison and Glaeser Agglomeration Index in the Case of Italy**

	2011	2014	2017	2020
Manufacturing	0.057	0.061	0.061	0.062
Natural Advantages	0.029	0.031	0.033	0.034
Services	0.045	0.047	0.048	0.048

Notes. Data source: Istat ASIA confidential data at establishment level. Manufacturing includes all 5-digit sectors from 10110 to 33200. Natural advantages include all 5-digit sectors from 05100 to 09900 and from 35110 to 53200. Services include all other 5-digit sectors except agriculture. Source: Author's own calculations.

2.1.3 Connecting the dots: localized external economies and increasing returns

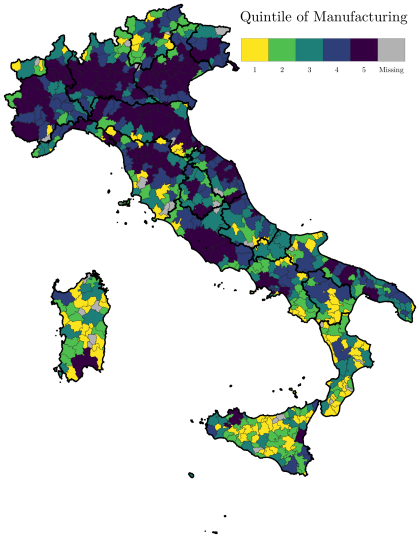
Given the increasing returns to scale in manufacturing and the fact that manufacturing activities are mostly concentrated in a few places, a theory linking manufacturing to a spatial production process is needed. Figure 2.2 provides such empirical regularities, showing that both labor productivity and wages increase with the geographic concentration of activities. Using 2020 (more recent) data for Italian LMAs, the unconditional elasticity of labor productivity with respect to manufacturing density is 0.12%, while that of wages is 0.08%. This suggests that a 1 p.p. increase in local manufacturing density generates a 0.12 p.p. increase in labor productivity and a 0.08 p.p. increase in wages[7].

However, this may arise as a consequence of two different contrasting hypotheses. First, manufacturing is characterized by a high degree of concentration of production in a few firms (the internal economies case). The places where these firms are located then account for most of the manufacturing output. Second, the manufacturing production process is vertically disintegrated and enjoys a high degree of industry-wide competition (the case for external economies). For a number of reasons, firms have incentives to cluster in the same locations despite high levels of competition.

One way to deal with such an impasse can be retrieved from the literature on *procyclical productivity*. This literature stems from an other empirical regularity: productivity is procyclical, that is, it rises during booms and falls during recessions. According to traditional theory, in perfect competition, productivity must be fixed during booms and busts because of the optimal reallocation of resources. This means firing workers and reducing the use of capital in proportion

[7]Theory about wage and agglomeration suggests that while nominal wages increase with agglomeration, real wages are constant over space revealing a spatial equilibrium (Glaeser & Gottlieb, 2008). Then, high local prices and low levels of amenities offset high nominal wages.

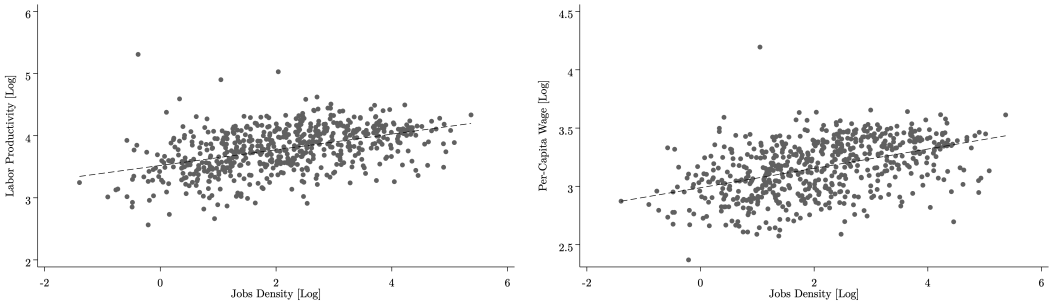
Figure 2.1: **Italian LMAs according to Quintiles of Manufacturing Distribution**



Notes. Data source: Istat confidential 'ASIA' dataset at the plant level. Data refers to year 2020. The figure shows the quintiles of manufacturing employment distribution. Lighter colors refer to LMAs with fewer manufacturing jobs. The darkest LMAs represent the fifth quintile (around 120 LMAs).

Figure 2.2: **Empirical Regularities of Manufacturing Geographic Concentration**

(a) Labor Productivity (b) Wages



Notes. The data source is the Istat dataset, freely available on its website. Labor productivity is the logarithmic transformation of manufacturing labor productivity. Wages is the logarithmic transformation of manufacturing wages. Employment density is the logarithmic transformation of the number of jobs relative to the surface of the LMA. Data refer to the year 2020, the most recent data available.

Source. Authors' elaboration on Istat data.

to reduced output during recessions, and vice versa during economic expansions. Eliminating the external to firms sources of such fluctuations, Hall (1988) explains that in the U.S. economy, procyclical productivity can be explained by increasing returns at the firm level, implying that firms enjoy some degree of market power. Since TFP is robust to *labor hoarding*[8], when we observe a fluctuation in TFP during cycles, Hall (1988) claims that this is due to the failure of marginal cost pricing because firms have some degree of market power. Market power derives from monopsony power in the product market, given competitive conditions in the labor market, and/or from monopsony power in the labor market, given competitive conditions in the product market[9].

However, the tendency toward increasing returns (procyclical productivity) can also be explained by external - to the firms - economies (Caballero and Lyons, 1990; Caballero and Lyons, 1992; Lindström, 2000). The main idea is based on the possibility of decreasing or constant returns to scale at the firm level and increasing returns at the aggregate level as theorized by Marshall (1890). According to Caballero and Lyons (1990), procyclical productivity arises from the existence of *inter-industry* externalities, where industries are strictly defined in 2-digit terms. The results obtained by Caballero and Lyons (1990) strongly reduce those obtained by Hall (1988); they suggest that there are relevant external economies at the manufacturing level, and that these are the main drivers of growth in European countries[10]. A similar exercise was done by Caballero and Lyons (1992), who proposed an increase in the efficiency of matching during booms, i.e. the *thick market effect*. The basis of this theory comes from the production side. Given the production function at the firm level and explicitly including an index of external economies in it, we have

$$dy_{it} = \boldsymbol{\gamma} \cdot dx_{it} + \boldsymbol{\beta} \cdot de_{jt} + \epsilon_{it} \tag{2.2}$$

where dy_{it} is the growth rate of gross output (or value added).

$$dx_{it} = \alpha_{it}^{l} \cdot dl_{it} + \alpha_{it}^{k} \cdot dk_{it} + (1 - \alpha_{it}^{l} - \alpha_{it}^{k}) \cdot dm_{it}$$

is a weighted index of firm-level own-account growth, where l_{it} is labor measured as the number of

[8] Labor hoarding can be a source of measurement error that Hall (1988) solves by using an instrumental variable due to cyclical effort and the retention of workers during recessions due to labor market frictions

[9] Part of the variation in productivity may be due to the capacity utilization problem, where capital and labor work longer and harder during booms.

[10] However, this interpretation has been challenged by Basu and Fernald (1995), who show that a large part of the results obtained by Caballero and Lyons (1990) come from the choice of using value added rather than gross output. Again, aggregation bias is a possible problem.

employees[11], k_{it} is total capital, and m_{it} is the sum of prime materials and energy costs. α_{it}^{l} and α_{it}^{k} are the shares of labor (wage bill) and capital (depreciation) in total costs. de_{jt} is an index of external economies. Following Caballero and Lyons (1992) and Lindström (2000), I compute a weighted index of input (exactly as dx_{it}) at various level of aggregation to gauge external economies (de_{jt} where j stands here for various levels of aggregation but not the firm level). I use the AIDA dataset about firms in the Italian manufacturing sector over the span 2012-2021. As in Lindström (2000), I examine externalities from the point of view of firms. In this case, firms receive increasing returns due to externalities emerging at some levels of aggregation.

Table 2.4: **Estimate of External and Internal scale economies**

	(1)	(2)	(3)	(4)
Internal SE	0.781***	0.807***	0.796***	0.809***
	(0.018)	(0.018)	(0.015)	(0.020)
Industry-wide SE		0.119***		
		(0.029)		
Local-industry SE			0.223***	
			(0.043)	
Local-manuf. SE				0.587***
				(0.172)
Year FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
LMA FE			✓	✓
Instruments	L_i, K_i, M_i	L_i, K_i, M_i, Y_a	L_i, K_i, M_i, Y_a	L_i, K_i, M_i, Y_m
Observations	344,918	344,911	318,516	344,881
R2-within	0.494	0.488	0.433	0.419

Notes. Data source: Bureau Van Dijk confidential AIDA firm-level dataset. The main dependent variable is the growth rate of gross output, calculated as log differences. All independent variables are growth rates calculated as log differences. There are no other control variables as in Caballero and Lyons (1990). All columns include year fixed effects. Since the regression is run in growth rate, firm fixed effects are implicitly partialled out. All columns include 3-digit industry fixed effects. Columns (3) and (4) include LMA fixed effects to account for different regional areas and endowments. Errors are clustered at the 3-digit industry level in columns (1) and (2), and at the 3-digit industry and LMA level in columns (3) and (4). The indexes of internal economies are instrumented with the first 4 lags of K_i, M_i, and L_i, while the indexes of external economies are instrumented with the first 4 lags of ATECO 3-digit total gross output adjusted by the own-firm level (Y_a). In the last column, the index of external economies is instrumented with the lag manufacturing gross output adjusted for own 3-digit component (Y_m).
*** p<.01, ** p<.05, * p<.1

In the table 2.4 I can distinguish between internal and external economies. First, the coefficient γ is never greater than 1, meaning that there are no increasing returns at the firm level. Rather, firms operate in a regime of diminishing returns to scale (internal SE is always less than

[11] Data on worked hours were not available in this dataset

1). If input increases by 1 p.p., output increases by 0.81 p.p. However, once possible sources of external economies are taken into account, the coefficient β is always positive and statistically significant. The size of the external economies is ranked as follows: 1) local manufacturing external economies, 2) local industry external economies, and 3) industry-wide external economies. Thus, I show that external economies of scale are not due to an aggregation bias, since in column (2) the coefficient of industry-wide SE is smaller than the coefficient of local-industry SE, and that most external economies occur at the level of total localized manufacturing, where the coefficient of local-manufacturing SE is larger than the coefficient of local-industry SE. Rather, I show that firms operate in regimes of diminishing returns to scale, and that increasing returns at the aggregate level are obtained only when localized external economies are considered. The result of the coefficient in column (4), i.e. the highest estimate, shows that a 1 p.p. increase in the weighted index of local manufacturing inputs increases the gross output of manufacturing firm i belonging to the same LMA by 0.59 p.p. This is the starting point for the development of Chapter 4. The model of Chipman (1970) provides a good perspective for this analysis.

2.2 The economics of localized increasing returns

At this point I have clearly shown two main stylized facts: 1) there are increasing returns to manufacturing, 2) manufacturing is the most geographically concentrated economic activity. In the previous section, I showed the existence of a positive relationship between productivity, wage and manufacturing density. I also tried to connect the dots using the model proposed by Hall (1988) and then elaborated by Caballero and Lyons (1990) and Caballero and Lyons (1992). Among the two contrasting hypotheses described, I show that the more plausible reason for the two stylized facts is the presence of localized external economies. This generates increasing returns at the aggregate level, since part of the firm's own activity (through expansion of its own production) is not fully internalized. Part of its activity generates externalities for other firms[12].

What is missing here is the link that can explain how such externalities spread in the local market. As I suggested above, the existence of both pecuniary and technological externalities underlies this strand of economic literature, but a further taxonomy is needed to fully understand the mechanisms. On the one hand, Krugman (1991) suggests that transportation costs play a relevant role. Nearby firms reduce transportation costs when selling their intermediate goods. For these reasons, given the evidence for Italy in the table 2.1, since most of the trade in

[12]This is consistent with recent models of growth à-la Romer (1986), and Romer (1990)

intermediate goods between firms is within the manufacturing sector, there is an incentive to cluster in the same place. There is a large literature showing that external economies decrease with geographic distance (Dekle and Eaton, 1999; Rosenthal and Strange, 2020). When space is properly modeled in economic theory, the benefits from co-location emerge. On the other hand, according to Marshall and Marshall (1879), there is the trinity of external effects; *labor pooling*, *knowledge spillovers*, and *specialized input suppliers*. From this literature comes a large empirical debate on the factors of co-agglomeration (Rosenthal and Strange, 2001; Ellison et al., 2010; Diodato et al., 2018). Researchers look at the regression coefficients to determine what is the most important source of agglomeration[13].

Labor Pooling refers to the advantages firms gain from being located in a *thick* labor market. This means that 'a localized industry gains a great advantage from the fact that it offers a constant market for skill' (Marshall, 1890, p.271). From a static point of view, lower matching and search costs are offered in these local markets (Puga, 2010). From a dynamic perspective, during cycles of industry expansion, new and more specialized skills emerge from 'economies of specialization' at the firm level. As a firm in a particular industry expands its own output, the degree of division of labor increases in a perfectly competitive market, and new specialized skills emerge (Chipman, 1970). Such skills become available on the labor market. The larger the labor market, the greater the demand for such skills. As workers with new and specialized skills move between firms in the labor market, they bring and spread their knowledge (in the form of new skills). Similarly, new knowledge emerges through learning by interacting processes between specialized producers (Bellandi, 2009). This mechanism is often referred to as *knowledge spillovers* and is recognized as a source of technological externalities. Here, new skills are created as a consequence of the expansion of the industry (Viner, 1932; Stigler, 1951; Chipman, 1970; Bellandi, 1995). This is the main mechanism capable of explaining the aggregate increasing returns from the previous section.

There have been important efforts to measure and understand the externalities arising from labor market fluidity. Also based on the interpretation of Krugman (1991) about the role of labor pooling when idiosyncratic-to-firm shocks occur, many empirical papers have tried to measure the extent of such externalities (Overman and Puga, 2010; Ellison et al., 2010). A particular caveat arises when considering the definition of the reference market (industry). This concerns the extent to which skills can be transferred between sectors (this refers to the difference in the coefficient obtained between column (3) and column (4) of table 2.4). While part of this

[13]In addition to the trinity of externalities, natural advantages are also studied.

debate has been incorporated into the 'specialization' vs. 'diversification' debate (Glaeser et al., 1992), it has also been discussed in the literature on co-agglomeration patterns and is central to the considerations of Becattini (1962) and Becattini (1979). In Chapter 4, I follow this line of research to find out what is the relevant industrial unit of analysis when we consider external economies in expanding industries.

The third source of localized increasing returns comes from the presence of *specialized input suppliers*. This can be seen in several ways. First, it is consistent with the transportation cost argument. If proximity reduces transportation costs, the effect has a larger economic effect in markets where demand for intermediate goods is difficult and timely. In addition to transportation costs, there are advantages in terms of transaction costs. Cognitive proximity between actors settled in the same cultural and institutional context as firms co-localized in the same cluster reduces costs to access goods such as technical standards, jargons, information about technology and world market (Bellandi, 2002). Second, a proper model of increasing returns from co-localization of suppliers and customers is that of Abdel-Rahman and Fujita (1990). The basic idea of the model is that intermediate goods provided by the monopolistic supplier, i.e. the service sector, to the competitive customer, i.e. the manufacturing sector, create an incentive for the manufacturing sector to cluster in places. Increasing returns, resulting from the assumption of monopolistic competition in the service sector à-la Dixit and Stiglitz (1977), and the desire of the manufacturing sector to increasingly rely on a variety of intermediate goods, generate a positive relationship between the amount of service intermediates and productivity in the manufacturing sector.

At this point, a note on the organization of the local production process is necessary to introduce the rationale of Chapter 5. The same idea proposed by Krugman (1991) and tested by Overman and Puga (2010) about the pooling of labor can be applied to the market for intermediate goods. As discussed in Bellandi (2009), a possible source of external economies comes from the pooling of reserves of intermediate and raw materials. Such pooling does not come from the labor market. However, it is appropriate for a production process organized around teams of firms belonging to different phases of the production process (industries). The main idea is that when unexpected industry-specific shocks occur, and assuming that the shocks are orthogonal across industries, firms have to adjust their production process reducing/increasing output and employment. The larger the market for intermediates, the lower the volatility in the price of the intermediate goods in place, the greater the possibility for firms to adjust. Places where firms pool intermediates respond easily to such shocks, making employment and

output less volatile. The idea here is very similar to that proposed by Lucas (1977), where industry idiosyncratic shocks iron out at the aggregate level. A large concentration of firms that ultimately share intermediate inputs and have strong input-output linkages allows expanding and contracting firms to respond easily to shocks. In Chapter 5, I challenge this idea by arguing about possible *network effects*, following ideas proposed by Acemoglu et al. (2016). These increase, rather than reduce, fluctuations in the level of output and employment the more the economy is interconnected through IO linkages.

Thus, I have outlined here the possible sources of increasing returns to localized external economies at the aggregate level. The investigation of these sources is the core of the dissertation, and each chapter is an attempt to contribute to the literature on the topic. Having discussed the theoretical underpinnings of the dissertation, I now focus on the case of Italy, where localized external economies emerge in geographical units with peculiar characteristics. These places are Marshallian industrial districts, and they are more than just economic spaces. In the last decades, these areas have been facing relevant challenges due to the changing conditions of competition in global markets. The ICT revolution, together with the globalization trend, has put pressure on the traditional organization of the production process in industrial districts. This pressure is contributing to a transformation of the local structure of industrial districts, which are becoming less competitive[14] and less interconnected due to an influx of large firms (since local input-output relationships are less likely to occur). The implications of these changes for employment growth and productivity are examined in Chapters 3 and 4. The role of IO linkages is also examined in Chapter 5. In the next section, I briefly review the literature on industrial districts to highlight the emerging challenges. Before doing so, however, I briefly discuss the policy implications arising due to the emerging properties of this theory.

2.2.1 Inequalities and the space of policies

The policy debate is relevant in a model of development based on uncompensated externalities. There are two main policy issues raised by the literature. First, if there are local increasing returns, then a process of divergence between poor and rich regions is at stake. Through a process of circular causation and factor mobility, rich regions will become richer and vice versa. In 2020, the hourly wage of a manufacturing worker in Busto Arsizio, Lombardia (31.5€) - a LMA specialized in Made-in-Italy production - is more than double (13.3€) that of a manufacturing worker in San Giuseppe Vesuviano, Campania (same specialization as Busto Arsizio). While this

[14] I am referring here to the degree of local competition among manufacturing firms.

reflects differences in the composition of the workforce, with white collar workers increasingly concentrated in northern areas, the differences are still dramatic if we look at the distribution within the same level of education. For example, the hourly wage of a tertiary educated worker in the province of Milan (26.8€) is twice as high as in Ragusa, Sicilia (13.7€). A manager working in Milan earns 10€ more that the same manager in Ragusa. The same differences can be seen in the unemployment rates. For example, in 2020 the unemployment rate in Montegiorgio, Marche (industrial district specialized in leather production) is 3.83%, which is a quarter of the unemployment rate in Casarano, Puglia - same specialization as Montegiorgio - i.e. 16.05%.

The traditional dilemma of 'efficiency' vs. 'equity' opens up space for policy. For example, in recent decades the European Community has devoted considerable resources to cohesion policies to support lagging regions. While these policies have the goal of creating a balanced growth path in leading and lagging regions, on the other hand one could argue that these policies are highly inefficient (Boldrin & Canova, 2001). The rationale in this case is that the policy maker's goal should be to concentrate resources in those places that present increasing returns in order to maximize output, and eventually to use *lump sum* payments to redistribute resources among regions according to their marginal utility. This leads to the idea that 'Without a better understanding of nonlinearities in these externalities, any government spatial policy is as likely to reduce as to increase welfare' (Glaeser & Gottlieb, 2008, p.1). Moving manufacturing from one area to another runs the risk of being a *zero-sum* game. The economic motive is that there is a spatial equilibrium in which low levels of amenities and high prices offset high nominal wages, creating an equilibrium of real wages across space. Then the capitalization of benefits due to subsidies for job creation would be captured through land rent (Bartik, 2020). Even if the policy has the goal of increasing the welfare of poor people, if it is implemented locally, the effect will be to increase the benefit of richer people via *capitalization effect*.

On the other hand, relaxing the assumption of perfect mobility increases the leverage of government on policy. Certainly, there is some degree of labor mobility across areas that must be taken into account in the empirical application of place-based policies. Nevertheless, a large fraction of the labor force does not move out of the LMA in which it was born. As explained by Kline and Moretti (2014b), the most efficient demand-side subsidy is one that does not generate in-migration and raises receiving local wages. To achieve this effect, a community should be insensitive to price changes. In general, public policy responds to 3 main market failures:

1. *Involuntary Unemployment*, due to which shifting labor demand from advanced to lagging regions - where labor supply is more responsive - has overall national benefits. In general,

this is due to the fact that having high non-working rates produces externalities, i.e. higher crime rates, social negative spillovers sustained by family and friends, fiscal costs (Austin et al., 2018).

2. *Agglomeration externalities* that increase output the more inputs are spatially concentrated. Moving the agglomeration from LMA 1 to LMA 2 creates a productivity gain for firms in LMA 2 and a loss for LMA 1. If the benefits of such a policy are greater than the costs, i.e. the productivity gains in LMA 2 are greater than losses in LMA 1, then the policy has a positive national outcome. Kline and Moretti (2014a) and Bartik (2020) provide reasons to believe that this elasticity is constant, suggesting no overall social benefit from reallocation. The main upshot of this point is that manufacturing is a rival good.

3. *Local public goods* are under-provided in a competitive market. Public provision of uncongestible public goods is welfare enhancing (no efficiency costs), provided the government has an appropriate technology of provision (Kline & Moretti, 2014b). At the aggregate level, even with perfect worker mobility, the *capitalization effect* does not offset the benefits of provision. However, as highlighted in Bellandi and Di Tommaso (2006), positive externalities are not guaranteed even when public goods are provided. This depends on the presence of a cooperative nexus as well as the right governance structure, distributed among a set of independent producers.

The second area in which policies can be implemented is in the case of business cycles. Cyclical policies are also important when the desideratum of the policy maker is to fix the level of employment and avoid knowledge leakage from local labor markets. However, there is a recent interest in understanding the *cleansing effect* of recessions (Caballero & Hammour, 1994). It goes back to the Schumpeterian's idea of *creative destruction* i.e. during periods of recessions low productive firms are squeezed allowing a reallocation of resources generating a better match between high productive firms and workers. When some frictions are considered, there are impediments to an optimal allocation of resources, creating a slack in economic performance. During periods of economic downturn, profitability declines and less efficient uses of resources are no longer possible. In this case, owners of these resources as workers may move to find a better arrangement (unemployment search). Thus, an overall benefit in terms of productivity is obtained when: 1) less productive firms exit the market, so that aggregate productivity increases; 2) the reallocation of inputs such as labor after recessions cause surviving firms to be more productive. While this is the point from a positive point of view, it is not the goal of the

literature to suggest that recessions are desirable events (Caballero & Hammour, 1996).

On the other hand, economic downturns generate a related *sullying effect*, i.e. the jobs created during recessions are temporary and low-paid, causing job quality to be procyclical. If the literature on the cleansing effect of recessions assumes that workers only look for jobs when unemployed, including on-the-job search changes the results. This occurs because, unlike jobs, workers are less likely to quit their positions during economic turmoil and firms create fewer vacancies in recessions. Then, the opportunity for workers to find a better match in recessions is reduced. The conclusion of this reasoning is that 'while recessions hasten the destruction of less efficient matches, they also stifle the creation of the most efficient matches' (Barlevy, 2002, p.66). Accordingly, the extent to which recessions have a *cleansing* rather than a *sullying* effect is an empirical question. In general, high turnover rates are positively associated with productivity. However, in the U.S. market, Foster et al. (2016) found a reduction in reallocation during the Great Recession, leading to a reduced effect on productivity. Similarly, Kozeniauskas et al. (2022) found that, during Covid-19, worker retention is more likely to occur in more productive firms. However, less productive firms do not exit the labor market because of the policies implemented. Haltiwanger et al. (2024) found evidence of both the cleansing and sullying effects of recessions.

It is important to grasp the main policy implications. First, triggering a recession is certainly not a policymaker's desideratum, although it may have positive cleansing effects. Second, even if a recession does occur, the efficiency of the policies implemented is not guaranteed. Caballero and Hammour (1996) explain that a combination of production and creation incentives can both encourage creative destruction through creation incentives and discourage unemployment through production incentives[15]. In a geographic context where some labor markets are denser than others, place-based incentives can be a way to reduce the cost of policy. Again, however, the effectiveness of the policy changes depending on the degree of labor mobility. This branch of the literature is not yet born, but it is likely to emerge in the next future[16].

The goal of this section was to briefly give an overlook of the place-based feasible policies and their economic rationale. On the one hand, there is a divergence issue due to localized increasing returns; this generates increasing spatial inequality. On the other, the presence of external economies modify the response of places to global shocks. While Chapters 3 and 4

[15]As explained by Caballero and Hammour (1996), while *creation incentives* (e. investment tax credits) are likely to encourage investment and the creation of new productive arrangements at the cost of increasing job destruction, *production incentives* (e. g., corporate tax cuts) extend the life cycle of obsolete capital and temporarily reduce unemployment.

[16]This literature will emerge at the intersection of procyclical productivity, the cleansing effect of recessions, labor pooling, and labor hoarding in locally dense labor markets.

deal with to issues related to emerging spatial inequalities, Chapter 5 provides insights regarding responses of places to business cycle. There are no many policy insights in the chapter, since the literature is not yet robust enough to provide them. A brief summary of the findings is offered in the general conclusions of the thesis where, according to the presented framework, I rescue some policy implications in the case of Italy.

2.3 The new Italian economic geography

Thus, I have shown that a large part of the national manufacturing sector is concentrated in a few LMAs. These areas are mainly *Marshallian Industrial Districts*. In the following sections I present: 1) some empirical regularities concerning the case of industrial districts in Italy, 2) a brief instrumental review of the theoretical foundations of Marshallian Industrial Districts and 3) the main challenges due to the changed global competition. These can be seen as the starting points for the three chapters of the dissertation.

2.3.1 Some empirical considerations

According to the 2022 classification, Italian labor markets can be divided into 610 local labor markets. These in turn can be subdivided into *industrial districts* 141 LMAs out of 610. Figure 2.3-a shows a map dividing the national territory into industrial districts and other LMAs. In the following, I propose some statistics concerning this classification[17]. Most districts are concentrated in the northern center of the country - 120 out of 141. While industrial districts are mainly specialized in light industry - 108 out of 141, 4 are urban systems and 27 are specialized in heavy industry (see figure 2.3-b). In general, industrial districts have a very low unemployment rate, around 7%, while other LMAs have an average rate of 11%. The labor force participation rate is also higher in industrial districts, with an average of 52% compared to 45% in other LMAs. In general, they are also more densely populated (200 persons per square kilometer) compared to all other LMAs (160).

In terms of production characteristics, labor productivity is on average higher in industrial districts (55.2 €) than in other LMAs (46.5 €). Certainly, this reflects the industrial composition and the composition of the workforce; however, the results do not change if we look within the

[17]The following statistics do not imply any causal relationship between the variables. As such, they must be considered as summary statistics that provide a snapshot of the Italian productive geography in 2020. There is, of course, an aggregation bias in deriving micro-level results from aggregate data. Nevertheless, it is an interesting exercise to measure the main characteristics of industrial districts compared to other LMAs. The choice of the year 2020 is due to the availability of data on the Istat website.

Table 2.5: **Main Empirical Regularities**

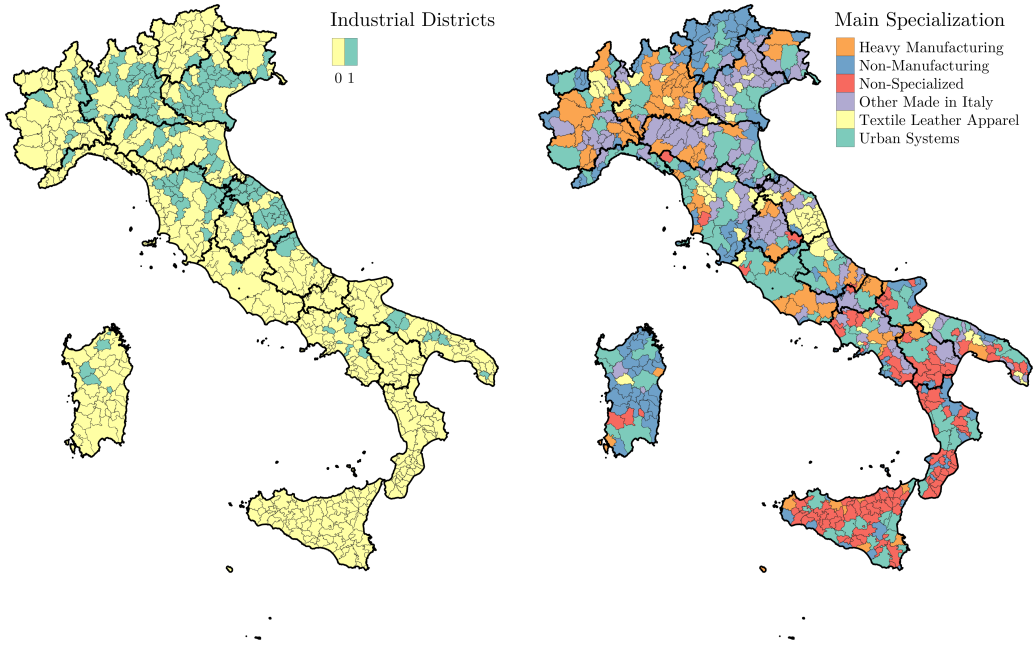
	Main Specialization				
	Non Spec.	Non Man.	M. in Italy	Heavy Man.	Total
Industrial Districts (141)					
National Jobs Share		0.06	0.65	0.39	0.37
Establishments per Kms		5.00	4.64	5.09	4.91
Size of Establishments		5.89	6.15	6.81	6.29
Labor Productivity		52.70	50.86	61.92	55.16
Labor Force Participation		51.44	50.99	52.49	51.64
Unemployment Rate		7.40	7.23	6.29	6.97
Population Density		0.21	0.19	0.20	0.20
Other LMAs (469)					
National Jobs Share	1.00	0.94	0.35	0.61	0.72
Establishments per Kms	1.14	3.24	2.78	2.86	2.51
Size of Establishments	3.10	3.75	5.85	6.25	4.74
Labor Productivity	34.34	46.83	48.77	56.33	46.57
Labor Force Participation	38.75	46.64	48.49	47.56	45.36
Unemployment Rate	15.57	10.45	8.61	8.79	10.86
Population Density	0.11	0.21	0.18	0.16	0.16

Notes. Data source: Istat open data on LMAs. All values but population density, unemployment rate and labor force participation refer to the manufacturing sector. Population density and establishments are per square kilometer. Labor productivity is calculated as value added per personnel.

main specialization classes. Labor productivity in Made in Italy (€50.9) and heavy industry (€61.9) was higher than in other LMAs (€48.8 and €56.3 respectively). By definition, there are many more manufacturing establishments per square kilometer in industrial districts than in other LMAs (4.91 vs. 2.51). However, the average size of manufacturing establishments is larger in industrial districts than in other LMAs (6.29 vs. 4.74). Of course, the size of the establishment reflects the main technology of production, but within the class of specialization the results are still consistent. Establishments involved in Made in Italy production (mainly light manufacturing) are smaller than those in heavy manufacturing, but in industrial districts they are larger than in other LMAs. Industrial districts account for 35% of total generic manufacturing employment in Italy. If we look specifically at Made-in-Italy, they account for 65% of total employment, while in the case of heavy industry, industrial districts account for 39% of total employment. All in all, these empirical regularities suggest that industrial districts are still the real engine of manufacturing production in Italy. They are mainly specialized in light industry, yet there is a relevant portion of them involved in heavy industry. The empirical literature on industrial districts is vast, and there is no room here for a comprehensive review. Since they reflect the typical characteristics expected in places that enjoy agglomeration externalities, it

Figure 2.3: **Italian Productive Geography**

(a) Industrial Districts (b) Main Specialization



Notes. The data source is the Istat dataset, freely available on its website. Data refer to the year 2022, the most recent data available.

Source. Authors' elaboration on Istat data.

is also relevant for the research to understand the extent to which industrial districts can be analyzed using the traditional lens of urban and regional economics.

2.3.2 Theoretical foundation

The rediscovery of geography, and more specifically to spatial organization of production, in Italy is due to the work of Giacomo Becattini. In his seminal work (Becattini, 1962), the author focused on a part of the Cambridge controversy about the existence of external economies that was heavily downsized by the critique of Knight (1924) and Sraffa (1926). He pointed out that a necessary condition to gauge external economies in production was by looking at a different aggregate in respect to the industrial one. First of all because via the definition of industry is also possible to distinguish increasing from decreasing returns to scale. If we look at the smaller case, the tendency toward increasing returns is guaranteed by technical progress as in Adam

Smith. Rather, if we look at the large aggregate, tendency toward decreasing returns is forced by the availability of resources in a limited world as in Ricardo. External economies, if existing, are a way to reconcile the theory of 'perfect competition' with increasing returns (Sraffa, 1926).

External economies in industrial districts arise from the division of labor of many small and medium firms operating in different phases of the production process (Becattini, 1979; Bellandi, 1995). However, external economies in Marshallian industrial districts are not only a technological matter, they require specific cultural and institutional settings (Becattini, 1989). The main characteristic required of these settings is that they should not be detrimental to entrepreneurship, since this is one of the main sources of local externalities.

Industrial districts are not only economic regions, they are: 1) a unit of economic classification for defining industry; 2) a unit of study for interpreting economic change; 3) a socio-economic concept for understanding the organization of production (Sforzi & Boix, 2015). It includes a local community, a population of industrial firms, a well-defined historical and natural territory. Retrieving the idea of Marshall about 'economic nations', Becattini leverages the presence of a strong local community for defining the industry through its awareness . The population of firms is strictly interconnected, often organized in phases of production (Bellandi, 2009). This is composed of many small and medium industrial firms that belong to the manufacturing sector. Recently, Bellandi and De Propris (2017) has discussed the extent to which industrial districts are still places for a manufacturing specialization because of the increasing de-industrialization of developed economies. In the context of recent challenges due to globalization and digitalization, can industrial districts still offer a platform for the creation of new and attractive jobs? In the next section, I try to discuss the emerging challenges for industrial districts.

2.3.3 Emerging challenges

Important changes in the global economy challenge the ability of Marshallian industrial districts to generate self-sustaining local development. Three main challenges are posed to the model of industrial districts and are clearly stated in the introduction of the 'handbook of Industrial districts' (Becattini et al., 2009). First, the increasing penetration of scientific knowledge into the production process makes the community of firms in industrial districts less able to adapt to change. From a different perspective, this has been highlighted by Pellegrino and Zingales (2017), who show how Italian firms have been unable to cope with changes in production technologies stemming from the ICT revolution. While smaller firms innovate less and tend to be anchored in the family dimension, recent literature shows that both firm size (Giovannetti et al., 2011) and

family structure (Cucculelli & Micucci, 2008) act as a threat to firm survival over time. While industrial districts rely more on 'contextual' knowledge (Becattini, 2002), a global economy where production processes are based on codified and scientific knowledge threatens the possibility of generating new qualities and new markets for industrial district products.

The second reason comes from *globalization*. Industrial districts are increasingly exposed to the pressures of international competition and the global disintegration of the production process. For example, China's entry into world trade in the last 30 years has dramatically reduced employment in manufacturing sectors of developed economies such as the U.S. (Autor et al., 2013). The effect has been greater in cities that were specialized in activities challenged by Chinese competition. Citino and Linarello (2022) showed that the effect in Italian LMAs was reduced because of the industrial composition of the LMAs. That is, while some could argue that Chinese exports were challenging traditional Italian production such as textiles and apparel because of competition on labor costs, Chinese exports in the 2000s were mainly concentrated in electronics (Citino & Linarello, 2022) - a sector in which Italy was less specialized overall. This, plus a strict employment protection legislation and contextual large increase in non-tradable activities (services), produce a moderate effect of Chinese import on Italian manufacturing employment. Another point of view comes from the *quality upgrading* strategy of Italian firms, which compete more on the quality of products than on quantity (Buciuni and Pisano, 2018, Arrighetti et al., 2024). However, even if such an adaptation fixed employment levels, in this period of global integration, the 'de-territorialization' of the production process is a serious threat to the industrial district model. Boix and Trullén (2010) demonstrated the importance of territory from an empirical point of view, by separating the industry effect coming from local concentration of an industry to the territory effect. They find territory being more important than specialization for the industrial district effect (the presence of gains in terms of innovative activity due to externalities).

The third critical node for Italian industrial districts is the changing industrial structure that is emerging as a response to the two previous points (technology and globalization). This is because smaller firms have to compete with larger ones, where the latter *poach* more productive labor from the former (Combes and Duranton, 2006; Haltiwanger et al., 2024). Also, while theories of dynamic externalities suggest that a more concentrated local industrial structure promotes growth (MAR externalities) (Glaeser et al., 1992), competition is a necessary condition in contexts where external economies lead to productivity gains (Stigler, 1951; Chipman, 1970; Bellandi, 1995). This is the main challenge I face in the dissertation.

In short, the main rationale of the dissertation is the decomposition of the forces able to generate external economies into Marshallian industrial districts. I do this by bridging the literature coming from the new Italian economic geography - as defined by Sforzi (2002) - with the literature on urban and regional economics. The latter has the advantage of being internally consistent and sensitive to quantitative analysis, while many concepts of the former have the disadvantage of being still fuzzy from an empirical point of view. For this reason, I focused on concepts that seemed to be easily operationalized also in the literature on industrial districts. More specifically, I focused on manufacturing external economies as my main unit of analysis in all three chapters. I take advantage of the recent challenges posed by globalization to examine the impact of changes in the industrial structures of places to determine the extent to which external economies may be weakened. Accordingly, this dissertation seeks to contribute to the recent debate on business demography, the labor market, and manufacturing productivity. Chapter 3 examines the effect of the entry of tradable firms of different sizes on non-tradable employment. Chapter 4 examines the role of local competition for external economies. Chapter 5 examines the role of external economies in the business cycle and, in particular, estimates the differential response of places to global shocks.

Part II

Original Contributions

Chapter 3

Firm size and local multipliers

Abstract

When a new establishment in tradable sectors enters a local market, it potentially creates additional jobs in non-tradable sectors. If market size or cost-linkage effects offset the negative effect of increased local competition, the effect of entry is to generate additional jobs in non-tradable sector. We document that the three effects change according to the size of the firm entering the tradable sector. The relevance of the local multipliers are assessed using a dataset on Italian local labor market areas for the period 2012-2020. Using these data, our contribution to the literature is twofold. First, we review and replicate previous studies and find that they are driven by the instrumental variables used and their construction. Second, we show that the impact of the entry of tradable establishments on non-tradable jobs is a function of their size. The results indicate that small establishments generate higher relative multipliers. Large establishments have the highest absolute multipliers, and the effect is driven by an increase in wages and a reduction in cost linkages. The entry of tradable micro firms does not generate additional jobs in non-tradable or other tradable sectors. The effect of the medium firm is mainly through cost linkages. The analysis is extended by introducing robust estimates for territorial heterogeneity.

3.1 Introduction

The Italian economy has struggled to grow over the past few decades. Changes in global production as a consequence of the ICT revolution rendered its entrepreneurial system obsolete and inadequate. On the one hand, the ownership and management structure of firms has been studied as a cause of missed opportunities. The familism in the management leading to succession within the family proved to be detrimental to firms (Cucculelli & Micucci, 2008) and aggregate performance also due to lack of meritocracy (Pellegrino & Zingales, 2017). On the other hand, and strictly related to the family dimension, the literature showed that the size of firms is also a barrier to their survival in the international market (Giovannetti et al., 2011). Only very few firms compete on the global market and successfully export their products (Mayer and Ottaviano, 2008, Coltorti and Venanzi, 2017). One of the most controversial points concerns the presence of industrial districts (Becattini & Musotti, 2003). These are the cores of the national manufacturing industry (Bellandi & De Propris, 2015). In these regions, small-sized firms have traditionally gained competitive advantages from the spatial division of labor (Stigler, 1951, Arrighetti and Traù, 2007). While it is true that, compared to other European nations, Italian establishments are among the smaller in size[1], they are also strongly concentrated in industrial districts where establishments are on average larger than in other areas (e.g. tradable establishments in industrial districts have ≈ 3 more employees than those in non-districts, see table 3.1).

This is not a puzzle. Manning (2010) explains this as a sort of selection process: firms in agglomerations have to pay higher wages because more densely populated areas have higher levels of labor market competition. In consequence, only those firms that are more efficient and larger in size are able to survive in densely populated areas. For example, the standard deviation of establishment size, as shown in Table 3.1, indicates that not only are firms larger in industrial districts, but their minimum efficient size is also larger ('SD-B' in industrial districts is a half that in non-districts). In recent years, Italian local economies have undergone a slow structural transformation. Looking at business demography statistics, we can observe some stylized facts:

1. *Size effect.* In general, the size of establishments in tradable sectors have been increasing. The trend has been stronger in industrial districts than in non-district (see $\Delta Size$ in Table 3.1).

[1]This observation can be deduced by using data coming from the Eurostat structural business statistics available here
https://ec.europa.eu/eurostat/databrowser/view/sbs_r_nuts06_r2/default/table?lang=en&category=reg.reg_sbs

Table 3.1: **The size of establishments in district and non-district areas**

	Non-District			District		
	Mean	SD-B	SD-W	Mean	SD-B	SD-W
			Tradable			
$\Delta Size$	5.84			13.19		
$Size$	6.18	4.23	0.64	9.26	2.53	0.63
			Non-Tradable			
$\Delta Size$	0.56			1.56		
$Size$	2.58	0.51	0.11	2.66	0.31	0.12

$Size$ is calculated by dividing the number of persons employed by the number of enterprises. The table is obtained by aggregating LMAs into district and other LMAs. The mean value represents the average calculated over the period 2012 to 2020 for each class (district/other LMAs). The term 'SD-B' denotes the standard deviation between LMAs in each class. The within standard deviation (change over time) is represented by 'SD-W'. The $\Delta Size$ is the annual percentage change. We use data freely available on the Istat website.

2. *Pouring-out effect*. As tradable employment has been stable in industrial districts and decreasing in non-districts (see Figure 3.1-e and Figure 3.1-f), employment has been decreasing in smaller establishments and increasing in larger classes (see Figure 3.1-a and Figure 3.1-b), smaller establishments have been decreasing relative to larger classes (see Figure 3.1-c and Figure 3.1-d).

3. *Polarization effect*. This is the case for tradable activities, which have declined nationwide, but less so in industrial districts (see Figure 3.1-e and Figure 3.1-f).

Taken together, these effects suggest that a slow trend toward geographical concentration of production activity as well as an increasing leverage on internal economies in tradable sectors is taking place (e.g. Cucculelli and Storai (2018) suggested that this is occurring via the increasing role of medium firms in industrial districts). Yet, industrial districts and their production process leveraging on external economies guaranteed high levels of employment in the last 50 years, Graziani (1998) referred to this condition as full employment.

So, what is the effect of such a re-organization of the production process on employment growth? Traditionally, the efficiency of larger firms is reached, being equal levels of output, through a reduction in employment levels (a *productivity effect*). The *pouring-out* effect suggests this is not the case for Italy where employment in tradable sectors is maintained stable over this period (even if only in industrial districts). Rather, levels of employment in non-tradable sectors has been increasing over this span of time. We assess the extent of this transformation

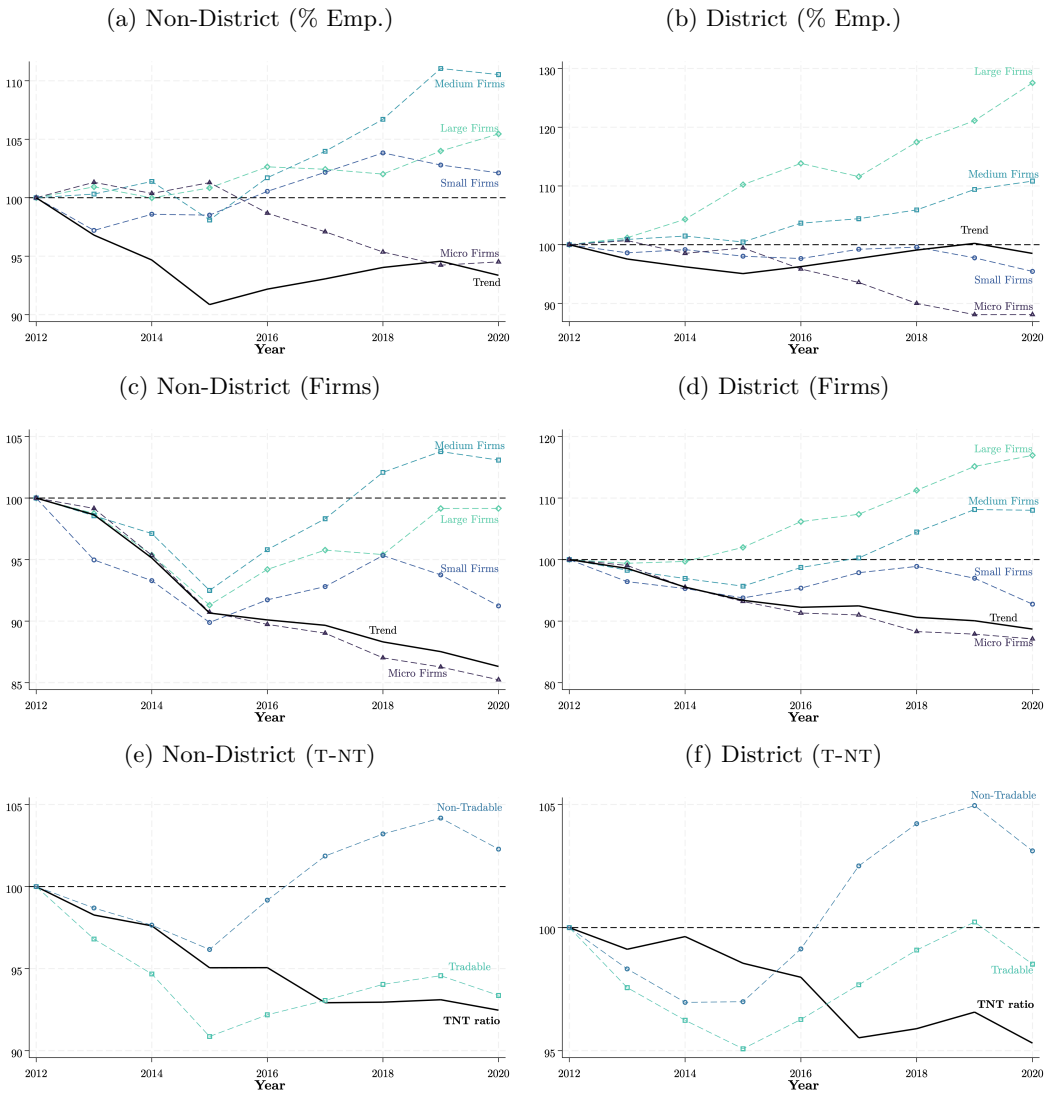
by focusing on the basic to non-basic sector multiplier (Malizia et al., 2020). By grouping local economies into two main pools, the 'base theory' provides a causal mechanism that explain how places grow. Through export base activities (manufacturing and extraction activities), financial assets flow into the local market and generate rounds of income multiplier. Such a multiplier allows the development of non-tradable sectors in places. In the Italian context this took place in a peculiar way. Moving jobs from smaller to larger firms, being equal levels of employment, creates jobs in non-tradable sectors. We leverage on the model of Ottaviano and Thisse (2001) to show how this transformation can be interpreted through the lens of pecuniary externalities[2].

There have been several attempts to estimate the effect of the growth of tradable sectors on non-tradable sectors, also in the context of Italian LMAs. The first and seminal attempt was that of Moretti (2010), who found a positive multiplier in US cities. According to Moretti and Thulin (2013), the multiplier effect depends on the level of human capital, which in turn affects wages. In Italy, De Blasio and Menon (2011) found no evidence of a positive multiplier effect, while Cerqua and Pellegrini (2020) found a positive multiplier effect in 'Mezzogiorno' regions. Based on the hypothesis of Moretti and Thulin (2013) about the role of wages for local multipliers, we exploit the changing business demography in Italy to assess whether the increase in non-tradable jobs is due to the *pouring-out* effect from smaller to larger firms as these are more efficient and offer higher wages (Drucker & Feser, 2012). We also offer a counterfactual hypothesis based on the model of Venables (1996), retrieved some years later by Ottaviano and Thisse (2001). Smaller firms tend to buy intermediate goods from local suppliers. If the cost linkage due to the existence of a local value chain is higher than the demand effect due to higher wages offered by large firms, the *pouring-out* effect generates a reduction in employment growth.

We use data on establishments and jobs in Italy over the period 2012-2020 to accurately assess the magnitude of local multipliers, differentiating by the size class of the establishment entry. This allows us to present several reasons for the novelty of the paper. Using these data, we first review the previous empirical literature on the subject and replicate their model. We then add our original contribution to the literature. First, we assess the effect of a change in the population of tradable establishments rather than jobs. To our knowledge, we are the first to do so. Second, we examine the effect of entry by establishment size. This is a way of dealing with the *pouring-out* and *size* effects. Our review suggests that the results of the previous empirical literature are strongly influenced by the model and the instrumental variable

[2]This can also be partially explained in a scenario of de-industrialization and servitization of the manufacturing process (Bellandi & Santini, 2019).

Figure 3.1: **Business Demographics in Italian LMAs**



Notes. This figure shows the business demographics in Italian LMAs, distinguishing between industrial districts and non-districts. Using this classification, there are 141 industrial districts and 469 non-districts. To draw these graphs we use data freely available on the Istat website. Panels (a)-(b) show the evolution of the share of employment accounted for by different size classes of establishments. The panel on the left shows graphs for non-districts, while those on the right show graphs for industrial districts. Panels (c)-(d) show trends in the number of establishments by size class. Panels (e)-(f) show trends in tradable and non-tradable sectors using employment data. Tradable sectors include extractive and manufacturing activities and is the sum of those employed in these sectors after distinguishing between districts and non-districts. Non-tradable is the sum employees in all remaining non-agricultural sectors. TNT is the ratio of these two measures.

Source. Authors' elaboration on Istat data.

used. After accounting for these limitations, our results suggest that: 1) Small firms are those with higher employment multipliers. This is because they generate local multipliers through the creation of jobs, but also because they use *cost-linkages* for their production process. 2) There are no significant effects for micro establishments. This suggests that their closures (openings) do not affect employment growth trends, once controlled for the *competition effect*. 3) Large establishments generate large employment multipliers. This effect, we argue, is driven by the fact that, given the same number of jobs, they pay higher wages, thereby increasing local demand for non-tradable goods. 4) Medium-sized firms have low multipliers relative to the other firm size classes, but they generate higher levels of multipliers on other tradable jobs. Our results are robust to several heterogeneity tests.

The remainder of this article is organized as follows. Section 3.2 presents the theory of local multipliers, its antecedents and empirical development. In section 3.3, drawing on the model of Ottaviano and Thisse (2001) and leveraging the idea of Moretti and Thulin (2013) about the role of nominal wage for local multipliers, we sketch the working mechanisms when entry into the local market differs according to the size of the firm. Section 3.4 presents the econometrics of the paper, focusing on the identification strategy to deal with possible sources of endogeneity. We explain how we modify traditional instrumental variables used in the previous literature to look at the change in the establishments population rather than jobs. Section 3.5 presents the main results. Section 3.6 provides a summary and some concluding remarks.

3.2 An overview on local multipliers

The 'base theory' is a demand-driven formulation of the Keynesian theory of regional income determination. It is based on the distinction between two main classes of economic activity:

- The export sector - i.e. the basic sector - which includes all economic activities that produce goods that are sold to non-local agents (households, firms, governments);

- the non-basic sectors - i.e. all domestic activities - producing for consumption in the local market.

Here is an explanation of how it works:

$$b + r = t \tag{3.1}$$

where b stands for basic, r for residential, and t for total.

$$r = f(t) = at \tag{3.2}$$

Also, the residential activities are a proportion a of the total t. Thus, by substituting 3.1 in 3.2, we get a clear notation for estimating the multiplier of basic activities in non-basic activities.

$$\left(\frac{1}{1-a}\right) b = t \tag{3.3}$$

The term $\frac{1}{1-a}$ is the economic base multiplier. In other words, it can be thought of as the propensity to spend locally. In a nutshell, tradable sectors (b) export goods outside the home region, which generates income in the tradable sector of the home region, which in turn pays for local factors such as labor. Then, local factors employed in the tradable sector spend part of their income on residential activities (r) such as restaurants, hair salons, movie theaters, theaters, and so on. In turn, residential activities also pay local factors employed in production processes, and another round begins.

Recently, there has been renewed interest in estimating the developmental role of local multipliers, but the evidence has been ambiguous. The very first and notorious attempt was that of Moretti (2010), who estimated the effect as follows:

$$\Delta E_{c,y}^{NT} = \beta_0 + \beta_1 \Delta E_{c,y}^{T} + \epsilon \tag{3.4}$$

where NT stands for non-tradable, T for tradable, E is the level of employment, and the subscripts c and y stand reciprocally for city and year. The multiplier is estimated by the formula 3.4:

$$M = \beta_1 * \left(\frac{E_{avg}^{NT}}{E_{avg}^{T}}\right) \tag{3.5}$$

where subscript avg stands for average over the cases considered by the implemented regression. In the case of Moretti (2010), he used data on the sample of U.S. metropolitan areas over the period 1980-2000 with observations' counter every 10 years (three waves). He estimated the effect of local multipliers in three different models:

1. tradable (basic) on non-tradable

2. durable tradable and non-durable tradable on non-tradable

3. tradable to other tradable

He finds positive evidence for the effect of tradable on non-tradable sectors (for each new job in manufacturing, 1.59 additional jobs were created in non-manufacturing). Moreover, in the split sample, he found that the larger effect was explained by nondurable goods, while the elasticity was lower for durable goods. Finally, he found no effect of durable goods on other durable goods. Due to endogeneity issues, he had to use an instrumental variable technique to deal with reverse causality that might bias his results (section 5.1 further analyzes the instrumental variable).

After the paper of Moretti (2010) several attempts have been made in different contexts and for different time spans. One of the first was that of De Blasio and Menon (2011). They use the same approach and estimate the effect in the Italian case. Like Moretti, they distinguish between tradable and non-tradable, adopting the manufacturing/non-manufacturing distinction. Their results suggest no statistically significant results, which they interpret as a multiplier of 0. Their main units of analysis were the Italian (LMA), a function of geographical agglomeration computed using data on commuting flows. They analyze the period 1991-2001. They give several reasons to explain the null effect of an increase in tradable sectors on tradable sectors, such as: the 'regulation of non-tradable sectors', the 'national wage bargaining' and 'other obstacles to labor mobility'. As we will see, this attempt is the benchmark for interpreting our results.

Again, Moretti and Thulin (2013) estimated the multiplier effect for Swedish LMAs, also introducing the novelty of human capital. Basically, they estimate the local multiplier as in eq. 3.4 and find a positive but lower multiplier compared to the one obtained using US data. Their result suggests that an increase in tradable employment leads to an increase in non-tradable employment by about 0.4-0.8. However, when they take into account the effect of an increase in high-skilled workers within the tradable sector, they find a positive effect of about 2.7. This is a very high result compared to the previous one. They also estimate the effect according to the technological level of the firms. They find a positive effect only for high technology firms. They explain these results by: the technology used in the non-tradable sector, i.e. the more labor-intensive the technology in the non-tradable sector, the higher the multiplier. Second, higher effects are found for high technology firms and workers with high human capital, because higher levels of productivity command higher wages.

In what follows, I present a brief review about more recent econometric results. Gerolimetto and Magrini (2014) estimated the effect for Spanish LMA and found no significant results. Kazekami (2017) did the same for Japanese commuting areas, finding positive effects over the period 1986-1996. He also showed that the effect is moderated by agglomeration economies and

labor mobility. Van Dijk (2017) estimated the effect for U.S. cities and found a positive effect, adding differences between high-wage and low-wage sectors. Specifically, the latter has no significant results while the former has a higher effect than the average in the same vein of Moretti and Thulin (2013). Wang and Chanda (2018) found an average positive effect across Chinese cities at the prefecture level. Finally, more recently, Cerqua and Pellegrini (2020) estimated the effect for Italian LMA in 'mezzogiorno' (southern Italy and islands) from 1995 to 2006, finding a positive effect and using a different instrument for the estimation process. More recently, Gutierrez-Posada et al. (2023) estimated the multiplier effect of creative industries on non-basic sectors and Osman and Kemeny (2022) revised the evidence on local multipliers. The former found a positive effect of the creative industries on non-tradable sectors, while the latter changes the terms of the matter to a finer distinction of sectors, the need for a long panel data set, and the different results obtained in different types of urban agglomerations such as metropolitan and medium-sized cities.

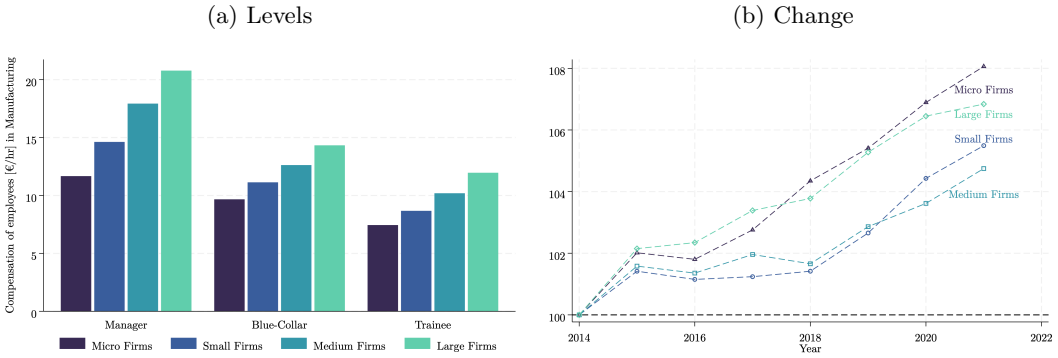
3.3 Pecuniary externalities and the working mechanisms

Traditional estimates of local multipliers rely on changes in tradable jobs to assess changes in non-tradable jobs. In contexts where job creation is driven by turnover of firms rather than internal growth, it is important to disentangle the two separate effects. In general, the growth of firms corresponds to internal economies of firms (Bellandi, 2001), while the entry and exit of firms in local markets is a source of external economies (Glaeser & Kerr, 2009). This is the case of Italy, where the turnover of firms allows the flourishing of industrial districts that prosper through Marshallian external economies (Markusen, 1996, Bellandi and De Propris, 2015). We leverage on the model of Ottaviano and Thisse (2001) to suggest how pecuniary externalities are related to different modes of spatial organization of production. This introduces monopolistic competition in a spatial framework where the entry of firms causes a perturbation of the previous equilibrium.

When a firm entries a local market, it generates three pecuniary externalities. First, it creates a *competition effect*. This reduces industry-wide profits in the tradable sector and forces less efficient firms to leave the local market. The mechanism operates at the level of the labor market. The entry generates an increase in the demand for labor with a corresponding increase in labor costs. Overall, when such a pecuniary externality offsets the benefits of agglomeration[3]

[3]Firms can benefit from co-locating with other firms because of labor pooling, knowledge spillovers, and the

Figure 3.2: **Compensation of Employees**



Notes. This figure plots employee compensation by firm size in the manufacturing sector (extraction activities are excluded from the sample). Panel (a) shows the average level of compensation over the period 2014-2021. Panel (b) shows the evolution of these levels over the same period. The unit of measurement is euro per hour worked. The data used are freely available on the Istat website.

Source. Authors' elaboration on Istat data.

the effect of competition can also be negative (Moretti, 2010). Similarly, there is an effect in the housing market (Fujita & Thisse, 1996). Entries of firms press prices in the housing market[4], which affects the profits of firms. Again, if the pressure on housing prices is greater than the positive effect coming from agglomeration, the *competition effect* can be negative.

Second, there is the *market size effect*. In general, when competition in the market is imperfect, the larger the firm entering the market, the higher the surplus income. This happens because of two mechanisms. First, the larger the firms entering the local market, the more additional jobs are created. Second, larger firms are more productive, pay higher wages and offer more stable jobs (see figure 3.2-a). So, assuming the same number of jobs, higher wages increase local demand. When such a surplus is spent on local goods and services, it creates the *local multiplier* (Moretti, 2010). Larger firms generate larger multipliers. This also creates a circular effect: the larger the local market, the greater the likelihood of new firms entering the market.

Third, the negative effect due to increased competition in the own-industry also produces a positive effect in local downstream sectors (Venables, 1996). In this case, the *cost-linkage effect* is

presence of specialized input suppliers (Rosenthal & Strange, 2004). However, as suggested here, there is a *trade-off* for firms to locate in dense local markets. This is modeled by Combes and Duranton (2006), who showed that there are two separate forces in the labor market: *labor poaching*, which pushes up wages, and *labor pooling*, which increases firms' productivity.

[4]The effect on housing prices depends on the elasticity of housing supply. When supply is rigid, housing prices and relative wages increase. In the case of perfectly elastic supply, there are no increases in housing prices and an increase in employment (Hsieh & Moretti, 2019).

observed. The effect of new entry has a negative impact on the revenue side of firms in the own-industry, but it also has an indirect effect on the downstream sectors, which enjoy benefits on their cost side due to a reduction in the selling price of the upstream sectors. Traditional Marshallian districts rely heavily on this mechanism (Becattini, 1989). In particular, smaller firms tend to entrust other firms through market relationships, generating local production processes that increase the degree of vertical disintegration of the local industry. On the other hand, larger firms rely less on cost linkages than smaller ones (Drucker & Feser, 2012). As highlighted by Chinitz (1961), the source of the location decision changes with the firm size. As the presence of smaller competitive firms supplying inputs is a source for the location of small firms that mainly met their needs through local sources (Glaeser & Kerr, 2009), the strength of the customer and input market is less relevant for large firms that tend to trade off transportation costs.

The sum of these three effects indicates whether the firm entry has an overall positive effect. However, the mode of propagation of entry changes according to the dominant effect. Given the countervailing power of the competitive effects, there are two different regimes. These regimes are also related to the size of the entry firm. On the one hand, the larger the firms entering the local market, the higher the wages paid. Ceteris paribus, higher wages allow larger multipliers for customer-oriented firms. Workers tend to buy more, and given their willingness to buy locally, a larger pool of local products is sold. On the other hand, the smaller the scale of entry, the greater the need for inputs and intermediates sold locally. Then, upstream and downstream sectors that sell to tradable firms will thrive as a result of smaller entry.

3.3.1 Testable implications

That said, the mechanisms proposed in the previous section suggest some testable implications that we decline in light of the context depicted in the introduction section.

Implication 1 *The pouring-out effect, given the level of tradable jobs, leads to an increase in non-tradable jobs (the T-NT effect) when large firms pay wage premium. So, tradable to non-tradable jobs multipliers is higher for large firms than for the other categories.*

Implication 2 *Since the decision to outsource varies with firm size, the multiplier of tradable jobs to other tradable jobs is positive for small and medium-sized firms and negative for large firms.*

Implication 3 *In thick local markets such as industrial districts, the entry of tradable large firms has a positive effect on non-tradable jobs if the reduction in the cost-linkage effects due to the change in optimal outsourcing is smaller than the stronger market size effect due to the large firm wage premium.*

3.4 Data and econometric design

The main source of data is the Istat dataset[5] at the municipal level, containing information on the number of jobs and local units covering all non-agricultural activities, 4 different local unit size classes (micro, small, medium and large), over the period 2012-2020. We pair each municipality with its related LMA, which is a self-contained commuting area, and sum to obtain information at the level of the LMA. In a second step, each 2-digit industry m is categorized as *tradable* (T) or *non-tradable* (NT):

$$m = \begin{cases} \text{Tradable} & \text{if } m \in T, \quad T = \{05, 06, 07, \ldots, 33\} \\ \text{Non-Tradable} & \text{if } m \in NT, \quad NT \notin T \end{cases} \tag{3.1}$$

We follow Moretti and Thulin (2013) in defining tradable sectors as extraction (carbon, oil, metals, and related services) and manufacturing (all ateco 2-digit industries between 05 and 33), while non-tradable sectors include all remaining industries. Next, we aggregate the number of establishments (n_m) and jobs (e_m) in each LMA, distinguishing by sector classification and firm size for the tradable sectors. Let Θ be the set of all Italian establishments,

$$\Theta = \{i_1, i_2, i_3, \ldots, i_n\}, \quad n = \sum_{i \in \Theta} 1$$

divided by firm size:

$$\begin{aligned} \Theta^L &= \{i \in \Theta : e_i > 250\}, \quad \Theta^L \subset \Theta \\ \Theta^M &= \{i \in \Theta : 50 \leq e_i \leq 250\}, \quad \Theta^M \subset \Theta \\ \Theta^S &= \{i \in \Theta : 10 \leq e_i < 50\}, \quad \Theta^S \subset \Theta \\ \Theta^m &= \{i \in \Theta : e_i < 10\}, \quad \Theta^m \subset \Theta \end{aligned} \tag{3.2}$$

[5] available here: http://dati.istat.it/

For tradable sectors, we aggregate jobs and establishments within each firm size class:

$$\begin{aligned} \mathrm{eT}^L &= \sum_{m \in T} e_m^L, \quad \mathrm{nT}^L = \sum_{m \in NT} n_m^L \\ \mathrm{eT}^M &= \sum_{m \in T} e_m^M, \quad \mathrm{nT}^M = \sum_{m \in NT} n_m^M \\ \mathrm{eT}^S &= \sum_{m \in T} e_m^S, \quad \mathrm{nT}^S = \sum_{m \in NT} n_m^S \\ \mathrm{eT}^m &= \sum_{m \in T} e_m^m, \quad \mathrm{nT}^m = \sum_{m \in NT} n_m^m \end{aligned} \tag{3.3}$$

In the case of non-tradable sectors, we only sum total jobs.

$$\mathrm{eNT} = \sum_{m \in NT} e_m \tag{3.4}$$

We estimate local multipliers as in Moretti and Thulin (2013). However, we originally contribute to the literature by modifying the main independent variable. The main reasons why we use changes in the number of local units rather than jobs are: 1) the presence of a "regression fallacy" presented by Davis and Haltiwanger (1992) and 2) the fact that the Italian economic system relies more on firms' turnover than on internal growth. The former has to do with the fact that when researchers analyze the extent to which different classes of firm size account for changes in the number of jobs in the economy, they face a bias due to transitions between size classes. The bias overestimates the contribution of smaller firms to job growth (see Davis et al. (1996) for a detailed explanation). Accordingly, we use the number of local units to avoid this potential bias. Moreover, looking at the net change in the number of local units instead of jobs allows us to consider the mechanisms introduced in the theoretical section. The latter then allows to take into account different regimes of tradable growth. In fact, changes in jobs could be due to growth (loss) of workers within local units as well as to changes in the number of local units. However, we also include in the appendix results obtained using changes in the number of jobs.

We estimate the model as follows:

$$\begin{aligned} \Delta eNT_{rt} &= \alpha + \beta \Delta nT_{rt} + \gamma \Delta eT_{rt}^{OF} + \tau_t + \epsilon_{rt} \\ \epsilon_{rt} &= \mu_r + \upsilon_{rt} \\ \Delta nT_{rt} &= nT_{rt} - nT_{rt-3} \\ \Delta eNT_{rt} &= eNT_{rt} - eNT_{rt-3} \end{aligned} \tag{3.5}$$

It estimates the growth change in the number of jobs in non-tradable activities (ΔeNT_{rt}) as a function of the net change in the population of tradable establishment (ΔnT_{rt}). We distinguish between micro, small, medium, and large firms as defined in eq. 3.3. We also include a control variable to avoid the possibility of gross rather than net effects. We then use the change in the number of jobs in the large category of 'other tradable establishments' ΔeT_{rt}^{OF}. It represents the employment in all the classes of firms analyzed but the one used in each specification. Accordingly, when we look at the effect of the entry of, say, a large firm, we also include a control for the change in employment in other (non-large) firms. Even if this is not a pure competition effect, we maintain that it is a proxy for a competition-by-cost effect as described in the theoretical framework: larger firms outperform smaller ones by paying higher wages and offering more stable jobs.

We also include time fixed effects and the error term is specified to include an idiosyncratic component (v_{rt}) and unobservable specific characteristics of the LMA (μ_r). The change in the number of non-tradable jobs as well as the net population of tradable establishments is estimated over three years to avoid possible bias due to skewed observations in a given year (Moretti & Thulin, 2013). Accordingly, we estimate four different specifications of the same model (eq. 3.5) to capture differences in the contribution of firms of different sizes to the multiplication of non-tradable jobs. In addition, we also include the division into two different territorial settings (district and non-district areas) as well the case for backward linkages.

3.4.1 Identification strategy

OLS are likely to be inconsistent if unobserved shocks to the size of non-tradable activities also affect tradable activities, i.e. a change in the labor supply of the LMA due to changes in amenities, crime, school quality, local public services, local taxes (Moretti & Thulin, 2013). That is, the change in tradable jobs is correlated with the error term due to local shocks. Let's consider a region, say A, that experiences a labor supply shock due to, say, new public transportation infrastructure. Such new infrastructure reduces transportation costs and increases the availability of workers living in remote areas of Region A. After the introduction of this public transport line, the residents of the remote areas can now move to the inner district, where the demand for labor allows them to find a new job. Such a shock generally affects the number of jobs in tradable and non-tradable sectors in Region A leading to a bias in the estimate of the coefficient of interest.

To address endogeneity issues, we design an instrumental variable following the previous

literature (Moretti, 2010). We define the instrument as:

$$\begin{aligned} Z_{rt} &= \sum_{m \in T} n_{rmt-3} \cdot \Delta \ln n_{r'mt} \\ n_{r'mt} &= \sum_{r} n_{rmt} - n_{rmt} \\ \Delta \ln n_{r'mt} &= \ln n_{r'mt} - \ln n_{r'mt-3} \end{aligned} \tag{3.6}$$

As before, the subscript m stands for a generic 2-digit industry, T for tradable, r for generic LMA, and t for time (year). Then $\Delta \ln n_{r'mt}$ represents the net change in the population of tradable firms nationwide. In this way, we modify the original Bartik instrument by removing the own region effect from the nationwide shift (Van Dijk, 2017; Osman and Kemeny, 2022). Accordingly, the subscript r' refers to a nationwide index, although each LMA has its own nationwide change, which is obtained by purging the nationwide indicator i.e. the sum of all tradable firms $i \in m$ from the r^{th} observation. We differentiate our instruments according to the size classes of the firms to match the relevance property of the instrumental variable. We obtain 4 instruments, one for each class of size of the firms entering in the LMA.

$$Z_{rt} = \begin{cases} Z_{rt}^{L} & \text{if } n_m \in \Theta^L \\ Z_{rt}^{M} & \text{if } n_m \in \Theta^M \\ Z_{rt}^{S} & \text{if } n_m \in \Theta^S \\ Z_{rt}^{m} & \text{if } n_m \in \Theta^m \end{cases} \tag{3.7}$$

We then estimate the effect of the increase in tradable firms, according to their size, on non-tradable jobs conditional on national exogenous (to local) shocks affecting the size of tradable firms.

3.5 Main results

This section is divided into several subsections. The initial subsection replicates previous empirical studies about multipliers. Once the limitations of the approaches have been demonstrated, the primary findings will be presented. The subsequent subsection illustrates how the impact of the multiplier varies in accordance with the size of the firm entering the local market. Subsequently, a series of robustness tests will be provided, examining different territorial settings and

the local value chain.

3.5.1 Replication

Table 3.2 provides several estimates according to the most commonly used methods in the literature. The aim of presenting such evidence is to show how much the effect of a multiplier depends on the model and the instrument used. Among the methods developed, only that of Moretti and Thulin (2013) provides satisfactory results in terms of the validity of the instruments used and the statistical significance of the results. The model of Moretti (2010) (column 2), used in his seminal paper and also re-evaluated for the Italian context by De Blasio and Menon (2011), does not provide statistically significant results. According to it, when a new job is created in the tradable sector, no additional jobs are created in non-tradable activities. However, the F-statistic of the first stage is lower than 10, which is the traditional threshold provided by the literature to say that an instrument is valid. The second model analyzed is the one used by Moretti and Thulin (2013). The results obtained with such a model (column 4) are positive and statistically significant, as well as valid in the instrument, and even the results are dramatically higher than those obtained in the previous literature. According to such a model, if one new tradable job is created in the LMA, then 2.8 additional jobs are created in non-tradable activities. Third, columns 5 and 6 re-estimate the model of Van Dijk (2018). The results in column (6) suggest that increasing the number of tradable jobs by 100 more units creates 67 additional jobs. Again, the first stage F-statistic is below the threshold of 10. Finally, column 8 presents the more recent attempt in the literature made by Osman and Kemeny (2022). It results in a job multiplier of 0; however, the instrument is not valid. Accordingly, our results suggest that there is heterogeneity between the results and the model; we suspect that the results are driven by the strength of the instrument. For this reason, we follow the model used by Moretti and Thulin (2013) in the following to obtain insightful results.

Our doubts about the results obtained by Moretti and Thulin (2013) are mainly based on the lag used to construct the net change in jobs. In their paper they used a lag of 3 years, while Moretti (2010) used 10 years and similarly Van Dijk (2018). We test whether the positive effect is driven by such a choice. Figure 3.3 uses different lags to assess the effect of a change in tradable jobs on non-tradable jobs[6]. Figure 3.3 suggests that the effect of tradable jobs multipliers decreases with the length of the lag used. When a 7-year lag is used, the effect is even negative. We argue that considering long lags more directly captures the working effect

[6]In the appendix, results and instrumental variable statistics are presented in table 4.

Table 3.2: **Baseline results of changes in tradable on non-tradable**

	(Moretti, 2010)		(Moretti & Thulin, 2013)		(Van Dijk, 2018)		(Osman & Kemeny, 2022)	
	1. OLS	2. IV	3. OLS	4. IV	5. OLS	6. IV	7. OLS	8. IV
ΔeT	0.44***	-0.42	2.32***	2.83***	0.08***	-0.33*	0.55***	2.20
	(0.01)	(2.16)	(0.35)	(0.17)	(0.01)	(0.19)	(0.14)	(2.24)
Observations	4,826	4,826	3,606	3,606	4,826	4,826	5,436	4,844
N. Clusters	610	610	610	610	610	610	610	610
LMA fixed effects			✓	✓	✓	✓	✓	✓
Clustered Std. Error			✓	✓	✓	✓	✓	✓
1st Stage F-stat		0.26		363.60		5.01		0.71
Jobs Multiplier		0X		2.83x		.67X		0X

Notes. For the style of the instruments and the model specifications, refer to the original paper. All specifications include year FE. The main independent variable is always the change in non tradable jobs; however, the variable changes according to the model developed by the cited authors (see appendix B for an analytical description of the models).
$***$ p<.01, $**$ p<.05, $*$ p<.1

of competition, holding constant all other possible factors affecting the estimates. This is what Moretti (2010) calls general equilibrium effect. The long-run effect of increases in the size of tradable activities is offset by increases in housing and labor price when the elasticity of labor and housing supply is rigid. The larger the elasticity of labor and housing supply to the shock, the larger the multiplier. In the following, we still follow Moretti and Thulin (2013) and use a 3-year lag.

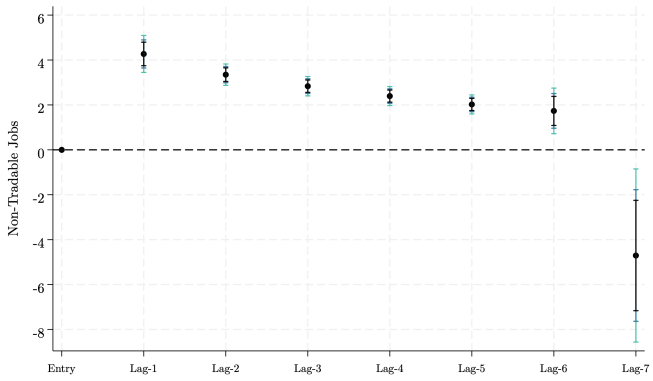
3.5.2 The impact of entry varies by firm size

Table 3.3 estimates the model described in equation 3.5. Column 1 shows the effect of a net change in the population of firms, regardless of size. The entry (exit) of an average firm in tradable activities generates (destroys) 50 additional jobs in non-tradable sectors[7]. We try to relate this result to the previous literature by reporting the traditional job multiplier[8]. Such a value is a relative multiplier; it is intended to provide insight into the capacity of a single job within different size classes to generate additional jobs in non-tradable sectors. Column (2) reports the results for micro firms, which indicate the gross effect of entry. The difference between the specifications in columns (2) and (3) is that the former does not include the control variable (all specifications follow the same pattern). Then the differences between the coefficients are an approximate measure of the *competition effect*. While the result is positive, strong, and statistically significant in column (2), when we control for the change in employment in the other size class (column 3), the result becomes statistically insignificant. This suggests that the

[7]In all the following descriptions, we use 'entry', but the result can be interpreted symmetrically in the case of 'exit'.

[8]The job multiplier is obtained by dividing the coefficient of the regression by the average size of the firm in tradable activities, and in columns 2 to 9 according to the size of the firm.

Figure 3.3: **The heterogeneous effect of an increase in tradable jobs on non-tradable jobs**



Notes. The figure plots the coefficients estimated in the table 4. Each point represents the effect of an increase in tradable jobs on non-tradable jobs after different lags, e.g. the coefficient estimated at 'lag-1' is the effect on non-tradable jobs one year after the creation of one tradable job. The Y-axis reports point estimates and indicates how many non-tradable jobs are created by the tradable job. *Entry* on the X-axis represents time 0, when the new tradable job is created. The figure reports the coefficient (black dot) along with the 90% (black), 95% (dark blue), and 99% (light blue) confidence intervals. Standard errors are clustered at the level of the LMA. Point estimates are from regressions that include time and LMA fixed effects. Control variables are not included. The instrumental variable used is the same as described in section 3.4.1, but at the same time as the main lagged independent variable.

Source. Author's elaboration on Istat data

competition effect is particularly strong in the micro size class.

Table 3.3: **Effect of changes in tradable heterogeneous firms size on non-tradable**

	Average entry	**Micro Firms**		**Small Firms**		**Medium Firms**		**Large Firms**	
	1. IV	2. IV	3. IV	4. IV	5. IV	6. IV	7. IV	8. IV	9. IV
ΔnT	50.44***	37.66***	4.17	173.42***	162.17***	756.74***	246.21***	11,780.51***	3,147.72***
	(9.56)	(10.46)	(7.76)	(25.66)	(29.60)	(163.95)	(94.82)	(4,076.38)	(831.14)
ΔeT_{rt}^{OF}			2.49***		0.52		2.05***		3.03***
			(0.57)		(0.62)		(0.39)		(0.39)
Observations	3,606	3,606	3,606	3,606	3,606	3,606	3,606	3,606	3,606
1st Stage F-stat	47.68	25.93	50.28	98.48	73.46	38.39	19.90	6.90	6.02
N. Clusters	610	610	610	610	610	610	610	610	610
Jobs Multiplier	3.88X	14.21X	0X	8.86X	8.28X	7.95X	2.59X	23.83X	6.37X

The main dependent variable is the 3-year change in non-tradable jobs. The independent variable is Δn_{rt}, which is the 3-year change in the number of establishments in each size class (micro, small, medium, and large). The control variable is $\Delta^{OF} e_{rt}$, which is the change in jobs in 'other firms', where other refers to the other class of establishment with respect to the one used for the estimation. For example, column (2) estimates the effect of the entry (exit) of a micro enterprise. The control variable refers to small, medium and large firms only. All specifications include local labor market area (LMA) fixed effects and year fixed effects. Errors are clustered at the LMA level. The 'job multiplier' is estimated by dividing the coefficient of Δn_{rt} by the average size of the firm in the corresponding size class. The number of clusters refers to the number of LMAs included in the regressions. The number of observations refers to the number of Clusters × the number of years considered. The 1st stage F-statistic works as a statistic for the relevance of the instrument. Values greater than 10 indicate strong instruments.
*** p<.01, ** p<.05, * p<.1

Looking at the other specification, we find that the stronger relative effect is that for small firms (≈ 8.3 additional jobs generated for each worker of the new entry), followed by large (≈ 6.4) and medium (≈ 2.6). Interestingly, the stronger absolute *competition effect* is for large firms, which account for 8.5 thousand jobs (the difference between coefficients in column 8 and 9). This fits very well with mechanisms depicted in section 3.3. Larger firms are more efficient and pay higher wages than smaller ones. This works as a strong negative competition effect through increased demand of labor. However, large firms are also the ones that create the largest number of additional jobs ($\approx 3,147$). The stronger *competition effect* in relative terms is that for micro enterprises, which goes from 38 potential additional jobs to 0 when controlling for the *competition effect*. In this case, the negative *competition effect* completely offset the *market size* and/or the *cost-linkages* effect. In the case of small firms, the *competition effect* is very weak, crowding out only 10 jobs. For medium-sized firms, the *competition effect* accounts for about 500 jobs (≈ 5.36 in terms of jobs multipliers). In short, our results suggest that while small firms generate relatively more additional jobs, large firms create more jobs in absolute terms.

3.5.3 The effect of tradable firm entry on other tradables

In this section, we focus on the effect that the entry of tradable firms has on other tradable jobs. This is one way of dealing with the *cost-linkage effect*. When a tradable firm enters a local market, it increases competition in the local tradable sectors, reducing industry-wide profitability. However, the effect of the entry of a firm in a generic tradable sector, say m_1, have

positive effects on employment in $m_2, m_3, m_4, \ldots, m_T \in T$ if the local market for intermediates is thick. Our point here is that we expect to find a multiplier effect that is reduced from the one obtained in the case of tradable to nontradable, and that the effect is mediated by the class size of the firm entering the market. Since larger firms tend to trade off transportation costs more than smaller firms, we expect the *cost-linkage* effect to be smaller for larger firms. Rather, since smaller firms rely more on local intermediates, we expect a positive effect of smaller firms through *cost-linkages* on other tradable sectors. Thus, by comparing these results with those obtained in the previous tables, we can determine whether the increase in non-tradable jobs due to the entry of tradable firms of different sizes depends on a *market size effect* (driven by higher wages and higher demand) or on *cost-linkages* effects.

To make such a comparison, we need to divide the tradable jobs and establishments into two random subsets, as in Moretti (2010). Let T_1^* and T_2^* be two randomly drawn subsets of the tradable sector set T such that

$$T_1^* \subset T, \quad T_2^* \subset T \tag{3.1}$$

with:

$$T_1^* \cap T_2^* = \emptyset \tag{3.2}$$

Accordingly, we evaluate the effect of an increase in jobs, establishments, and establishments of different sizes in the subset of tradable sectors (T_1^*) on the number of jobs in the other subset of tradable sectors (T_2^*). Of course, the instrument has to change accordingly. Thus, the sum of 2-digit industries will be related to the subset of tradable industries used and, unlike the previous specification, not to the entire population of tradable establishments. Thus, the instrument is obtained as:

$$Z_{rt}^{T_1^*} = \sum_{m \in T_1^*} n_{rmt-3} \cdot \Delta \ln n_{r'mt} \tag{3.3}$$

Table 3.4, column (1) refers to the number of additional jobs obtained in other tradable sectors (T_2^*) when 1 additional tradable job is added to the tradable sectors T_1^*. The effect is positive and statistically significant and, as expected, lower than the one obtained in table 3.2, column (4). Thus, if 100 additional jobs are created in some random tradable sectors, 97 jobs are created in other tradable sectors. Column (2) reports the same estimate in the case of an average entry. Again, the effect is positive and statistically significant. The effect is twice as large as the one obtained using the jobs in column (1), and half as large as the one estimated in column (1) of Table 3.3.

Table 3.4: **Effect of tradable on other tradables**

	(1) **Emp. Change**	(2) **Avg. Entry**	(3) **Micro Entry**	(4) **Small Entry**	(5) **Medium Entry**	(6) **Large Entry**
ΔeT	0.97***					
	(0.15)					
ΔnT		19.59***	4.30	40.84***	189.34***	584.26
		(7.54)	(3.72)	(6.37)	(36.14)	(453.60)
Observations	3,606	3,606	3,606	3,606	3,606	3,606
1st Stage F-stat	232.20	21.60	37.43	140.99	27.39	1.73
N. Clusters	610	610	610	610	610	610
Control Variables			✓	✓	✓	✓
Jobs Multiplier	0.97X	1.92X	0X	2.03X	2.08X	0X

The main dependent variable is the 3-year change in random tradable jobs. Random refers to a subsample of the entirety of the tradable sectors selected randomly. The independent variables are: Δn_{rt} which is the 3-year change in the number of tradable establishment in each size class (average, micro, small, medium, and large) and Δe_{rt} that is the 3-year change in tradable jobs. The control variables are $\Delta^{OF} e_{rt}$, which is the change in jobs in 'other firms', where other refers to the other class of establishment with respect to the one used for the estimation. Estimates are not reported. See example in table 3.3 for an explanation. All specifications include local labor market area (LMA) fixed effects and year fixed effects. Errors are clustered at the LMA level. The 'job multiplier' is estimated by dividing the coefficient of Δn_{rt} by the average size of the firm in the corresponding size class. The number of clusters refers to the number of LMAs included in the regressions. The number of observations refers to the number of Clusters × the number of years considered. The 1st stage F-statistic works as a statistic for the relevance of the instrument. Values greater than 10 indicate strong instruments.
*** p<.01, ** p<.05, * p<.1***

Among the different classes of firms studied, the stronger impact on other tradable jobs, in both relative and absolute terms, is that of medium-sized firms, which create ≈ 189 additional jobs after entering the LMA (with an associated relative job multiplier of 2.08). This is still lower than the same estimate in table 3.3. While a very similar relative multiplier is obtained for the entry of small firms, in absolute terms the entry of a small firm generates 40 additional jobs in other tradable sectors. On the other hand, both micro and large firms do not generate any additional jobs in other tradable sectors. As expected, small and medium firms are the class size of firms to activate more of the cost linkages, while large firms have no effect. In the case of micro establishments, no effects are found.

3.5.4 Territorial heterogeneity and firms size

In the following, we re-estimate the previous specifications on the entry of firms of different sizes, but according to different territorial settings. Table 3.5 re-estimates column 4 of Table 1, distinguishing between district and non-district areas. In general, the results suggest that the creation of a new job in tradable sectors in non-district areas generates more jobs in non-tradable activities than in district areas. In the case of firm entry, a new firm creates 59 new jobs in non-district areas (≈ 4.57), but only ≈ 20 in district areas (≈ 1.78 in terms of job multipliers). The differences in the results flatten out when we look at changes in jobs. The job multiplier rises from 1.78 when considering changes in the population of firms to 2.2 when considering changes in jobs. In fact, the trend is reversed in non-district areas, as the number of additional jobs

decreases from specification 2 to specification 4. Again, this is a clear confirmation of the role of the *competition effect* for local multipliers. District areas have a high number of tradable firms relative to non-district areas, and for this reason each new entry produces a strong *competition effect*.

Table 3.5: **Effect of changes in tradable on non-tradable according to different territorial settings**

	Non-district Areas 1. IV	**District Areas** 2. IV	**Non-district Areas** 3. IV	**District Areas** 4. IV
ΔnT	59.33***	19.61**		
	(6.89)	(9.45)		
ΔeT			2.97***	2.20***
			(0.21)	(0.47)
Observations	2,763	843	2,763	843
N. Clusters	469	141	469	141
1st Stage F-stat	29.16	33.43	407.29	23.18
Clustered Std. Error	✓	✓	✓	✓
Jobs Multiplier	4.57X	1.78X	2.97X	2.2X

The main dependent variable is the 3-year change in non-tradable jobs. The independent variable is Δn_{rt}, which is the 3-year change in the number of tradable establishments for columns (1) and (2). The independent variable is Δe_{rt}, which is the 3-year change in the number of tradable jobs for columns (3) and (4). There are no control variables in these estimations. However, all specifications include local labor market area (LMA) fixed effects and year fixed effects. Errors are clustered at the LMA level. The 'job multiplier' is estimated by dividing the coefficient of Δn_{rt} by the average size of firms in the corresponding area (non-district/district). The number of clusters refers to the number of LMAs included in the regressions (141 industrial districts and 469 non-districts). The number of observations refers to the number of clusters × the number of years considered. The 1st stage F-statistic acts as a statistic for the relevance of the instrument. Values greater than 10 indicate strong instruments.
*** p<.01, ** p<.05, * p<.1

Table 3.6: **Effect of changes in tradable heterogeneous firms size on non tradable according to different territorial settings**

	Micro Firms		**Small Firms**		**Medium Firms**		**Large Firms**	
	1. Non-District	2. District	3. Non-District	4. District	5. Non-District	6. District	7. Non-District	8. District
ΔnT	-0.81	5.54*	223.26***	68.82**	129.71	271.97***	2,351.51**	2,760.36**
	(13.32)	(3.15)	(16.39)	(28.18)	(259.01)	(80.56)	(992.82)	(1,394.08)
ΔeT_{rt}^{OF}	2.99***	1.07***	-0.06	0.13	2.55***	0.92***	3.48***	2.11***
	(0.62)	(0.12)	(0.73)	(0.28)	(0.68)	(0.20)	(0.43)	(0.51)
Observations	2,763	843	2,763	843	2,763	843	2,763	843
1st Stage F-stat	58.15	30.75	204.21	9.83	6.25	11.86	2.43	3.37
N. Clusters	469	141	469	141	469	141	469	141
Jobs Multiplier	0X	.51X	11.41X	3.18X	0X	3.13X	4.75X	8.56X

The main dependent variable is the 3-year change in non-tradable jobs. The independent variable is Δn_{rt}, which is the 3-year change in the number of tradable establishments in each size class (micro, small, medium, and large). The control variable is $\Delta^{OF} e_{rt}$, which is the change in jobs in 'other firms', where other refers to the other class of establishment with respect to the one used for the estimation. See example in table 3.3 for an explanation. All specifications include local labor market area (LMA) fixed effects and year fixed effects. Errors are clustered at the LMA level. The 'job multiplier' is estimated by dividing the coefficient of Δn_{rt} by the average size of the firm in the corresponding size class and area (industrial districts/non-districts). The number of clusters refers to the number of LMAs included in the regressions. The number of observations refers to the number of Clusters × the number of years considered. The 1st stage F-statistic works as a statistic for the relevance of the instrument. Values greater than 10 indicate strong instruments.
*** p<.01, ** p<.05, * p<.1

Table 3.6 looks at the effect of entry size on different territorial settings. We complete the analysis of the results also including a summary of the effect of the entry of plants of different size according to the degree of urbanization of LMAs (see table 3.7). We found heterogeneous results.

As in Table 2, the results suggest that the entry of micro firms does not generate additional jobs in non-district areas, while in districts it generates a multiplier of less than one. In table 3.7, micro firms have positive multipliers in 'other LMAs' - another proxy for non-competitive rural places. Small firms multiply more in non-district areas than in districts. This is also reasonable in terms of . Certainly, *cost-linkages* are more relevant in non-district areas but the *competition effect* is stronger as well. Overall, the magnitude of *competition* in respect of *cost-linkages* is larger in district areas more than in non-district areas. The effect of the entry of a small firm in non-district areas is almost four times greater than in district areas. While medium firms generate additional jobs only in industrial districts (≈ 272), large firms have strong multipliers both in districts (≈ 2760) than in non-districts (≈ 2352). However, in the case of large firms, the first stage F-statistic is less than 10, so the results should be interpreted with caution. When the sample is reduced as in table 3.7, the weak instrument issue generates statistically insignificant results.

Table 3.7: **Summary of effects of changes in tradable heterogeneous firms size on non-tradable according to the degree of urbanization**

	Average Firms	**Micro Firms**	**Small Firms**	**Medium Firms**	**Large Firms**
Large Cities	63.96***	-9.89	164.89***	47.94	1,569.04
$n = 21$	(9.81)	(13.67)	(21.80)	(284.14)	(922.08)
Medium-sized Cities	9.65	2.49	30.27	305.56**	-2,444.09
$n = 87$	(6.58)	(2.07)	(20.07)	(150.67)	(4,322.71)
Other LMAs	32.30***	29.46***	79.63***	398.60***	10,509.29
$n = 502$	(6.70)	(8.17)	(10.24)	(114.19)	(37,098.65)

The main dependent variable is the 3-year change in non-tradable jobs. The independent variable is still Δn_{rt}, which is the 3-year change in the number of tradable establishments in each size class (average, micro, small, medium, and large). The control variable (not showed in the table) is $\Delta^{OF} e_{rt}$, which is the change in jobs in 'other firms', where other refers to the other class of establishment with respect to the one used for the estimation. See example in table 3.3 for an explanation. All specifications include local labor market area (LMA) fixed effects and year fixed effects. Errors are clustered at the LMA level. The 'job multiplier' is estimated by dividing the coefficient of Δn_{rt} by the average size of the firm in the corresponding size class and area (large cities, medium-sized cities and other LMAs). The number of clusters refers to the number of LMAs included in the regressions. The number of observations refers to the number of Clusters × the number of years considered. The 1st stage F-statistic works as a statistic for the relevance of the instrument. Values greater than 10 indicate strong instruments.
*** p<.01, ** p<.05, * p<.1

Table 3.7 sketches some other insights into the effect of entry. First, when we look at other LMAs, all but the large firm classes generate positive multipliers. The *competition effect* in these places is very small and the entry of a large firm is very rare. The class of medium-sized cities, which partially overlap with industrial districts, offers a perspective on the role of medium-sized firms, the only class able to generate additional jobs (≈ 306). In the case of large cities, only small firms create additional jobs (≈ 165) in non-tradable sectors. Overall, our estimates suggest that

- Places that experience larger multipliers, regardless of which firms enter, are those where competition is soft (e.g. other LMAs);
- Small firms generate positive multipliers in most areas;
- In industrial districts where competition is particularly fierce, local multipliers are positive for all classes of firms because, we maintain, of the importance of the *cost-linkage* effect.
- Even though there is a problem of instrumental variable weakness, large firms are the class of firms that generate higher absolute and relative multipliers when we distinguish between districts and non-districts.

3.6 Summary and conclusive remarks

This paper starts from the observation of a slow structural change in Italian local tradable activities. We point to three main effects that have occurred in Italy over the last 10 years. First, there is a *size effect* next to a *pouring-out* effect. The former suggests an increase in the average size of firms in tradable activities, while the latter suggests that jobs in smaller firms move to larger classes, keeping the level of employment constant. The third change is a *polarization effect*: tradable activities become more and more concentrated in fewer LMAs. This raises some questions about the traditional industrial context in Italy, which has traditionally relied on local external economies and firms of smaller size. While such an organization of the production process has produced a 'full employment'-like equilibrium in the last 50 years, it is unclear what is the effect of increasing leverage on internal economies. We use local multipliers to understand the effect of such reorganization on employment growth. In particular, we extend Moretti and Thulin (2013)'s hypothesis about human capital and wages as the main levers of local multipliers to the case of firm size.

We follow Ottaviano and Thisse (2001) to sketch the working mechanisms based on pecuniary externalities with a focus on business demography. We base our argument on two main hypotheses related to three pecuniary externalities. When a firm enters a local economy, it produces three main effects: 1) a *competition effect* that reduces profits and employment in its own sector; 2) a *market size effect* that operates in a non-perfectly competitive market by increasing the number of jobs; 3) a *cost-linkage effect*, i.e. by increasing competition in backward sectors, forward ones gain in their cost-linkage because of the reduced price of intermediate goods. If the *cost-linkage*

or *market-size-effect* is greater than the *competition-effect*, then there is an increase in the number of jobs in tradable sectors, which via the basic-non/basic multiplier produces additional jobs in non-tradable sectors. After presenting these mechanisms, we offer two hypotheses based on the role of firm size. This also acts as a corrective in the case of Italy, where non-tradable jobs increase even if tradable jobs are constant. First, larger firms, being more efficient than smaller ones, offer higher wages and more stable jobs. Given the *competition effect*, a *pouring-out* effect from smaller to larger firms can generate a relatively higher multiplier through the increase in local demand. However, larger firms tend to trade off transaction costs more than smaller firms when dealing with their intermediate goods needs. For this reason, given the *competition effect*, the *cost linkage* effect may be reduced in the case of an increase in the average size of firms (*size effect*).

We test such predictions by dividing local economies into two main sectors, namely tradable (manufacturing and extraction activities) and non-tradable (all remaining non-agricultural activities). We rely on data on jobs and establishments in Italian local labor market areas (LMAs) over the period 2012-2020. With our dataset, we are able to distinguish the population of firms according to their size (micro, small, medium and large). We then exploit the traditional econometrics of local multipliers, correcting a couple of points to address our mechanisms: 1) we use the change in the population of firms according to their size rather than the change in jobs; 2) we correct the instrumental variables traditionally used in the literature to account for the change in the population of firms according to their size. The results of our estimations suggest that:

1. Micro firms do not generate multipliers, suggesting that the reduction in their population (see Figure 3.1-c and Figure 3.1-d) does not destroy jobs in non-tradable activities or in other tradable jobs.

2. Small firms are those that create (and destroy) more additional jobs in non-tradable activities (≈ 8 jobs for each job they create (destroy) internally), due to the presence of the *market size* and the strong *cost-linkage* effect.

3. Medium firms are those with lower multipliers (≈ 2.6 jobs), but they are the class size that generates higher multipliers in terms of other tradables.

4. Large firms create the higher number of jobs in absolute terms, corresponding to ≈ 6 jobs for each one they create internally. However, as expected, they do not activate other tradable jobs through cost-linkage effects.

Following the lesson of Becattini and Dei Ottati (2006), we also analyze employment growth using the classification of Istat in non-district areas (469 LMAs) and district areas (141 LMAs). These are areas where the *competition effect* is likely to operate strongly due to the *polarization effect*. In fact, we find that the local multiplier in industrial districts (≈ 1.8 jobs) is lower than that in non-districts (≈ 4.6). We also look at the effect of the entry of firms in terms of their size according to different areas. In this case, we find that micro firms have very low local multipliers in industrial districts (that is 0 in non district areas), which means that their closures had a negative effect on jobs in non-tradable activities over the period studied. Similarly, the number of small firms decreases over the period in both districts and non-districts (although their share of employment increased in industrial districts). Their multiplier is again higher in non-district areas (where they account for the largest share of the reduction in tradable and non-tradable jobs). Medium-sized firms do not create additional jobs in non-districts, but a positive and statistically significant effect is found in industrial districts (but it is lower than that for small firms, suggesting that the absorption of lost jobs by small firms is not only through this size class). Large firms are again those with the largest multipliers in absolute terms. In industrial districts, they also have the largest relative multiplier (≈ 8.6 jobs for each job they create internally). This supports the idea that the reallocation of workers from smaller to larger firms (*pouring-out effect*) is beneficial for employment growth due to the demand effect generated by increasing wage levels. This effect is confirmed by table 3.4 where large firms generate no additional jobs in other tradable sectors. We conclude with some robustness tests using a classification of LMAs in terms of their degree of urbanization. The results are robust to the theoretical predictions.

In conclusion, our results suggest that the main trend running over Italian LMAs, that is the *pouring-out effect*, i.e. a reallocation of jobs from smaller to larger firms, increases the number of jobs in non-tradable activities (larger firms are those more responsible for such a change), especially in industrial districts (where most of the production of tradable activities is concentrated *polarization effect*). We maintain that this effect is transmitted through an increase in the disposable income of tradable workers, whose wages increase in the span of the investigation. On the other hand, it is difficult to say whether this has an impact on the local value chain. Our results suggest that larger firms have no local multipliers on other tradable activities, while small and medium firms have higher multipliers. In general, the results raise some concerns about the role of large firms in disrupting local value chains. However, some limitations remain. First, the instruments for large firms are weak. Second, the choice of the instrument to be used changes the results significantly. This calls for caution when looking at

the results of estimations of local multipliers.

Appendices

A Tables of Statistics

A.1: **Structural composition of Italian LMAs in 2012**

	1. Non-District Areas	**2. District Areas**	**3. Large firms Areas**
mFC	546.04	918.11	929.11
mFE	1360.72	2659.72	2586.28
SFC	71.31	200.36	208.79
SFE	1336.75	3832.82	4072.95
MFC	10.31	30.64	37.32
MFE	1009.27	2927.94	3712.72
LFC	1.46	2.37	6.39
LFE	926.21	1020.06	3132.50
LFE (%)	7.60	7.51	23.88
MFE (%)	14.51	27.09	26.94
SFE (%)	27.44	37.78	29.04
mFE (%)	50.45	27.61	20.14
TNT-ratio	0.23	0.60	0.61

A.2: **Summary statistics and correlation matrix**

	Mean	SD	1	2	3	4	5
1. Δn_{rt} Micro Firms	-31.17	93.21	-				
2. Δn_{rt} Small Firms	0.03	19.00	0.0403**	-			
3. Δn_{rt} Medium Firms	0.69	3.59	-0.0430***	0.2651***	-		
4. Δn_{rt} Large Firms	0.06	0.87	0.0655***	0.1058***	-0.0104	-	
5. Δe^{NT}	772.09	5292.01	-0.6794***	0.2085***	0.2482***	0.0314*	-

A.3: **Summary statistics and correlation matrix**

	Mean	SD	1	2	3	4	5
1. Δe_{rt} Micro Firms	-78.32	241.22	-				
2. Δe_{rt} Small Firms	11.98	352.78	0.2619***	-			
3. Δe_{rt} Medium Firms	63.61	350.99	0.0427**	0.2905***	-		
4. Δe_{rt} Large Firms	25.52	365.35	0.1399***	0.1420***	-0.0754***	-	
5. Δe^{NT}	772.09	5292.01	-0.5067***	0.2876***	0.1333***	0.0240	-

A.4: **Effect of changes in tradable on non-tradable according to different time spans**

	Δ = **1-year** 1. IV	Δ = **2-years** 2. IV	Δ = **3-years** 3. IV	Δ = **4-years** 4. IV	Δ = **5-years** 5. IV	Δ = **6-years** 6. IV	Δ = **7-years** 7. IV
Δe_{rt}	4.27*** (0.32)	3.35*** (0.18)	2.83*** (0.17)	2.39*** (0.16)	2.02*** (0.16)	1.73*** (0.39)	-4.71*** (1.49)
Observations	4,826	4,216	3,606	2,996	2,368	1,776	1,184
N. Clusters	610	610	610	610	592	592	592
1st Stage F-stat	284.69	253.36	363.60	388.90	190.12	103.40	13.75

Notes. We re-estimate the specification in column (4) of table 3.2. Every column refers to a different lag for the dependent, independent and instrumental variable. Point estimates are plotted in figure 3.3.
*** p<.01, ** p<.05, * p<.1

B Models of Local multipliers

In this section, we briefly review the main model developed to estimate local multipliers. These models are replicated in Table 3.2. Here, we basically retrieve their analytical models to sketch insights about the main differences.

B.1 Moretti (2010)

The first attempt to model 'local multipliers' is that of Moretti (2010). His model is developed as if follows.

$$\Delta e_{ct}^{NT} = \alpha + \beta \Delta e_{ct}^{T} + \gamma d_t + \epsilon_{ct}$$

where e_{ct} are change over time in the number of jobs (in absolute terms) in city c and year t. Time trends d_t are decade fixed effects. No city fixed effects are included in the model. Regarding the instrument for e_{ct}^{T}, the analysis is based on a shift-share instrument.

$$Z_{ct} = \sum_{j} \omega_{jc} \times \Delta e_{jt}^{T}$$

where ω_{jc} is the share of manufacturing jobs in the first year analyzed (in his case 1980) while Δe_{jt}^{T} is the change in nation jobs in manufacturing sector j over the period 1980-1990.

B.2 Moretti and Thulin (2013)

The next wave of local multipliers is quite identical to the previous but include city fixed effects. So:

$$\Delta e_{ct}^{NT} = \alpha + \beta \Delta e_{ct}^{T} + \gamma d_t + \epsilon_{ct}$$

where

$$\epsilon_{ct} = \mu_c + v_{ct}$$

In this case, μ_c is the vector of city fixed effects.

The instrument is:

$$Z_{ct} = \sum_j \omega_{jct-1} \times \Delta e_{c'jt}^{T}$$

where ω_{jct} is the share of manufacturing jobs at time t while $\Delta e_{c'jt}^{T}$ is the change in national manufacturing jobs j minus the growth in manufacturing jobs in sector j and city c, so c'. Basically, here authors are removing the own city component from the national growth in manufacturing jobs.

B.3 Van Dijk (2018)

The model of Van Dijk (2018) is a bit different from the previous ones. First, the estimation uses the share of non-tradable jobs as main dependent variable and the share of tradable jobs as independent variable.

$$\Delta \frac{e_{ct}^{NT}}{e_{ct}^{NT} + e_{ct}^{T}} = \alpha + \beta \Delta \frac{e_{ct}^{T}}{e_{ct}^{NT} + e_{ct}^{T}} + \boldsymbol{C'_{ct}\gamma} + \epsilon_{ct}$$

where $\boldsymbol{C'_{ct}\gamma}$ is a vector of control variables also including city and year fixed effects. In our replication, we do not include control variables. Accordingly, he changed also the instrument used.

$$Z_{ct} = \sum_{j \in T} \left[\frac{e_{ct-1}^{j}}{e_{ct-1}^{NT} + e_{ct-1}^{T}} \times \frac{\sum \Delta e_{jt}^{j}}{\sum \Delta e_{jt-1}^{j}} \right]$$

Here, the author use the share in sector j of tradable jobs rather than the value in the share part of the shift-share while the change rate is calculated as the ration between national employment less the oen city and its lagged value (the year before).

B.4 Osman and Kemeny (2022)

Finally, the model of Osman and Kemeny (2022) is estimated as following.

$$\ln e_{ct}^{NT} = \alpha + \beta \ln e_{ct}^{T} + \mu_r + \tau_t + \epsilon_{ct}$$

where they use the logarithmic transformation of employment to estimate the multiplier. Their approach changes substantially the instrumental variable:

$$Z_{ct} = \sum_j \frac{e_{cjt-1}}{e_{jt-1}} \times \left[\frac{(e_{jt} - e_{cjt}) - (e_{jt-1} - e_{cjt-1})}{e_{jt-1} - e_{cjt-1}} \right]$$

in which the share is the regional share of sector j in tradable in respect to the national level and the shift comes from the change rate in national jobs in sector j purged by the growth rate of city c.

Chapter 4

Local Competition and External Economies

Abstract

As an industry expands, tasks can be divided. New specialized skills emerge, workers absorb them, and external economies in the form of knowledge spillovers are generated via labor flows between firms. While the recent empirical literature is disconnected from the tradition of economic theory, such attempts to estimate spillovers are far from unanimous. This paper endeavors to bridge the theoretical and empirical literature on external economies by developing an oligopsonistic model in the local labor market. The second part of the paper shows that empirics and theory can be reconciled from a methodological point of view. It then develops a two-step econometric procedure to incorporate an interaction term between competition and specialization into the traditional estimation of the effect of external economies on total factor productivity (TFP). Using firm-level and confidential plant-level data for a large cross-section of Italian local labor market areas and a period of reduced local competition due to the influx of large manufacturing firms, this paper assesses the extent to which competition moderates the effect of specialization on local TFP. Endogeneity concerns regarding the quality and quantity of labor and TFP due to the simultaneity of productivity shocks and input choice are also addressed. The results suggest that even in an oligopsonistic market, competition is a necessary condition to benefit from external economies. There are thresholds of competition above which external economies in the labor market peter out. The HHI thresholds for competition range from 14.5 to 15.8. Finally, there are implications for the unit of local industry analysis when considering the labor market.

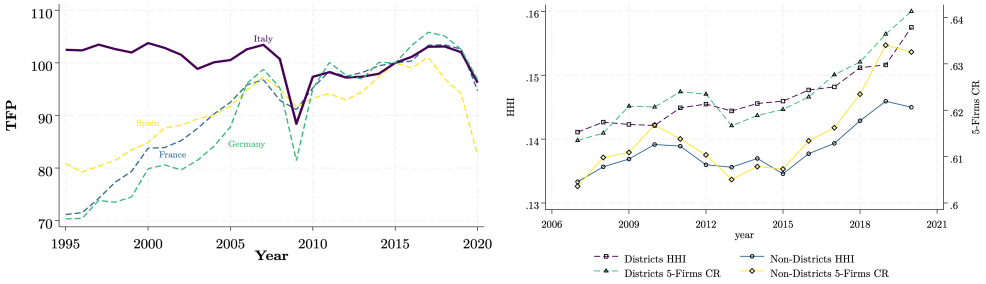
4.1 Introduction

When workers move between firms, they bring their knowledge with them, allowing hiring firms to realize productivity gains in the form of knowledge spillovers. This occurs in thick labor markets where many firms compete for the same pool of 'substitutable' workers. Such uncompensated externalities are one of the main pillars of urban and regional economics. They create incentives for both firms and workers to cluster. Even if these mechanisms occur spontaneously through market incentives, a better understanding of their origin as well as an assessment of their magnitude is important for predicting future trends in the geography of economic activity. However, the strand of the literature that has analyzed these effects has not reached unanimity in its empirics nor in its theoretical modeling.

There are three competing theories about the emergence of externalities in the labor market, systematized in the work of Glaeser et al. (1992). The first theory, known as the MAR (Marshall-Arrow-Romer) model, suggests that knowledge spillovers occur within the same industry and that proximity facilitates their diffusion. It also claims that weaker competition in the local labor market promotes growth and innovation. Second, there is the Porter model, which, unlike the MAR model, assumes that local competition promotes growth in specialized industries. Third, Jacobs' model of externalities is based on the diversity of economic activities in a local market and, like Porter, suggests that competition promotes them. However, it is not convincing the label of MAR externalities in a model that places side by side the original theory of Marshall about external economies and weak competition. This is because the economic tradition reached a consensus on the fact that external economies can be obtained by firms operating in an industry under *perfect competition* (Viner, 1932; Stigler, 1951; Chipman, 1970). While internal economies produce monopolies (Knight, 1924, Sraffa, 1926), external economies produce equilibria with many firms: a fact that better fits reality (Romer, 1994). However, following the MAR model, many empirical works still hypothesize negative effects of competition on output growth through external economies. On the other hand, reconciling theory with reality, Manning (2010) gave a new perspective on this issue. Every labor market has some degree of monopsonistic power, but those that are more geographically concentrated have less. This takes into account several relevant stylized facts. First, firms in the agglomeration are larger than those outside (Holmes and Stevens, 2002, Barrios et al., 2006; Lafourcade and Mion, 2007). Nominal wages are higher in the agglomeration, i.e. workers earn an urban wage premium (Glaeser and Maré, 2001; Gould, 2007). Firms in the agglomeration are more productive (Combes et al., 2012).

Figure 4.1: **Competition and productivity in Italy**

(a) Trends in manufacturing TFP (b) Trends in manufacturing competition



Notes. Panel (a) plots the trend of manufacturing TFP over year (1995-2020). Panel (b) plots trends in competition in different local labor market areas (districts and non-districts). It plots the HHI for competition and the five firms concentration ratio.

Source. My own elaboration on Asia data.

Given this, what is the role of competition for external economies? On the one hand, following the economic tradition, we expect to obtain external economies in industries where there is *perfect competition*. In this tradition, the model of Chipman (1970) provides an analytical perspective. On the other hand, the empirical literature dealt with MAR externalities, as opposed to Porter externalities, which are obtained in markets where monopsonistic power is strong. Based on Manning (2010), I try to reconcile theory and empirics by providing a suggestive model of parametric external economies in industries competing à-la Cournot in the labor market (*imperfect competition*). This allows to relax the strict hypothesis of *perfect competition*, which is rarely verified, and to explicitly include the role of competition in a model of parametric external economies. I also adopt the view of Becattini (1962) and Becattini (1989), who shift the unit of analysis from the industry to the district (the main local industry). This is because the movement of workers between firms is more frequent to observe at a given geographical scale e.g., a travel-to-work area, and also because the movement of workers between firms depends on the degree of substitutability between different tasks in different firms and industries (Neffke et al., 2017). This allows to find a testable equation that is partially different from the one obtained by Chipman (1970) for productivity. In the second part of the paper, I test such an equation using the approach developed by Combes et al. (2010).

To do so, I use a large cross-section of Italian travel-to-work areas, local labor market areas (hereafter LMAs), during a period of relevant change to examine the extent to which local

competition promotes external economies. There are two important stylized facts about Italian manufacturing. First, its productivity has not grown since the 1990s of the last century (see figure 4.1-a)[1]. Second, most manufacturing is concentrated in a few local market areas. These areas are traditionally defined as industrial districts: geographically bounded areas where a community of firms and people settle (Becattini, 1989). Here, the majority of manufacturing employment is accounted for by small and medium-sized firms. Recently, an influx of large firms has entered such markets, upsetting the previous equilibrium (see Chapter 1) and reducing local competition for labor (see Figure 4.1-b). While larger average size provides opportunities to exploit internal economies to some extent, industrial districts rely on external economies for their productivity growth. If the level of competition is reduced too much by the entry of large firms, the external economies in the labor market risk disappearing.

There are many empirical papers that test the hypotheses developed by Glaeser et al. (1992). In this strand of the literature, the debate is defined as 'MAR, Porter vs. Jacobs'. The seminal paper by Glaeser et al. (1992) found that diversity and competition promote growth. Henderson et al. (1995) found evidence for both MAR and Jacobs' externalities in US cities. Van der Panne (2004) found evidence of MAR externalities and found competition to be detrimental to growth. More recently, Beaudry and Schiffauerova (2009) found mixed evidence, explaining that much of the variation in results depends on the researchers' choice of unit of analysis. Bishop and Gripaios (2010) found evidence of a negative effect of specialization, a mixed effect of diversity, and a positive effect of competition on employment growth. Caragliu et al. (2016) at the regional level found evidence of both Jacobs and specialization externalities. While these contributions represent only a minimal part of the literature on such a debate, it is clear that the empirical evidence is particularly ambiguous. However, all these papers rely on an econometric approach that is not able to gauge the role of competition for diversity and specialization. Based on the result of the analytical model that I propose, I include an interaction term between competition and specialization to examine the effect of specialization on TFP growth. In this way, I am able to disentangle the effect of specialization at different levels of competition. This paper focuses only on industrial specialization, creating opportunities for future research interested in following the same approach in the case of diversity.

Thus, this paper has several goals. First, it has a pure theoretical interest to show that external economies can be obtained in a labor market with *imperfect competition* and that they

[1]However, it is relevant to note that the interpretation of the productivity of the manufacturing sector is subject to the choice of the indicator. The manufacturing production in Italy has grown in the last 30 years in terms of price, while in terms of output it has been decreasing (Arrighetti et al., 2024).

depend positively on competition. Second, there is an empirical interest in the case of Italy, where productivity gains in the form of external economies are threatened by reduced local competition. Third, a methodological interest to show that there is a more efficient way to estimate external economies due to specialization/diversity and competition, and this is via an interaction term. This work relates to several strands of economic literature other than the 'MAR-Porter vs. Jacobs debate': the literature estimating Marshall scale economies using the production function (Henderson, 1986, Henderson, 2003), the work of Drucker (2011) and Drucker and Feser (2012) on the effect of local industrial dominance on agglomeration externalities, the debate on procyclical productivity (Kaldor, 1966; Hall, 1988; Caballero and Lyons, 1990, Basu and Fernald, 1995, Biddle, 2014), to the industry life-cycle literature (Duranton and Puga, 2001, Neffke et al., 2011).

This reminder of this work is divided as follows. Section 4.2 presents a model of local labor oligopsony and external economies. Section 4.3 presents an econometric model to address endogeneity concerns and incorporate an interaction term between competition and regional specialization as suggested by section 4.2. In Section 4.4, I showcase the data sources used in the analysis. In Section 4.5, I provide detailed descriptions of the results. Finally, section 4.6 provides an overview of the results and some reflections on them.

4.2 A tentative model of oligopsony in local industries

In what follows, I briefly discuss a model of external economies. Following Chipman (1970), I model parametric external economies. I introduce Cournot competition in the labor market to show how external economies arise from increasing division of labor through *labor pooling* and *knowledge spillovers* even in oligopsonistic labor markets (Manning, 2010). Based on this, I make some additions to the model. First, I assume that workers may have a 'rational or irrational (preference) for working in an important rather than a minor industry, and should therefore be willing to accept lower wages as the industry expands' (Viner, 1932, p.39). Second, firms behave à-la Cournot in the labor market. This is a way of introducing imperfect competition into the model as in Combes et al. (2004). Third, preferences for important industries are a function of the degree of competition. This allows workers to obtain wage premiums and faster careers. The result of the model provides an analytical function for the productivity shifter A that can be tested empirically.

4.2.1 Labor Supply

Assumption 1. There is no inter-regional migration but only inter-sectoral movement of workers.

This helps keep the model lean, although it is not a central assumption of the model.

Assumption 2. Within the same region, workers offer their labor proportionally to the size of each industry. Accordingly:

$$L_j = w^{\epsilon}\phi_j^{\theta} \tag{4.1}$$

with

$$\theta = \begin{cases} 0 & \text{if } \phi \leq \hat{\phi} \\ \delta_0 + \delta_1(1 - HHI) & \text{otherwise} \end{cases} \tag{4.2}$$

i.e. the preferences of workers for heavily populated industries j are determined by the exponent θ. The direction of the preference depends on the 'empirical' value of ϕ, that is, a certain level of sectoral specialization[2] in a given region, say A. In the case in which $\phi \leq \hat{\phi}$, labor supply is only regulated by wages, and there are no additional effects due to preferences for the size of the industry. On the other hand, the exponent θ is equal to $\delta_0 + \delta_1 HHI$ in the case in which the industry size is over the threshold. This assumption relates to the hypothesis defined as 'endogenous quantity of labor' i.e., the larger the size of the industry, the more workers are willing to supply labor to that industry (Combes et al., 2010). This happens because larger industries allow firms and workers to benefit from better matching and searching, as well as increasing the frequency of job-to-job movement (Duranton & Puga, 2004). Workers show a preference for moving to high-demand industries, as such environments typically offer greater opportunities for rapid career advancement, a phenomenon observed in both blue-collar and white-collar segments. Especially for prospective white-collar workers, this preference may extend to their human capital investment decisions. If these individuals are located in region A and wish to pursue their careers within the same region, they are likely to align their educational choices with the dominant industry specialization of region A, thereby optimizing their potential for labor market integration and upward mobility within that region's specialized sector.

The specific functional form also suggests that the additional effect of specialization to labor supply depends on the degree of competition in the industry. This suggests that workers are able to discriminate between:

- monopsonistic power affecting their wage (ϵ),

[2]This can be thought of as a location quotient as well as a share of total activities or more generically as the total number of plants in the industry.

- industry size effect allowing them to work in a large industry θ,
- the fact that large industries offers a more dynamic environment only when firms neck-to-neck compete in the labor market.

The labor supply elasticity ϵ can be defined as

$$\frac{\partial L}{\partial W}\frac{W}{L} = \epsilon$$

with $\epsilon \in \mathbb{R}^+$. The more rigid ϵ is, the stronger the market power of firms. It is the elasticity of labor supply to wages. $\epsilon \to \infty$ represents perfect competition, that is, if a firm i marginally reduces W_i, it loses all of L_i. Recently, the metric ϵ has resurfaced in the industrial organization and labor economics literature to explain markups in U.S. markets (Azar et al., 2019). There is an interest to look at this metrics also in Italy (Ciapanna et al., 2024). Its resurgence in economic geography can be attributed to the work of Manning (2010), who shows how models of 'perfect competition' cannot account for many of the stylized facts about local labor markets. His point is that all labor markets have some degree of monopsonistic power, but those that are most agglomerated have less. In manufacturing agglomerations (e.g., industrial districts), wages are higher, firms are more productive and larger, and local competition is fiercer.

Inverting eq. 4.1:

$$w^S = \left(L_j * \phi_j^{-\theta}\right)^{\rho} \tag{4.3}$$

with $\rho = 1/\epsilon$. This is the supply curve.

4.2.2 Labor Demand

There are n firms in industry j that produce output Y_i with labor L_i and constant returns to scale[3].

$$Y_i = AL_i$$

A is a productivity shifter. Total employment in the labor market is $L = L_{-i} + L_i$. Where L_{-i} are all the other firms in the industry.

Assumption 3. Firms want to maximize their profits according to a Cournot model of competition:

$$\max_{L_i} \Pi_i = AL_i - w(L_{-i} + L_i)L_i \tag{4.4}$$

[3]The result does not change by modeling decreasing returns to scale.

w is taken by firms as given in each period. They only choose the optimal quantity of labor L_i^*. As well, they take A as given at each cycle of the production process.

$$\begin{aligned}\frac{\partial \Pi_i}{\partial L_i} &= A - \left(\frac{\partial w}{\partial L}\frac{\partial L}{\partial L_i}L_i + w\right) \\ &= A - w\left(\rho\frac{L_i}{L} + 1\right)\end{aligned}$$

Note that $\partial L/\partial L_i = 1$ and $(\partial w/\partial L) * (L/w)$ is equal to $1/\epsilon = \rho$. It also hold that:

$$A = w\left(\rho\frac{L_i}{L} + 1\right) \tag{4.5}$$

so, productivity is higher in industry where firms are larger (L_i/L).

Now, defining $L_i/L = s_i$ the employment share of firm i, multiplying both sides by s_i and summing over all firms in the market allow to obtain a function for the wage demanded by firms.

$$w^D = \frac{A}{\rho HHI + 1} \tag{4.6}$$

The latter is the Herfindahl-Hirschman index measuring concentration in the labor market. The equation explains that, given the monopsonistic power of firms, the wage paid is decreased by $(\rho HHI + 1)$. When the market is perfectly competitive, then $HHI = 0$ and workers are paid at their marginal productivity. This is the traditional insights provided by industrial economists to show the presence of a markdown in wages in labor market. Also, as in Azar et al. (2019), eq. 4.6 implies that $\rho \propto HHI$. So an increase in HHI reduces ϵ and increases ρ. So, a change in HHI affects ρ positively and wage negatively.

The equilibrium employment in the oligopolistic labor market is obtained through equalization of demanded and supplied wage Equalizing eq. 4.6 to eq. 4.3 and multiplying both sides for the specialization index:

$$L^* = \left[\frac{A}{\rho HHI + 1}\right]^{1/\rho}\phi_j^\theta \tag{4.7}$$

4.2.3 Parametric external economies in the case of monopsony in the labor market

Assumption 4. External economies are of the form proposed by Chipman (1970).

His concept was based on the traditional hypothesis of increasing returns stemming from increas-

ing division of labor in a given industry. It can be developed analytically as:

$$A = L^{\gamma}$$

The main idea is that when a particular firm, say i, in an industry, say j, expands its production, some of the work it relies on can be divided. In turn, such a division of labor creates special skills that become available in the labor market. These generate external economies in the form of 'specialized skills' for other firms $(i-)$ entering the same labor market of firm i. This hypothesis can be referred to as 'labor pooling'. In the static setting of the model proposed here, the productivity shifter A is equal to:

$$A^{\frac{\rho-\gamma}{\rho}} = \left[\frac{1}{\rho HHI + 1} * \phi_j^{\rho\theta}\right]^{\gamma/\rho}$$

That, since $\ln(1 + \rho HHI) \simeq \rho HHI$, and log-transforming, is:

$$\begin{aligned} \ln A &= \left(\theta\rho\frac{\gamma}{\rho-\gamma}\right)\ln(\phi) + \left(\frac{\gamma}{\gamma-\rho}\right)\ln(1+\rho HHI) \\ &= \left(\theta\rho\frac{\gamma}{\rho-\gamma}\right)\ln(\phi) + \left(\rho\frac{\gamma}{\gamma-\rho}\right)HHI \end{aligned} \tag{4.8}$$

The model suggests the existence of a relationship between productivity, specialization, and competition. In particular, it suggests that if the effect of specialization is positive, then the effect of competition (by reducing HHI) should also be positive, assuming $\theta > 0$. On the other hand, if θ is equal to zero, the productivity shifter depends positively only on competition. However, θ is defined in the equation 4.2 as:

$$\theta = \delta_0 + \delta_1(1 - HHI)$$

by replacing eq. 4.2 into eq. 4.8, I get

$$\ln A = \alpha \cdot \ln\phi + \beta \cdot HHI + \xi \cdot \ln\phi \cdot (1 - HHI) \tag{4.9}$$

where:

$$\begin{aligned} \text{Elasticity of industry size :} \quad & \alpha = \rho\frac{\gamma}{\rho-\gamma}\delta_0 \\ \text{Elasticity of competition :} \quad & \beta = \rho\frac{\gamma}{\gamma-\rho} \\ \text{Elasticity of the interaction :} \quad & \xi = \rho\frac{\gamma}{\rho-\gamma}\delta_1 \end{aligned} \tag{4.10}$$

The three coefficients (α, β, ξ) that are estimated in the econometric parts result from:

- ρ captures the inverse elasticity of labor supply with respect to wage. It is a parameter that introduces the effect of monopsonistic power into the model.
- δ_0 captures the elasticity of labor supply with respect to industry size when the local industry is perfectly competitive ($HHI \to 0$).
- δ_1 captures how much competition affects the elasticity of labor supply to industry size.
- γ represents the degree of increasing returns at the local industry level.

Low levels of competition for labor are detrimental to worker mobility. When competition is high, workers can move between firms in the same industry in the region, bringing with them their 'specialized skills' as in Chipman (1970).

4.2.4 Intuition and testable predictions

When workers have a preference for large and competitive industries, and competition in the labor market between firms is regulated à-la Cournot, there are external economies similar to those proposed by Chipman (1970). These arise when there are large oligopsonistic labor markets with high levels of competition. In the region, they spread through the labor market, within the industry to which firms belong, but not *between industries*. However, the definition of industry is particularly fuzzy in this case. As total industry output expands, tasks are divided, new specialized skills emerge, and through the movement of workers between firms, new knowledge is acquired for the firms that belong to the industry. The extent to which specialized tasks that workers learned in their previous occupation can be transferred to different industries is an empirical question. In what follows, I try to focus on these two issues.

Implication 1 *The effect of specialization on productivity is positive when there is strong competition in the local labor market.* To deal with this, I estimate two main coefficients of

interest, α and ξ, the latter being the effect of competition (HHI) on external economies (A) via specialization (ϕ).

Implication 2 *The effect of local specialization on productivity varies with the industry scope of external economies.* To test this, I look at different definitions of industry to show how the results are sensitive to them. In general, the larger the industry scope, the larger the productivity gains from considering a large set of manufacturing industries.

4.3 Model and identification

Based on the theoretical foundation of the study, this paper looks at:

- The effect of specialization (α) on local industrial total factor productivity (LITFP).
- The moderating role of competition on the effect of specialization on LITFP (ξ).
- The proper unit of analysis for measuring external economies in the labor market.

In order to test these, this paper must address several endogeneity concerns. I use micro data to deal with two main sources of endogeneity: first, simultaneity in the choice of inputs in estimating TFP; second, endogeneity in the effect of specialization on TFP. I follow the method of Combes et al. (2010) and Combes and Gobillon (2015), which is a two-step procedure. In the first step, I estimate an unbiased measure of TFP using various methods such as those developed by Levinsohn and Petrin (2003) and Wooldridge (2009). In a second step, I regress this unbiased measure of TFP on measures of specialization and competition. Remaining concerns about the 'endogenous quantity of labor' are addressed by using an instrumental variable technique in the style of Combes et al. (2010).

4.3.1 First step: LITFP estimation

The literature on estimating the production function has recently made important advances (Olley and Pakes, 1996, Levinsohn and Petrin, 2003, Wooldridge, 2009, Rovigatti and Mollisi, 2018). It has a long tradition in economic studies, and the main problem identified in the literature is that labor, capital, and other inputs can be chosen by firms in response to current and past shocks to their own productivity (see Wooldridge, 2009 for an analytical exposition). The solution presented by several authors is to use proxies for unobserved time-varying productivity. Olley and

Pakes (1996) claim that productivity can be expressed as a function of capital and investment in a two-step procedure. Similarly, Levinsohn and Petrin (2003) suggest that an alternative proxy is the use of intermediate inputs. More recently, Wooldridge (2009) has shown that the same complex estimation procedure used in Levinsohn and Petrin (2003) can be accomplished using a GMM estimation procedure and only two lines of Stata code (Petrin & Levinsohn, 2012). I use several methods to compute LITFP. Among them, the preferred estimator is a version of the Wooldridge-Levinsohn-Petrin (hereafter WLP) estimator provided in Petrin and Levinsohn (2012).

Let us consider a production function such as

$$\ln VA_{it} = \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \epsilon_{it} \tag{4.1}$$

where VA_{it} is value added, L_{it} is the vector of free variables (labor), K_{it} is the vector of state variables (capital); ϵ_{it} is the residual that can be used as a proxy for TFP. The first measure of TFP that I use is obtained as follows:

$$TFP_{it}^{OLS} = \epsilon_{it} \tag{4.2}$$

and then averaged over local industries

$$TFP_{rst}^{OLS} = \frac{1}{n_{rst}} TFP_{it}^{OLS} \tag{4.3}$$

where r refers to a generic local market area (LMA) and s refers, here, to a 3-digit manufacturing industry, t is time, i refers to a generic firm in region r and industry s, n is the number of firms within each local industry.

This measure is biased if input choices are related to past and current productivity shocks. When simultaneity exists but does not differ across areas, an OLS estimate of TFP on local industry characteristics is unbiased. On the other hand, as highlighted by Combes et al. (2010), if such simultaneity differs across areas, an OLS estimate of TFP on local characteristics in the second stage might be endogenous. Thus, I use the Levinsohn and Petrin (2003) method that proxies for unobserved productivity shocks with intermediate inputs. In this way, I deal with endogeneity in the choice of inputs. I then extrapolate the residual ϵ_{it}^{LP} from the LP method

and average it across years, LMAs, and industries:

$$TFP_{rst}^{LP} = \frac{1}{n_{rst}} \epsilon_{it}^{LP} \tag{4.4}$$

Third, I use the WLP method, which, like the LP method, proxies for unobserved shocks with intermediate inputs, but uses an efficient GMM procedure to estimate the residuals ϵ_{it}^{WLP}. Thus, local industry time-varying TFP is equal to

$$TFP_{rst}^{WLP} = \frac{1}{n_{rst}} \epsilon_{it}^{WLP} \tag{4.5}$$

All versions of TFP obtained by the estimation techniques developed above are logarithmic.

4.3.2 Further endogeneity concerns

According to Combes et al. (2011), there are two main other sources of endogeneity when trying to identify the effect of local characteristics on wages and/or TFP.

Endogenous quality of labor

It occurs when the productivity of own firms as well as that of workers is a consequence of local own industry size due to sorting (Combes et al., 2008). For example, the presence of industrial schools, which shape entrepreneurial skills as well as worker productivity, can influence average productivity levels, as in the case of the silk industry in Como and the shoe industry in Vigevano (see Merlo et al., 2009). An alternative explanation for the movement of firms and workers into larger local industries is their preference for highly concentrated industries, leading to the presence of local industry-specific amenities. Also, skilled workers may benefit more from the density or local concentration of industries because of their learning potential. In this case, the traditional way to deal with the problem is to include local fixed effects in the estimation. However, as shown by Combes et al. (2011), they do not deal with missing other local characteristics that vary over time, such as the development of specific local (industrial) public goods as well as airport and railway lines that affect or improve the performance of firms and workers. Consequently, the inclusion of local industry fixed effects may bias the estimation more than their exclusion.

Combes et al. (2010) and Combes et al. (2011) propose to include a time-varying version of the fixed effect directly in the estimation of the production function. In this way, it allows

unobserved local industry characteristics to vary over time, including that changes eventually bias the results, such as the construction of railroads. Accordingly, I impose such condition to obtain the previously described production function:

$$\ln VA_{it} = \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \epsilon_{rst} + \epsilon_{it} \tag{4.6}$$

where ϵ_{rst} is the vector of local industry time-varying fixed effects. I run the regression and save the coefficients of ϵ_{rst} from an OLS regression obtained:

$$\eta^{OLS}_{rst} = \epsilon^{OLS}_{rst} \tag{4.7}$$

and by a GMM estimation in the vein of WLP (Petrin & Levinsohn, 2012):

$$\eta^{WLP}_{rst} = \epsilon^{WLP}_{rst} \tag{4.8}$$

This procedure allows to take care of endogeneity concerns due to labor quality. As above, its values are in logarithms.

At this point, I have shown all the metrics used as dependent variables. They fall into four groups: 1) robust to endogenous labor quality and simultaneity in input choice (η^{WLP}), 2) robust to endogenous labor quality but not to simultaneity (efficient if simultaneity does not change across LMAs) (η^{OLS}), 3) robust to simultaneity but not to endogenous labor quality (TFP^{LP}; TFP^{WLP}), 4) neither robust to simultaneity nor to endogenous labor quality (TFP^{OLS}) (see table 4.1). My preferred dependent variable is η^{WLP}.

Table 4.1: **Metrics for TFP**

	Simultaneity	**Quality of Labor**	**S + QoL**	**None**
Dep. Variables	TFP^{WLP}; TFP^{LP}	η^{OLS}	η^{WLP}	TFP^{OLS}

Note. All the variables are in log. S + QoL stands for simultaneity and endogenous quality of labor.

Endogenous quantity of labor

A specialization index can be correlated with local industry fixed characteristics, such as proximity to watercourses, endowment of natural resources, or the development of specific local quasi-public goods, as in the case of ICT in industrial districts presented by Bellandi (2006). The

exploitation of these fixed characteristics can give the local industry advantages in production over industries located elsewhere. In this case, identification issues arise due to omitted variable bias. In addition, reverse causality occurs because higher levels of productivity can attract more firms interested in taking advantage of the external economies present in the local industry. The presence of certain local industry characteristics that make it more productive may be correlated with those that make it more spatially concentrated. For example, the land market may introduce bias in this case since the presence of amenities attracts more firms, which in its turn increases land prices. Higher land prices favor strategies aimed at reducing the optimal level of land. This, in turn, decreases the marginal product of labor and TFP. As previous literature has highlighted, the standard approach to dealing with the 'endogenous quantity of labor' is to adopt an instrumental variable.

Instrumenting using soil productivity data The remaining endogeneity concerns relate to the quantity of labor, which is due to 2 main factors:

- **Omitted variable bias**, which occurs when some other missing local industry characteristics affect both productivity and local industry size;
- **Reverse causality** due to the fact that more productive industries attract more firms and workers, making them larger.

To deal with them, it is possible to use an instrumental variable approach. This alleviates endogeneity concerns regarding the quantity of labor. A good instrument must satisfy: 1) the *relevance* condition, which can be tested using 1st stage F-statistics and requires the instrument to be highly correlated with the main independent variable (specialization)[4]. 2) The *exclusion* restriction, i.e. that the instrument z affects Y (LITFP) only through the main independent variable (specialization). The latter cannot be tested.

For this reason, I use two different tools that exploit insights from the previous literature. Similar to Combes et al. (2010), I use data on soil productivity. The two instruments used are:

- an index of *cropland productivity*;
- an index of *grassland productivity*.

They are *relevant* to the extent that they correlate with the location of historical (industrial) settlements. This is corroborated by results in appendix, table A.1. On the one hand, fertile

[4]In appendix B, table A.1 show how relevant are instruments in predicting specialization.

soils are expected to have influenced the location pattern of the population when agricultural surpluses allowed for the cycle of economic expansion. More fertile land facilitated the generation of surplus. On the other hand, it is less plausible that the actual productivity of land influenced the expansion and productivity of manufacturing. Moreover, there is a certain persistence in data on soil fertility that allow to measure historical trends (Combes et al., 2010). The instruments used together can predict different mechanisms that may affect the historical location of the industry based on dependency dynamics. This allows testing for over-identification.

4.3.3 Second step: Estimation on local and industrial characteristics

In the second step, I use the 5 measures of local industrial TFP (see table 4.1) to estimate a model including local and industrial characteristics. I estimate two main variants of the same model. The first is a model including the main variables of interest (specialization and competition):

$$\ln TFP_{rs} = \boldsymbol{\alpha} \cdot Specialization_{rs} + \beta \cdot Competition_{rs} + \gamma \cdot \boldsymbol{X} + \rho_s + v_{rs} \tag{4.9}$$

while the second also includes an interaction term:

$$\ln TFP_{rs} = \boldsymbol{\alpha} \cdot Specialization_{rs} + \beta \cdot Competition_{rs} + \boldsymbol{\xi} \cdot [Spec \cdot Comp]_{rs} + \gamma \cdot \boldsymbol{X} + \rho_s + v_{rs} \tag{4.10}$$

The used dependent variables for $\ln TFP_{rs}$ are all those in table 4.1. The model estimates the effects of:

$$specialization = \ln n_{rs}$$

where n is the number of plants in each 3-digit local industry.

$$Competition = HHI_{rs} = \sum_{i \in rs} \left[\frac{e_i}{\sum_i e_i} \right]^2$$

where HHI is the Herfindal-Hirschman index for competition, $0 < HHI < 100$, and $HHI \to 0$ means high competition while $HHI \to 100$ means monopoly. Here, i refers to plants.

A vector of control variables ($\boldsymbol{X}$) that include: average size of plants in the local 3-digit industry, the surface of LMAs, since large manufacturing industries can be found in large areas; average level of human capital in 2011 - the only available data for LMAs - computed as the population share of tertiary educated people, higher education can be an additional source of external economies (Moretti, 2004), the total number of local manufacturing employees. All

variables are averaged over time to partial out time effects and to allow identification through the time invariant instrumental variables. The main variables are at the local 3-digit industry level. Local refers to LMAs and 3-digit refers to manufacturing. The area of the LMAs as well as human capital and total employment vary at the level of each LMA.

Endogenous interaction term

At this point, a final endogeneity concern remains. The interaction term between the endogenous variable *specialization* and the assumed exogenous variable *competition* is also endogenous. In order to measure a heterogeneous effect of specialization according to the level of competition, I need to include another instrument for the interaction term. As highlighted by Wooldridge (2010), a minimum approach in this case is to include the interaction between the instrument and the exogenous variable as an additional instrument. Then I include two more instruments that are the interactions between competition with the indices of soil productivity.

4.4 Data

To estimate the two-step procedure, I used several sources of data. First, I used a firm-level dataset (AIDA) from Boureau Van Dijk, which contains accounting data for a sample of Italian firms. I focused only on the manufacturing sector because it is more prone to clustering (Ellison & Glaeser, 1997). I have data for about 200k firms, each of which is paired with its location (municipality). It is important to note that a municipality is the minimum administrative division of the territory. I am interested in local labor market competition, so I choose the local market area as the main geographic unit (Sforzi et al., 1991). These are socio-economic geographical units calculated by Istat using data on commuting flows. Each LMA is able to self-contain social and economic relationships, and it is composed of several municipalities. I observe the 5-digit Ateco sector, value added, number of employees, capital, wage bill, and intermediate inputs for nine years (2012-2020).

Secondly, I used a confidential dataset obtained directly from Istat at the Adele Laboratory (Laboratorio Adele) to calculate indices of specialization and competition in the labor market. The database used for the analyses is called 'Asia local units register' (Registro Asia unità locali) and all the calculations were carried out at the laboratory to ensure the protection of privacy and personal data. The ASIA dataset provides information on employees at the establishment level, while the AIDA dataset provides information at the firm level. By using ASIA, it is possible to

consider multi-level and multi-location firms, as well as plants of foreign firms located in specific areas and industries. To harmonize information from the two datasets, I sum employees and plants at the level of LMAs and 3-digit Ateco industry. Third, data provided by the European Soil Data Center (ESDAC) were used. The dataset includes several GIS maps containing indices for soil productivity in the European Union (Panagos et al., 2012). I leverage on soil and grassland productivity. The mean of this two soil productivity indices within the Italian LMAs unit of analysis was calculated using zonal statistics, averaging punctual observations within each LMA. Fourth, I use Istat data on the municipal area[5] to have the surface of the LMA, and to obtain the average level of human capital.

4.5 Results

Table 4.2 reports OLS regressions including specialization from column (1), competition in column (2), and all controls in column (3). Column (4) estimates the unconditional linear constant effect of specialization on LITFP using the soil productivity index. Column (5) uses the grassland productivity index, and column (6) uses both. This addresses endogeneity issues due to the 'quantity of labor'. Column (7) estimates the conditional - on control variables - constant and linear effect of specialization on LITFP. Column (8) estimates the interaction term using all instruments and including all control variables.

Columns (1) and (2) show positive and statistically significant coefficients for specialization. The effect of competition is positive and statistically significant in column (2), implying that lower levels of competition increase LITFP. The coefficient obtained for specialization is upward biased because the 'endogenous quantity of labor' bias is still present. Column (3) adds all control variables. The resulting coefficient for specialization and competition becomes statistically insignificant. Column (4) suggests a positive and statistically unconditional effect of specialization on LITFP when using soil productivity to predict specialization. On the other hand, column (5) suggests a not statistically significant result for specialization. In column (6), the use of both instruments suggests a positive and statistically significant result for specialization. The effect of specialization is reduced with respect to that in column (4) due to the inclusion of the additional instrument of grassland productivity. In column (7), once all control variables and the index of competition are included, I find a negative and statistically significant effect for specialization. Rather, the effect of competition is now negative and statistically significant, suggesting that

[5]available at https://www.istat.it/it/archivio/156224

Table 4.2: **Effect of 3-digit specialization, competition and their interaction on LITFP**

	Baseline Results: η^{WLP}			**Instrumental Variable**: η^{WLP}				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specialization	0.015***	0.021***	0.005	0.154***	0.023	0.125***	-0.601***	-0.249
	(0.004)	(0.005)	(0.006)	(0.036)	(0.036)	(0.032)	(0.196)	(0.169)
Competition		0.001**	-0.001				-0.021***	0.069**
		(0.000)	(0.000)				(0.006)	(0.034)
Spec · Comp								-0.031**
								(0.013)
Control Variables			✓				✓	✓
Instrumental Variables				Soil	Grass	Both	Both	Both+Int
Ateco-3 FE	✓	✓	✓	✓	✓	✓	✓	✓
Metropolitan areas FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	6,898	6,898	6,888	6,895	6,376	6,373	6,363	6,363
1st Stage F-stat				156.91	96.49	89.70	10.00	6.79
Hansen J-Stat						[0.00]	[0.62]	[0.71]

Notes. The main dependent variable is η^{WLP} from columns 1 to 9. The independent variable for specialization is the total number of plants in the 3-digit local industry, while the variable for competition is the $HHI \cdot 100$, where 0 stands for *perfect competition* and 100 for *monopoly*. Columns (1) through (3) show the baseline results. In column 3, the average level of human capital-measured as the ratio of tertiary-educated population to total population in the LMA, the area of the LMA, the average size of plants in the relative 3-digit local manufacturing industry, and the total number of employees in local manufacturing are added as control variables. Their coefficients are not reported. Column (4) includes land productivity, column (5) includes grassland productivity, and column (6) includes both as instruments for the main measure of specialization. Column (8) also includes the interaction between the two instruments and the HHI. They are described in section 4.3.2. All control variables are logarithmic. The instruments are standardized to better interpret the first stage results. The reported statistics are 1st stage and Hansen-J statistics. The former is a statistic for instrument weakness, the latter for over-identifying restrictions. P-values are in brackets, standard errors in parentheses. Standard errors are clustered at the level of each 3-digit industry in each LMA.
*** p<.01, ** p<.05, * p<.1

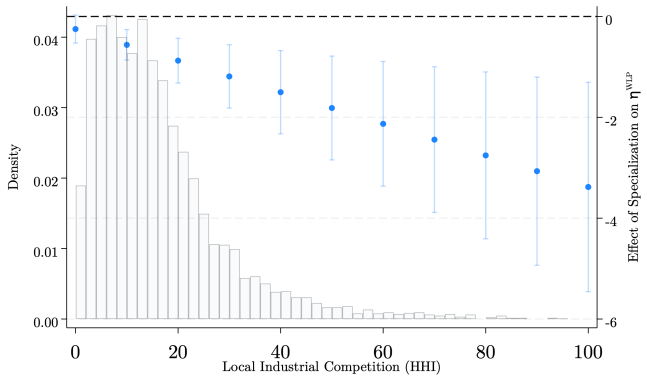
highly competitive local industries have, on average, high levels of LITFP. Finally, column (8) estimates the effect of the interaction between competition and specialization. The effect of specialization when competition is 0, i.e. a kind of 'perfect local competition', is not statistically significant. The effect of competition is positive and statistically significant when specialization is equal to 0 (only 1 plant in the local industry). The interaction term (Spec · Comp) indicates a negative and statistically significant result.

To facilitate the interpretation of such a result, figure 4.2 plots the marginal effect of specialization at different levels of competition. The effect is not statistically different from 0 when the HHI for competition is 0 ('perfect competition'). However, competition moderates this relationship, suggesting a negative trend. The negative trend suggests that for a given level of specialization, a decrease in the level of competition leads to negative externalities. Overall, the results suggest that

1. The effect of specialization is never positive, regardless of the level of competition.

2. Competition moderates the effect of specialization on LITFP: specialization in 3-digit industries with high levels of competition produces no positive externalities, while special-

Figure 4.2: **Effect of 3-digit industry specialization on LITFP**



Notes. It plots the estimated coefficient of the interaction term between competition and specialization from column 8 of table 4.2. It shows the effect of specialization and the associated confidence interval (90%) at different levels of competition. It also plots the distribution of the variable HHI for competition to understand how many observations are behind the estimate in each bin.

Source. My own elaboration on the Asia and Aida data.

ization in 3-digit industries with low levels of competition produces negative externalities.

The results are also strongly confirmed using different dependent variables (see appendix C, table A.2) and different independent variables (see appendix C, table A.3). Figure A.5 tests the robustness of 3-digit specialization trend.

4.5.1 Manufacturing as an industrial unit of analysis

In summary, the previous table suggests that the effect of 3-digit industry specialization on LITFP is negative when controlling for the average level of competition. There are both theoretical and empirical reasons for this. On the one hand, as shown in the theoretical model, this happens when θ is negative, meaning that workers do not necessarily prefer to work in a 3-digit industry that is highly concentrated geographically. This also depends on the assumption of the econometric model, i.e. that labor pooling only works within the same strictly defined 3-digit industry, and this implies that broadly defined *manufacturing* workers are weak substitutes. This means, for example, that switching a textile worker from weaving to finishing is costly. Accordingly, labor pooling and knowledge spillovers are expected to operate only within the same 3-digit industry. Also, the moderating effect of competition is as expected by the model in section 4.2. However, given these limitations, in what follows I try to relax the econometric assumption of

the model. Thus, I assume that workers can move freely (since they are substitutable) between different industries in the manufacturing sector.

Therefore, I focus on manufacturing as a whole rather than on a specific 3-digit industry. Regarding LITFP, this is the same measure that has been used previously at the LMA and 3-digit industry level. Rather, the measure used for specialization is an index of specialization of total manufacturing. Referring to the model in section 4.3, the index ϕ now no longer refers to a specific 3-digit industry, but to the manufacturing sector. This means that workers offer their labor elastically with respect to the size of manufacturing. This allows for movement between different manufacturing industries. To measure this, I use a specialization index for manufacturing as the total number of manufacturing establishments:

$$Specialization_{r(-s)} = \ln (n_r - n_{rs}) \tag{4.1}$$

where r is a generic LMA, and the difference between the first term n_r and the second term n_{rs} is an index of specialization for each 3-digit manufacturing sector s due to the number of other manufacturing industries $(-s)$ present in the LMA. So here I look at the effect of specialization in other $-s$ manufacturing industries on $LITFP_{rs}$. This measure, like the 3-digit industry measure, shows the size of the total manufacturing sector in each LMA. However, it is able to exclude its own industry from the estimation, thus generating a region-industry varying variable that measures how the external context affects 3-digit industry productivity (LITFP).

In the model, I also show that the level of competition is a factor that needs to be included in workers' preferences for specialization. In this case, I average the HHI for competition across all manufacturing industries s:

$$Competition_r = HHI_r = \frac{1}{m_r} \sum HHI_{rs} \tag{4.2}$$

where m_r is the number of 3-digit manufacturing industries in manufacturing and LMA r. If the assumption of weak substitutability of labor across manufacturing industries is relaxed to the point that it is costless to move a worker between 3-digit manufacturing industries, then there is no reason to continue using a 3-digit index of competition. Here I use an average local manufacturing competition index as Combes et al. (2012).

Table 4.3 is symmetrical to table 4.2. It looks at the effect of manufacturing specialization as a whole on each 3-digit industry that constitutes it. As before, it examines the role of the

Table 4.3: **Effect of manufacturing specialization, competition and their interaction on LITFP**

	Baseline Results: η^{WLP}			**Instrumental Variables**: η^{WLP}				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specialization	0.001	0.003	-0.007	0.078***	0.012	0.064***	0.067***	0.109***
	(0.004)	(0.004)	(0.005)	(0.018)	(0.019)	(0.017)	(0.026)	(0.040)
Competition		0.004***	0.003**				0.005***	0.031**
		(0.001)	(0.001)				(0.001)	(0.015)
Spec * Comp								-0.004*
								(0.002)
Control Variables			✓				✓	✓
Instrumental Variables				Soil	Grass	Both	Both	Both+Int
ATECO-3 FE	✓	✓	✓	✓	✓	✓	✓	✓
Metropolitan Areas FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	6,890	6,890	6,880	6,888	6,369	6,367	6,357	6,357
1st Stage F-stat				337.79	225.15	181.08	115.67	60.22
Hansen J-Stat						[0.00]	[0.00]	[0.00]

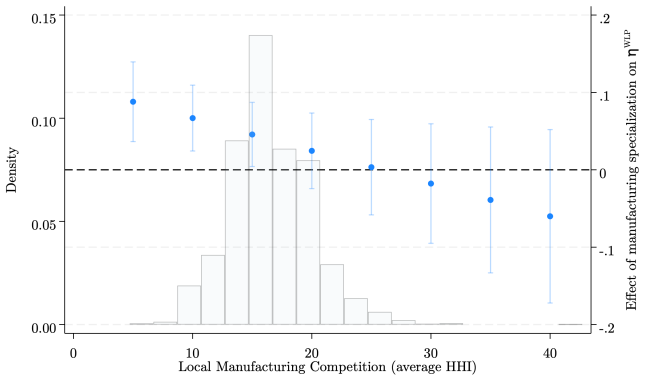
The main dependent variable is η^{WLP}. The main independent variable for specialization is the total count of plants in LMA r minus industry j. Columns 1 to 3 show baseline results. In column 3, the average level of human capital - measured as the ratio between tertiary educated population over the total population of the LMA, the surface of the LMA, the average plants' size in the relative 3-digit local manufacturing industry, and the total number of employees in each local 3-digit industry are added as control variables. Their coefficients are not reported. Symmetrically to table 4.2, column 4, 5 and 6 add the instruments for the main measure of specialization. Variables are transformed as in table 4.2. The HHI for competition is measured in level (0-100) where 0 means 'perfect competition' and 100 'monopoly'. It is the total average across all the 3-digit local industries. Reported statistics are 1st stage and Hansen-J statistics. P-values are in square bracket, standard errors in parentheses. Standard errors are clustered at the 3-digit local industry.
*** p<.01, ** p<.05, * p<.1

interaction between local manufacturing competition and specialization. It also takes care of endogeneity concerns regarding both metrics, using the same instrumental variables described in section 4.3.2. The weakness of the instruments is captured by the first stage F-statistics presented.

Columns (1) to (3) report the basic results. The effect of specialization is always not statistically different from 0, while competition is positive and statistically significant. Columns (4) to (6) report the estimated unconditional coefficient on specialization. The effect is positive in column (4), not statistically different from 0 in column (5), and positive and statistically significant in column (6). Column (7) adds all the control variables and the result is still positive and statistically significant, while that of competition is positive and statistically significant. The positive effect of HHI for competition suggests that an increase in competition reduces LITFP. The positive effect for specialization suggests that a 1 p.p. increase in total manufacturing specialization generates a 0.067 p.p. increase in each local 3-digit LITFP. Results are strongly confirmed also using different dependent variable (see Appendix D, table A.4) and different independent variables (see Appendix D, table A.5).

Finally, column (8) reports the coefficients of the interaction term. The effect of the inter-

Figure 4.3: **Effect of manufacturing specialization on 3-digit LITFP**



Notes. It plots the estimated coefficient of the interaction term between competition and specialization from column 8 of table 4.3. For further information, see notes to figure 4.2.

Source. My own elaboration on Asia and Aida data.

action is negative and statistically significant. The effect of specialization is now positive and stronger than before (when HHI for competition is 0 - 'perfect competition'), and competition is positive when specialization is 0 (only 1 plant in all other 3-digit manufacturing industries). To visualize the interaction term, I plot the marginal effect of specialization at different levels of competition in figure 4.3. The effect of specialization is higher when competition is very high (close to 0) and not statistically different from 0 when competition is lower (around values higher than 16). This suggests that high levels of competition in the broadly defined manufacturing sector are a prerequisite for external economies of specialization. Figure A.6 tests the robustness of the manufacturing specialization trend.

4.5.2 Fine tuning of the correct unit of analysis

In this section, I exploit the idea that workers can move between different industries to test the robustness of my previous estimates. First, I use the dataset developed by Neffke et al. (2017) to examine the empirical flows of workers between different industries. In this dataset, a measure of skill relatedness is provided for each pair of 3-digit industries. In the case of manufacturing, the Swedish Standard Industrial Classification coincides with Nace Rev. 2. As for SNI, the Ateco codes for manufacturing coincide with the Nace Rev. 2 classification. Then I can easily merge the two datasets, the one provided by Neffke et al. (2017) and the one I have used so far. However, before doing so, I have to create a new dataset, starting from the one obtained by 'Laboratorio

Adele Istat', in which I couple each local 3-digit industry with all the other local 3-digit industries. In this way, the ID of the dataset is the pair of each 3-digit manufacturing industry within each LMA. I then merge the two datasets, and I obtain a measure of skill relatedness for each local 3-digit by averaging the measure provided by Neffke et al. (2017).

To compute the skill relatedness for a given LMA r and a 3-digit industry, say y, I use a weighted average of the relatedness measure provided by Neffke et al. (2017) between each pair of industries x and y within each LMA. The weights are based on the employment figures in each industry x within the LMA r. The intuition is that, given the flows between each pair of 3-digit industries, 3-digit industries located in LMAs where there are many 'related' industries, i.e. whose skill demand is very similar (high levels of $Relatedness_{xy}$), will have a higher value of the skill relatedness measure. The formula is given by:

$$Skill\ Relatedness_{ry} = \frac{\sum_x e_{rx} \cdot Relatedness_{xy}}{\sum_x e_{rx}} \tag{4.3}$$

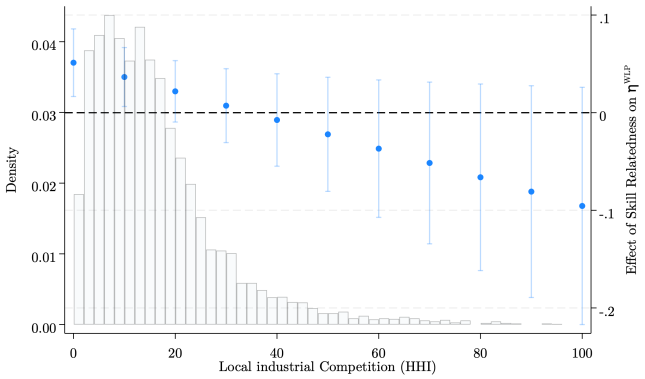
Where $Relatedness_{xy}$ is the measure of relatedness provided by Neffke et al. (2017) between industries x and y. e_{rx} is the number of employees in industry x within LMA r. This approach allows for the calculation of an LMA-specific measure of skill relatedness for each 3-digit industry y, taking into account the distribution of employment across industries within each LMA. The main assumption is that the flow of labor between industries is the same in Sweden and Italy, or more weakly, that the Swedish labor flows between each pair of industries can proxy the same flow for Italy. In table 4.4, I provide the results of the estimation using this measure.

Table 4.4: **Effect of skill relatedness, competition and their interaction on LITFP**

	Main Results				**Robustness check**			
	(1) η^{WLP}	(2) η^{WLP}	(3) η^{WLP}	(4) η^{WLP}	(5) TFP^{OLS}	(6) η^{OLS}	(7) TFP^{LP}	(8) TFP^{WLP}
Skill Relatedness	0.052***	0.051***	0.029	0.051**	0.027	0.030*	0.032*	0.052***
	(0.017)	(0.017)	(0.018)	(0.021)	(0.018)	(0.016)	(0.018)	(0.019)
Competition		0.000	-0.001*	-0.001	0.000	-0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Skill Rel * Comp				-0.001*	-0.001	-0.001	-0.001	-0.002**
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Control Variables			✓	✓	✓	✓	✓	✓
ATECO-3 FE	✓	✓	✓	✓	✓	✓	✓	✓
Metropolitan Areas FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	6,898	6,898	6,888	6,888	7,845	7,060	7,845	7,845

The main dependent variable is η^{WLP} in columns 1 through 4. Column (5) uses TFP^{OLS}, column (6) uses η^{OLS}, column (7) uses TFP^{LP}, column (8) uses TFP^{WLP}. See section 4.3.2 for details. The main independent variable is the weighted index of skill relatedness obtained from Neffke et al. (2011) between Italian 3-digit industries. From column 3, the average level of human capital - measured as the ratio between the tertiary educated population and the total population of the LMA, the surface area of the LMA, the average size of the plants in the local 3-digit manufacturing industry and the total employment in the manufacturing LMA are added as control variables. Their coefficients are not reported. All control variables are in logarithmic form. The HHI is measured in levels (0-100), where 0 indicates perfect competition and 100 indicates monopoly. Standard errors are in parentheses and clustered at the 3-digit local industry level.
*** p<.01, ** p<.05, * p<.1

Figure 4.4: **Effect of skill relatedness on 3-digit LITFP**



Notes. It plots the estimated coefficient of the interaction term between competition and specialization from column 8 of table 4.4. For further information, see notes to figure 4.2.

Source. My own elaboration on Asia and Aida data.

Table 4.4 has a different structure than the previous ones. Since no instruments are available for the measure of skill relatedness, I basically run the cross-sectional regression using different measures of LITFP. Columns (1) to (4) report the main results. Columns (5) to (8) use the different measures of LITFP to test the robustness of the results. The effect of specialization is positive and statistically significant in columns (1), (2), and (4). It is not statistically significant in column (3), which does not include interactions but does include control variables. The HHI for competition is negative and statistically significant in column (3). In column (4), when I add the interaction term, the result for competition is not statistically significant, while that for skill relatedness is positive and statistically significant. Again, this result needs to be interpreted in light of the interaction. Thus, the effect of skill relatedness is positive when HHI for competition is 0 - the situation of 'perfect competition' - and decreases as HHI for competition increases towards 'monopoly'. Figure 4.4 plots the marginal effect of skill relatedness at different levels of competition. It confirms the previous results. High levels of competition are necessary to enjoy external economies in the labor market due to labor flows (*Labor Pooling* and *knowledge spillovers*). In this case, the threshold above which external economies disappear in the labor market is $HHI = 14.5$.

Columns (5) to (8) confirm the results of column (4). The interaction term is always negative, although not statistically significant. Skill Relatedness is always positive, but in column (5), suggesting that the result is particularly robust to different measures of LITFP. Competition is

always statistically insignificant. In general, the results confirm that the movement of workers between firms in related industries depends on the substitutability of specialized tasks and that a high level of competition is a necessary condition to benefit from external economies in the local labor market. See also Figure A.7 to check the robustness of the results according to the estimation in columns (5) to (8).

4.6 Conclusive remarks

This paper begins with a discussion of the possibility to explicitly include competition in a model of parametric external economies in order to bridge the empirical literature on external economies with traditional economic theory. Section 4.2 shows that this is possible, and that strong local competition and preference for large and expanding industries are prerequisites. The idea is that as an industry expands, tasks become specialized. These specialized skills spill over into the labor market of the same industry, allowing local firms to enjoy productivity gains. There is one major issue that arises from the model, and that is the definition of industry. This issue has been at the core of the considerations of Giacomo Becattini, who changes the unit of analysis from the sector to the industrial district (the main local industry) (Becattini, 1962; Becattini, 1979; Becattini, 1989). This is because the model requires a geographic component to capture the movement of workers and an industrial component that measures the substitutability between tasks in different industries. I draw on his approach by addressing the problem from the perspective of local industry. However, this paper focuses specifically on one of the sources of external economies, namely those arising in the labor market (*labor pooling* and *knowledge spillovers*).

In the second part of the paper I test the predictions of the model. The results are consistent with the theoretical predictions and provide some results regarding Italian manufacturing, productivity and the unit of analysis. In this case, the contribution of the paper stems from the methodological side. In comparison with previews studies in which 'the MAR-Porter vs Jacobs' debate was addressed, here I add an interaction term between the index of specialization and competition. In this way, the model is able to look at the effect of specialization at different levels of competition. A synthesis of the results suggests that:

1. Given the average level of competition, regions with a high degree of specialization in a single 3-digit industry tend to have lower average TFP in that industry (see table 4.2, column 7).

2. Competition moderates this relationship; however, even when competition is very fierce ($HHI = 0$, as in 'perfect competition'), the result for external economies of specialization is 0 (see figure 4.2). The results depend on the choice of 3-digit industries, since *labor pooling* and *knowledge spillovers* can only take place within the same 3-digit industry.

3. When I deal with broadly defined manufacturing specialization, the coefficient of specialization becomes positive at average levels of competition (see table 4.3, column 7). This is because the model is now able to account for labor flows between different 3-digit industries in manufacturing.

4. Again, competition moderates this relationship. The larger coefficient of specialization is obtained when competition is fierce ($HHI = 0$, 'perfect competition') and decreases to zero as HHI increases towards 'monopoly'. I find a threshold above which externalities disappear in the labor market, equal to $HHI \geq 15.8$ (see figure 4.3).

5. Because the result for manufacturing may account for phenomena other than those in the labor market, I also test the robustness of this result using a measure of skill relatedness.

    5a. I find that the movement of workers across firms and industries has no effect on LITFP at the average level of competition (see table 4.4, column 4).

    5b. Though, competition moderates this relationship, and a positive effect is found in the left tail of the HHI distribution, where competition is more intense. I found here that the threshold above which external economies fade out is $HHI \geq 14.5$ (see Figure 4.4).

Beyond the theoretical and methodological considerations, there is a relevant policy implication for the Italian economy from the empirical result. External economies require strong competition in the local labor market to generate productivity gains for local firms. According to the most conservative estimate, external economies in the labor market occur at a level of HHI for competition lower than 14.5. Since the HHI has been increasing over time, we expect this number to continue to decrease in the future. In general, this suggests that there is a trade-off between the gains from internal and external economies when the increase in average size is accompanied by a decrease in the level of competition. While firms that increase in size can exploit internal economies to some extent, this also reduces the opportunities for others to benefit from external economies. Future work can explore this trade-off. In particular, it seems interesting to look at segments of the labor market. In these segments, only some firms belonging

to related sectors compete with each other for workers. The classification can be done by looking at the size of the firm as well as the level of productivity. Related industries are those where labor flows are likely to occur. The limitation of the more conservative estimate is that it uses Swedish data on labor flows. An update of the available data on inter-sectoral labor mobility in Italy can help to estimate such an effect more precisely.

Appendices

A Chipman external economies

The Chipman's model of external economies demonstrates that an equilibrium with increasing returns and externalities is possible. Now, let's think about a firm and its production function:

$$Y(i) = K_j L(i) \tag{1}$$

where $Y(i)$ is the output produced by firm i, K_j is a constant for each firm belonging to sector, say j, and $L(i)$ is the amount of labor to produce $Y(i)$. Since the production function exhibits constant returns to scale, we can aggregate the the total output to show the total production of sector j:

$$\sum_N Y(i) = Y_j \tag{2}$$

and

$$\sum_N L(i) = L_j \tag{3}$$

where N is the count of firms in sector j. So, we obtain:

$$Y_j = K_j L_j \tag{4}$$

Then, we allow K to vary as:

$$K = kL^{\rho-1} \tag{5}$$

Now, inserting eq. 5 in eq. 4:

$$\begin{aligned} Y_j &= kL^{\rho-1}L \\ &= kL^{\rho} \end{aligned} \tag{6}$$

In this notation, k represents the parametric external economies as in Chipman (1970), and the aggregate function for the industry exhibits increasing returns to scale while firms face constant returns to scale. Here, k is the parameter governing the extent of external economies.

B Relevance of the soil productivity indices

A.1: **Predicting specialization using soil and grassland productivity**

	(1)	(2)	(3)
Soil Productivity	0.11***		0.10***
	(0.01)		(0.01)
Grassland Productivity		0.11***	0.04***
		(0.01)	(0.01)
ATECO-3 FE	✓	✓	✓
Observations	8,148	7,558	7,552
F-Statistics	168.75	119.23	98.23
R-Squared	.16	.15	.16

The main dependent variable for specialization is the log number of establishments in each LMA. All columns include 3-digit industry fixed effects.
*** p<.01, ** p<.05, * p<.1

C Robustness tests for table 4.2

A.2: **Effect of 3-digit manufacturing specialization, competition and their interaction on different measure of LITFP**

	Replication column (7) table 4.2				**Replication column (8) table 4.2**			
	(1) TFP^{OLS}	(2) η^{OLS}	(3) TFP^{LP}	(4) TFP^{WLP}	(5) TFP^{OLS}	(6) η^{OLS}	(7) TFP^{LP}	(8) TFP^{WLP}
Specialization	-0.30**	-0.32***	-0.35***	-0.60***	-0.11	-0.08	-0.14	-0.21*
	(0.12)	(0.12)	(0.13)	(0.20)	(0.10)	(0.11)	(0.11)	(0.13)
Competition	-0.01**	-0.01***	-0.01***	-0.02***	0.04**	0.05**	0.05**	0.06**
	(0.00)	(0.00)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
*Spec * Comp*					-0.02**	-0.02***	-0.02**	-0.03***
					(0.01)	(0.01)	(0.01)	(0.01)
Control Variables	✓	✓	✓	✓	✓	✓	✓	✓
Instrumental Variables	Both	Both	Both	Both	Both+Int	Both+Int	Both+Int	Both+Int
ATECO-3 FE	✓	✓	✓	✓	✓	✓	✓	✓
Metropolitan Areas FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	7,260	6,525	7,260	6,363	7,260	6,525	7,260	7,260
1st Stage F-stat	14.97	11.60	14.97	10.00	9.31	7.68	9.31	9.31
Hansen J-Stat	[0.70]	[0.52]	[0.92]	[0.62]	[0.56]	[0.59]	[0.68]	[0.68]

The main independent variable for specialization is the total count of plants in the 3-digit local industry. Columns 1 to 4 replicate column 7 of table 4.2. In all columns, the average level of human capital - measured as the ratio between tertiary educated population over the total population of the LMA, the surface of the LMA, the average plants' size in the relative 3-digit local manufacturing industry, and the total number of employees in the local manufacture are added as control variables. Their coefficients are not reported. All the control variables are in log. Instruments are standardized in order to better interpret the result from the first stage. The HHI is measured in level (0-100) where 0 means 'perfect competition' and 100 monopoly. Reported statistics are 1st stage and Hansen-J statistics. The former is a statistics for the weakness of the instrument, the latter for over-identifying restrictions. P-values are in square bracket, standard errors in parentheses. Standard errors are clustered at the 3-digit local industry.
*** p<.01, ** p<.05, * p<.1

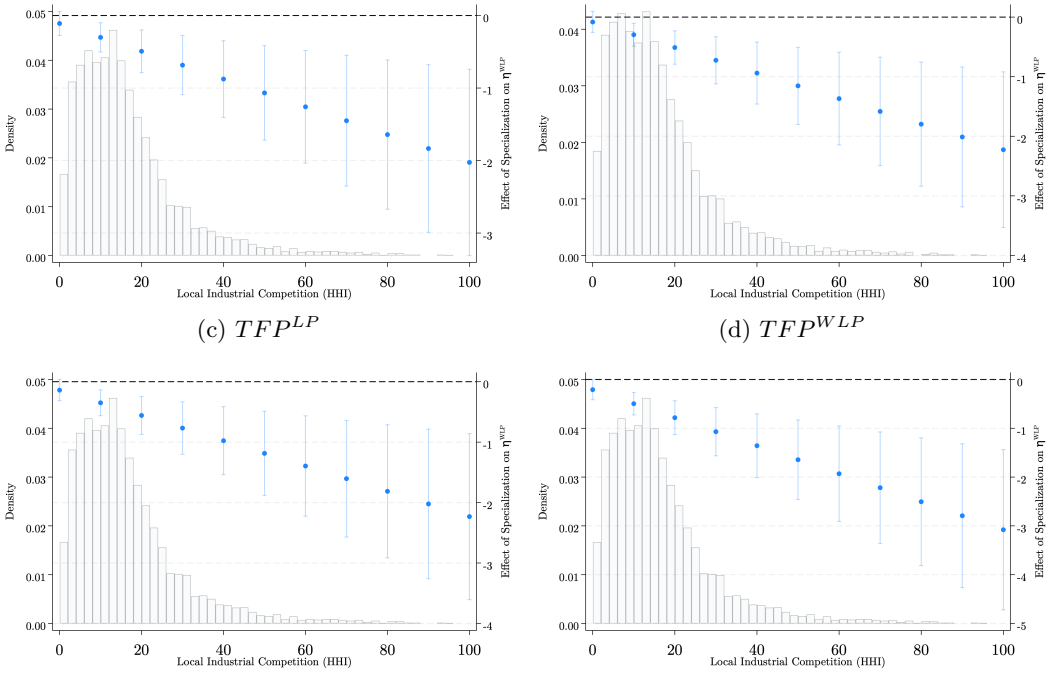
A.3: **Effect of 3-digit manufacturing specialization, competition and their interaction on different measure of LITFP**

	Replication column (7) table 4.2			**Replication column (8) table 4.2**		
	(1)	(2)	(3)	(4)	(5)	(6)
Specialization	-0.60***	-0.40***	-0.40***	-0.21	-0.15	-0.28
	(0.20)	(0.14)	(0.14)	(0.14)	(0.19)	(0.17)
Competition	-0.02***	-0.02***	-0.02***	0.03**	-0.02***	-0.02
	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)	(0.03)
Spec * Comp				-0.01***	-0.01	-0.00
				(0.00)	(0.00)	(0.01)
Control Variables	✓	✓	✓	✓	✓	✓
instrumental Variables	Both	Both	Both	Both+Int	Both+Int	Both+Int
ATECO-3 FE	✓	✓	✓	✓	✓	✓
Metropolitan Areas FE	✓	✓	✓	✓	✓	✓
Observations	6,363	6,363	6,363	6,363	6,363	6,363
1st Stage F-stat	10.00	7.64	7.64	6.65	4.85	4.03
Hansen J-Stat	[0.62]	[0.74]	[0.74]	[0.32]	[0.66]	[0.11]

The dependent variable is always η^{WLP}. The main independent variable for specialization is: $\ln e$ for columns 1 and 4, $\ln e/area$ for columns 2 and 5, $\ln n/area$ for columns 3 and 6. Columns 1 through 3 replicate column 7 of table 4.2. In columns 1 and 4, the average level of human capital - measured as the ratio of the tertiary educated population to the total population of the LMA, the area of the LMA, the average size of establishments in the relative 3-digit local manufacturing industry, and the total number of employees in the local manufacturing industry are added as control variables. In columns 2, 3, 5 and 6, the area of the LMA is removed. The coefficients of all the control variables are removed. All control variables are in logarithmic form. The instruments are standardized to better interpret the result of the first stage. The HHI is measured in levels (0-100), where 0 means "perfect competition" and 100 means monopoly. The statistics reported are the first stage and the Hansen-J statistics. The former is a statistic for instrumental weakness, the latter for over-identifying restrictions. P-values are in brackets, standard errors in parentheses. Standard errors are clustered at the 3-digit local industry level.
*** p<.01, ** p<.05, * p<.1

A.5: **Marginal Effects of estimation in table A.2**

(a) TFP^{OLS} (b) η^{OLS}



(c) TFP^{LP} (d) TFP^{WLP}

Notes. This figure plots all the marginal effects of specialization at different level of competition, obtained in table A.2. Findings confirm previous results.

Source. Authors' elaboration on Istat data.

D Robustness tests for table 4.3

A.4: **Effect of manufacturing specialization, competition and their interaction on LITFP**

	Replication column (7) table 4.3				Replication column (8) table 4.3			
	(1) TFP^{OLS}	(2) η^{OLS}	(3) TFP^{LP}	(4) TFP^{WLP}	(5) TFP^{OLS}	(6) η^{OLS}	(7) TFP^{LP}	(8) TFP^{WLP}
Specialization	0.057**	0.059***	0.051**	0.067***	0.093***	0.087***	0.087**	0.266***
	(0.023)	(0.020)	(0.024)	(0.026)	(0.036)	(0.028)	(0.037)	(0.103)
Competition	0.003***	0.004***	0.003***	0.005***	0.027**	0.020*	0.026*	0.085*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.013)	(0.011)	(0.013)	(0.045)
Spec * Comp					-0.004*	-0.003	-0.004*	-0.013*
					(0.002)	(0.002)	(0.002)	(0.007)
Control Variables	✓	✓	✓	✓	✓	✓	✓	✓
Instrumental Variables	Both	Both	Both	Both	Both+Int	Both+Int	Both+Int	Both+Int
ATECO-3 FE	✓	✓	✓	✓	✓	✓	✓	✓
Metropolitan Areas FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	7,243	6,517	7,243	6,357	7,243	6,517	7,243	7,243
1st Stage F-stat	114.26	116.54	114.26	115.67	61.69	61.30	61.69	8.33
Hansen J-Stat	[0.04]	[0.03]	[0.01]	[0.00]	[0.01]	[0.04]	[0.01]	[0.00]

The main independent variable for specialization is the one developed in section 4.5.1. Columns 1 to 4 replicate column 7 of table 4.3. In all columns, the average level of human capital - measured as the ratio between tertiary educated population over the total population of the LMA, the surface of the LMA, the average plants' size in the relative 3-digit local manufacturing industry, and the number of employees in relative 3-digit local industry are added as control variables. Their coefficients are not reported. All the control variables are in log. Instruments are standardized in order to better interpret the result from the first stage. The HHI is measured in level (0-100) where 0 means perfect competition and 100 monopoly. Reported statistics are 1st stage and Hansen-J statistics. The former is a statistics for the weakness of the instrument, the latter for over-identifying restrictions. P-values are in square bracket, standard errors in parentheses. Standard errors are clustered at the 3-digit local industry.
*** p<.01, ** p<.05, * p<.1

E Robustness tests for table 4.4

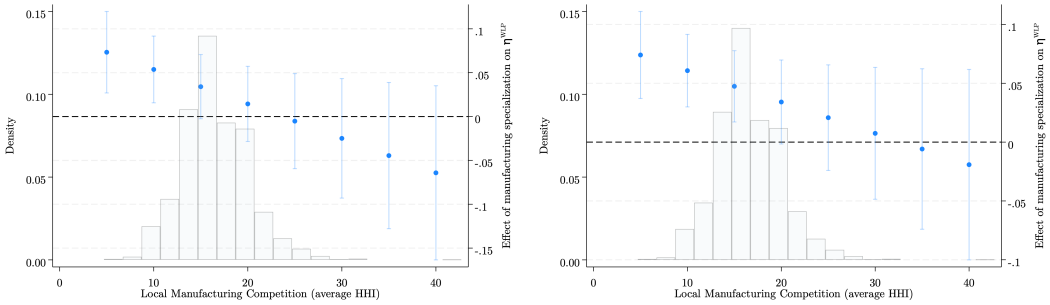
A.5: **Effect of manufacturing specialization, competition and their interaction on LITFP**

	Replication column (7) table 4.3			**Replication column (8) table 4.3**		
	(1)	(2)	(3)	(4)	(5)	(6)
Specialization	0.047***	0.002***	0.020***	0.075**	0.003*	0.023**
	(0.016)	(0.001)	(0.007)	(0.032)	(0.001)	(0.011)
Competition	0.002**	0.006***	0.008***	0.025	0.006***	0.007***
	(0.001)	(0.002)	(0.002)	(0.017)	(0.002)	(0.002)
Spec * Comp				-0.003	-0.000	-0.001
				(0.002)	(0.000)	(0.001)
Control Variables	✓	✓	✓	✓	✓	✓
instrumental Variables	Both	Both	Both	Both+Int	Both+Int	Both+Int
ATECO-3 FE	✓	✓	✓	✓	✓	✓
Metropolitan Areas FE	✓	✓	✓	✓	✓	✓
Observations	6,357	6,363	6,363	6,357	6,363	6,363
1st Stage F-stat	170.06	289.68	175.09	71.25	195.36	129.76
Hansen J-Stat	[0.01]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]

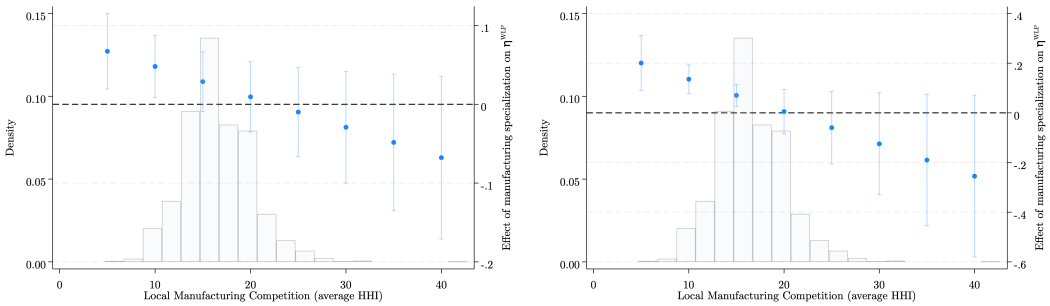
The dependent variable is always η^{WLP}. The independent variable for the specialization is: $\ln Ne$ for columns 1 and 4, $\ln Ne/area$ for columns 2 and 5, $\ln Nn/area$ for columns 3 and 6. Ne and Nn are constructed as in section 4.5.1. They are the number of establishments (Nn) or employees (Ne) in all 3-digit industries except the one I am regressing on. Columns 1 through 3 replicate column 7 of table 4.3. In all columns, I include as control variables the average level of human capital - measured as the ratio of the college-educated population to the total population of the LMA - the area of the LMA, the average size of establishments in the respective local 3-digit industry, and the total number of employees in the local 3-digit industry. In columns 2, 3, 5 and 6, the area of the LMA is removed. The coefficients of all control variables are removed. All control variables are in logarithmic form. The instruments are standardized to better interpret the result of the first stage. The HHI is measured in levels (0-100), where 0 indicates perfect competition and 100 indicates monopoly. The statistics reported are the first stage and the Hansen-J statistics. The former is a statistic for instrumental weakness, the latter for over-identifying restrictions. P-values are in brackets, standard errors in parentheses. Standard errors are clustered at the 3-digit local industry level.
*** p<.01, ** p<.05, * p<.1

A.6: **Marginal Effects of estimation in table A.5**

(a) TFP^{OLS} (b) η^{OLS}



(c) TFP^{LP} (d) TFP^{WLP}

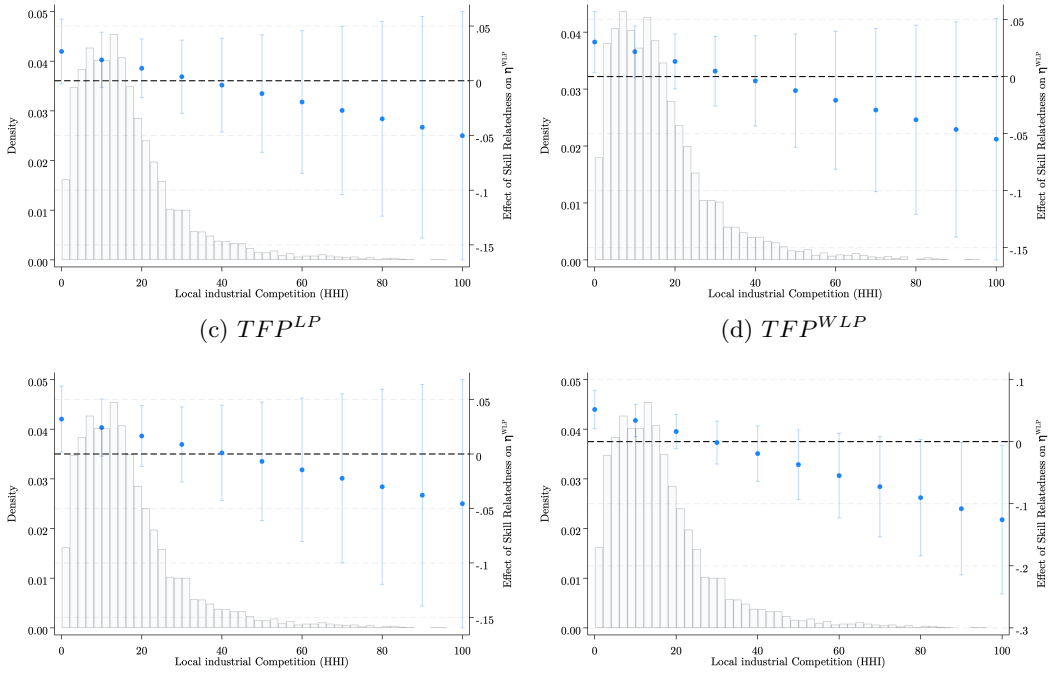


Notes. This figure plots all the marginal effects of specialization at different level of competition, obtained in table A.5. Findings confirm previous results.

Source. Authors' elaboration on Istat data.

A.7: **Marginal Effects of estimation in table 4.4**

(a) TFP^{OLS} (b) η^{OLS}



(c) TFP^{LP} (d) TFP^{WLP}

Notes. This figure plots all the marginal effects of skill relatedness at different level of competition, obtained in table 4.4. Findings confirm previous results.

Source. Authors' elaboration on Istat data.

Chapter 5

Global Shocks, Local Responses

Abstract

When a global shock hits a national economy, places react differently. Differences in shock responses depend on local economic structures. In this paper, I focus on the role of local input-output linkages in the manufacturing sector in responding to crises. I use a dataset on Italian local labor market areas covering the period 2006-2022 to assess differences in unemployment responses to common shocks. I use national input-output tables as well as confidential plant-level data to proxy cross-sectional variation in local manufacturing input-output flows. Using shocks due to the financial crisis and the Covid-19 pandemic, I assess the additional effect of a local IO linkages on unemployment rates. After partialling-out the role of manufacturing specialization, which is highly sensitive to global demand, if a residual effect is found, it depends on the additional effect propagating through the input-output network. Taking advantage of a DiD setting, I find that LMAs with strong manufacturing input-output linkages suffer a 4% higher increase in unemployment relative to LMAs with weak IO.

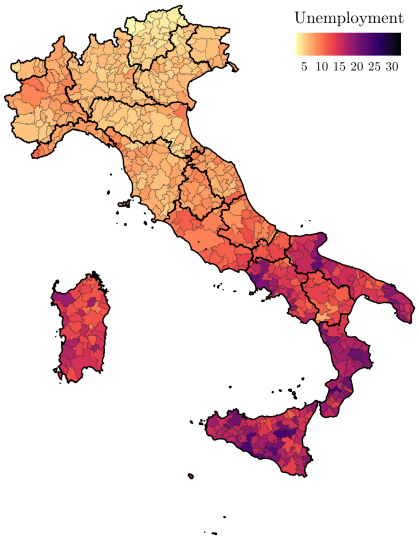
5.1 Motivation

Over the past two decades, the Italian economy has experienced a prolonged period of economic turbulence, accompanied by a gradual but protracted recovery. This challenging environment has had a significant impact on the country's production geography. The peculiarity of the Italian economy is the existence of significant structural differences in economic activity, which have led to a dual pace of development. This is illustrated by the north-south divide in terms of unemployment, as shown in Figure 5.1 (panel a) (Kline & Moretti, 2013). These differences are considerable, with unemployment rates as low as 0.42% in some northern local labor market areas (LMAs) and as high as 25-30% in many southern LMAs (see table 5.1). Over the last 20 years, unemployment has been shaped by two different global shocks: 1) the financial crisis, exacerbated by the sovereign debt crisis, and 2) the Covid-19 pandemic. In figure 5.1 panel (b), I show that the long-run unemployment fluctuation is strongly related to local structural characteristics. Manufacturing LMAs (e.g. industrial districts) experienced dramatic increases in unemployment due to the financial crisis, while other types of LMAs fluctuated less. There are a number of relevant pieces of information to highlight. First, even though trends in economic aggregates are traditionally reported at the national level, a large part of the variation is often due to local phenomena (local structures). Second, depending on the economic model assumed by policymakers, the dead-weight loss of jobs during recessions may be reduced (Overman & Puga, 2002). But even if such variation could be explained by traditional trade theory, with global shocks affecting regions that are more exposed to export activities (such as manufacturing), there is another relevant channel through which global shocks generate differences in local responses. An external shock can be amplified by the local structure of the economy through input-output linkages. The sector-specific shock, which initially affects only one sector, propagates its negative effect through its local value chains.

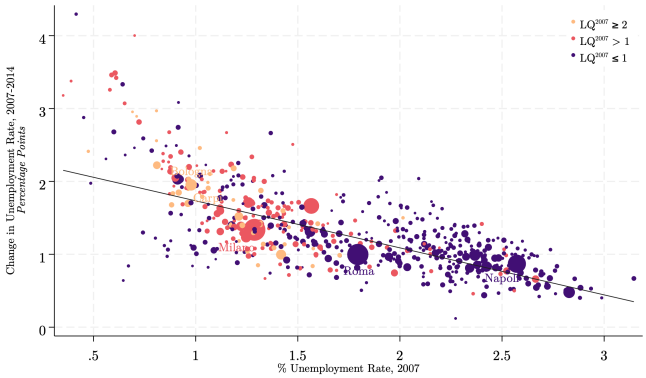
To what extent can differences in unemployment responses to common shocks can be explained by *thick* input-output linkages in the local economy? Regarding the 2007 crisis, Caivano et al. (2011) suggested that the collapse of international trade was the main factor that transmitted the financial crisis to the real economy. What is missing from their analysis is how the crisis spread differently across territories. Acemoglu et al. (2016) suggested that any small shocks spread through the economy due to a *direct* effect (the shock itself) and an *indirect* one due to the thickness of the input-output linkages. This is a *network* effect due to the relationship between firms (sectors) belonging to different phases of the production process. In general, manufacturing

Figure 5.1: **Structural and dynamic unemployment in Italy (2006-2022)**

(a) Unemployment Rates



(b) Crisis and Unemployment



Notes. Panel (a) plots the unemployment rates of LMAs averaged over the period 2006-2022. Panel (b) plots the change in unemployment rates over the period 2007-2014. Increasing brightness of the colors indicates a high degree of manufacturing specialization. X-axis is in logarithm.

Source. My own elaboration on Istat data.

Table 5.1: **Unemployment rates in 2022 (highest and lowest)**

Rank	**Unemp. (%)**
LMAs with lowest rates	
San Leonardo in Passiria	0.42
Malles Venosta	0.85
Modigliana	1.34
Brunico	1.67
Silandro	1.86
San Marcello Pistoiese	2.10
Bressanone	2.25
San Candido	2.46
LMAs with highest rates	
Napoli	20.81
Adrano	21.08
Messina	21.41
Agrigento	21.82
Mondragone	21.97
Leonforte	22.65
Cammarata	25.29
Bagheria	31.48

activities tend to be highly export-oriented and highly localized (Ellison & Glaeser, 1997). In Italy, most manufacturing production is concentrated in "Marshallian industrial districts" (Bellandi, 2016). In an econometric approach, if an additional effect is found after controlling for the concentration of manufacturing production and/or the presence of industrial districts in the LMAs, it could be due to the strength of such local input-output linkages.

There is a long tradition of questioning the role of local structures in moderating unemployment fluctuations. On the one hand, there is a very large literature that shows that a high degree of industrial diversity protects the local economy from sectoral shocks (Simon, 1988, Malizia and Ke, 1993, Frenken et al., 2007). Every time one industry lays off workers, another industry can hire them. Frenken et al. (2007) refers to this hypothesis as derived from a portfolio diversification strategy. Conversely, if a high degree of diversification is associated with lower unemployment fluctuations over the business cycle, specialization in a few industries could produce the opposite result. Another branch of the literature relates unemployment fluctuations to city size (Vipond, 1974, Gaigné and Sanch-Maritan, 2019). In this case, job competition negatively affects workers' decisions to live in the agglomeration, while job pooling allows them to earn higher incomes, creating an incentive to live in the agglomeration. These two effects lead to higher unemployment and lower turnover in cities. On the other hand, regional literature also

focuses on local resilience. Here, some regional characteristics help regions to react differently to booms and busts. However, it is still a matter of local economic structure (Martin et al., 2016).

In this paper, I assess the additional effect on unemployment of the local IO linkages. While it is possible to distinguish between inter-local and intra-local input-output linkages, the former occurring when industrial trade takes place between different LMAs (also belonging to the same NUTS 2 regions), I focus here on intra-local linkages, which are flows of goods between industries within the same LMA. I use the financial crisis and Covid-19 pandemic as exogenous shocks to implement a Difference-in-Differences (DiD) setting where the cross-sectional variation comes from a measure of input-output thickness. As it is common in the literature, since all units are treated at the time of the shock, I compare the last tertile of my measure of IO thickness to the lower ones (1st and 2nd tertiles). To do this, I make use of several data sources. First, I use available Istat data on unemployment rates in LMAs for the period 2006 to 2022. Second, I use a confidential plant-level dataset from Laboratorio Adele of Istat from 2007 to 2020 and national input-output tables (2010) to construct a proxy variable for the thickness of the IO linkages in each LMA. Third, I use the Istat shapefile on LMAs to establish the spatial dimension of the database. I leverage on the recent 'quasi experimental' literature to implement a difference-in-differences (DiD) estimator (De Chaisemartin & d'Haultfoeuille, 2023). This is able to precisely estimate the differential impact, given a vector of control variables, of having thick IO linkages. The results of the econometric investigation suggest that there is a significant and positive effect of the input-output linkages on unemployment response to crisis. The paper maintains that this effect, once partialled out the effect of manufacturing specialization, is the additional 'network' effect due to the local propagation of the global shock. In fact, once included in the regression manufacturing specialization as a control variable, the effect of IO linkages reduces 6 point percents. The full model suggests that LMAs with strong IO linkages experience in comparison to the control group a larger increase in unemployment during the financial crisis equal to 4%. On the other hand, due to the large use of temporary *work-sharing* and *wage subsidies* mechanisms such as 'Cassa integrazione guadagni straordinaria' (CIGS) to reduce unemployment fluctuations, no relevant effects are found due to the Covid-19 pandemic.

This paper contributes to several strands of the literature. First, it provides evidence on the mechanisms of (co)-agglomeration. In this stream, many papers have focused on the determinants of agglomeration through labor pooling, knowledge spillovers, input-output linkages, and natural advantages. Several attempts have been made from the co-agglomeration level (Rosenthal and Strange, 2001; Ellison et al., 2010; Faggio et al., 2017, Diodato et al., 2018; Steijn et al., 2022)

through the city level (Glaeser & Kerr, 2009) to the definition of clusters in the case of IO linkages (Delgado et al., 2016). Here, I focused specifically on the role of IO linkages. Second, it works on the dynamics of places during booms and busts, looking at the moderating effect of local economic structures. This is related to the literature on the relationship between local economic resilience/instability (Martin and Sunley, 2015; Martin et al., 2016) and the effect of economic structures (Simon, 1988; Diamond and Simon, 1990; Malizia and Ke, 1993) also with a specific focus on the Italian economy (Lagravinese, 2015; Di Caro, 2015). In particular, it overlaps strongly with the more macro-level literature on the role of the *network* effect in the propagation of (non-)idiosyncratic shocks (Acemoglu et al., 2012; Acemoglu et al., 2016). Third, it provides new insights on the transmission mechanisms of the financial crisis, moving from the institutional literature (Caivano et al., 2011; Romano, 2021) to the local one (Ruiz-Fuensanta & Bellandi, 2019). It also refers to the literature on the effect of Covid-19, although exploiting its shock as a placebo treatment (Bellandi et al., 2020). Finally, it relates to the literature on regional inequality, spatial misallocation, and unemployment (Boldrin and Canova, 2001; Overman and Puga, 2002; Blanchard, 2006; Kline and Moretti, 2013; Hsieh and Moretti, 2019; Boeri et al., 2021).

This study is unique in several respects. First, it takes a local perspective, using the local labor market area as the geographical unit of analysis. While this is a relevant spatial unit of analysis, this work also focuses on the relevant industry as one that is interconnected through local input-output linkages. Many studies offer a perspective on the different impacts of the crisis on Italian regions (NUTS-2), but there is a lack of studies from the perspective of local-industry. This is in line with the theoretical foundation of Giacomo Becattini on the definition of industry and its boundaries (Becattini, 1962; Becattini, 1979). Second, it bridges the macro-level literature (Acemoglu et al., 2016) to the local level, claiming that most fluctuations in national economies depend on local *evolutions* (Blanchard et al., 1992). Third, it provides a very precise estimate of the differentiated impact of the recession on LMAs. While it is clear that the local economic structure plays a role, this is the first paper to look specifically at the transmission channel of the *local value chain*. The value of this paper lies in: 1) the novel mechanism it provides for studying regional developments during booms and busts, and 2) the insights it provides for policy makers. It helps to understand that a country's performance during recessions is derived from the average variation across locations.

The following is a brief overview of the structure of the paper. Section 5.2 provides an overview of the transmission mechanisms in the context of the Italian economy. Section 5.3 presents the

data sources and offers a concise narrative of the shocks that occurred over the period under investigation. Section 5.4 outlines the implemented model (DiD setting), the primary variables, the identification strategy, and provides insights into the parallel trend assumption. Section 5.5 presents the econometric model results and some robustness tests. Section 5.6 offers a brief conclusion, a summary, and provides policy implications.

5.2 Regional Unemployment and Input-Output Linkages

Regional unemployment can vary considerably within countries. This is the case for Italy, where very large differences in unemployment are observed between northern and southern LMAs. If wages are set at the national rather than the regional level, and if local productivity differs across areas, structural differences in (un)employment are bound to be observed (Overman & Puga, 2002). The intuition is based on the fact that differences in productivity force firms to employ fewer workers where productivity is lower, given the level of nominal wages. As a result, large differences in real wages are observed. An anecdotal example comes from the fact that the 80% of applicants for public jobs in Italy come from the southern regions (Boeri et al., 2021). This is because the purchasing power of public wages is dramatically higher in the southern regions than in the northern regions. On the other hand, countries (e.g. Germany) where wages are set at the regional (city) level have observed smaller regional differences in unemployment levels. Yet, while it is true that manufacturing wages may be more flexible than service and public wages, Boeri et al. (2021) show that there are very small spatial differences in Italian manufacturing wages, while in the German case wages are substantially different and linked to productivity levels. They explain differences in unemployment levels as a queuing for jobs in the south. Since jobs in the south pay higher real wages than those in the north, there is a long queue for jobs in the south, with northern regions systematically offering more jobs than the south[1].

In such a scenario (local productivity differences and compressed nominal wages), what are the consequences of a negative national (global) shock? First, wages are not free to fluctuate. Then, the consequences of the adverse shock affect employment rather than wages. The reduction in global demand due to the financial shock worked in this direction. Employment declined starting from the sectors exposed to the shock. Places specialized in sectors more sensitive to

[1] In Italy, the bargaining process is differentiated by narrowly defined industries (e.g., 31 contracts in the textile industry, 34 in the chemical industry). It is centralized and employers can only offer more than the minimum wage, with a few exceptions. However, Boeri et al. (2021) has shown that compared to Germany, which has similar differences in productivity levels across provinces, wage differentials in Italy are a quarter lower after controlling for worker characteristics. Nominal wages are shown to be mainly unrelated to productivity levels in Italy.

the global demand, such as manufacturing, observed a large reduction in employment (Di Caro, 2015; Lagravinese, 2015). This is the case of industrial districts and manufacturing areas. For example, Brunello and Langella (2016) found that during the 2008 financial crisis, entrepreneurship declined more in industrial districts than in the comparison group. Such a shock is exacerbated by the presence of (negative) local multipliers and input-output linkages (Moretti, 2010; Acemoglu et al., 2016). First, the initial reduction in employment in tradable sectors reduces 'local demand' for non-tradable activities. This is due to a reduction in local tradable employment, which in turn reduces the local tradable wage bill, which has a negative impact on non-tradable activities by reducing local demand for local goods and services. This in turn has a negative impact on employment in non-tradable sectors. Accordingly, the effects are stronger in regions that are more specialized in tradable activities. Second, there is a further reduction in tradable sectors due to the input-output linkages. It is still a demand channel, but it operates along the local value chain rather than through local multipliers. Buyers and suppliers not directly affected by the common shock suffer an indirect effect through the reduction of their own local demand for intermediate goods.

Such a framework has been analyzed empirically and theoretically by Acemoglu et al. (2012) and Acemoglu et al. (2016), who show the relevance of such a *network* effect for the propagation of idiosyncratic shocks. When a sector - or a group of them - is affected by shocks, the direct effect is amplified by an indirect one that occurs through their IO linkages. The presence of input-output linkages in the production function causes amplified fluctuations at the aggregate level (Acemoglu et al., 2016). Their argument denies the point of Lucas (1977), who suggested that there are no aggregate effects due to sectoral idiosyncratic shocks - *diversification argument*. In particular, as suggested by Acemoglu et al. (2012), when looking at the aggregate level, an independent shock may cause a fluctuation equal to $1/\sqrt{n}$, where n is the number of sectors in an economy. Such an effect is negligible at the aggregate level. A very similar argument was made by Frenken et al. (2007), who suggested a portfolio diversification effect due to the diversity of local economic structure. However, such an issue has been raised by several authors before (Simon, 1988; Diamond and Simon, 1990). The point, also related to unemployment fluctuations, was that when an industry lays off workers, other industries can hire them. At the aggregate (city) level, the effect of idiosyncratic shocks is then negligible. There is strong empirical evidence for this (Vipond, 1974; Malizia and Ke, 1993; Gaigné and Sanch-Maritan, 2019). *Mutatis mutandis*, in specialized cities the risk of unemployment is higher, so workers should be compensated with higher wages (Diamond & Simon, 1990).

The framework of the present paper partly differs from that proposed by Acemoglu et al. (2012) and Acemoglu et al. (2016). Rather than looking at idiosyncratic shocks, I look at the effect of global common shocks. However, as the authors suggest, there is room to study how such an indirect effect works in the case of global non-idiosyncratic shocks. In fact, every time a crisis hits an economy, economists have built narratives about the transmission channels. Usually, it starts in certain sectors and propagates upstream and/or downstream according to shock-specific nexuses. A comparable phenomenon occurred during the global financial crisis. Using the point made by Caivano et al. (2011), I identified the relevant shock as one that hit manufacturing activities through the reduction in global demand for their products. Similar to Acemoglu et al. (2016), who analyzed idiosyncratic shocks at the aggregate level with a special focus on the role of geographical proximity, I consider the manufacturing crisis through its IO linkages.

IO linkages are one of the main sources of agglomeration (Ellison et al., 2010). Starting from the seminal work of Rosenthal and Strange (2001), several papers have investigated the causes of (co-) agglomeration (Diodato et al., 2018; Steijn et al., 2022). Firms cluster with their buyers/suppliers in order to achieve productivity gains. The economic geography literature suggests that this occurs because of a reduction in transportation costs (Fujita et al., 2001). Also, in a decentralized production process, firms can reduce transaction costs in evolving economies by operating in the same district (Stigler, 1951; Bellandi, 1995). Finally, another relevant channel is the presence of knowledge spillovers, where proximity acts as a facilitator (Porter, 2008; Glaeser and Kerr, 2009). While several studies have highlighted the importance of such characteristics as agglomeration forces, few have examined their role in local dynamics. In particular, there is no evidence on the role of such input-output linkages in moderating shocks. In the Italian case, we exploit the strong tendency of manufacturing sectors to cluster in the same areas to build on the argument of Acemoglu et al. (2016). The role of industrial districts in the Italian economy is still relevant and provides an optimal perspective from which to examine the desired effect.

Main implication *The spread of unemployment due to crises is larger in places where IO linkages are stronger.* Accordingly, there are larger unemployment fluctuations in places like industrial districts. In the next section, I use an econometric methodology to investigate this effect.

5.3 Data and context

As outlined in the theoretical framework above, an additional effect of global shocks may be observed in regions with more robust input-output (IO) linkages. We focus here only on those IO linkages occurring within the same geographical unit of analysis, the LMA in this case. To identify such an effect, I use a variety of data sources. The main variable of interest is unemployment. The variable is calculated by Istat at the level of each local labor market area (LMA). The data cover the period from 2006 to 2022[2]. During this period, two exogenous shocks can be exploited for the DiD estimator. The first shock is the financial crisis of 2007. In Italy, the effect was transmitted through two channels. On the one hand, there was a restriction in the global demand for tradable products that started in 2008 (Caivano et al., 2011). Conversely, the financial crisis of 2007 led to a political fragility that ultimately led to the resignation of the fourth Berlusconi government in 2011. The resignation was precipitated by the significant divergence in yields between Italian and German bonds. The second shock was the global pandemic caused by the SARS-CoV-2 virus, commonly known as coronavirus disease (Covid-19). According to official sources, the first case was identified in Wuhan in December 2019. In Italy, the spread of the novel coronavirus (Covid-19) forced the government to impose a nationwide lockdown from March to May 2020. The measures taken to contain the spread of the SARS-CoV-2 virus began to be relaxed around the summer of 2021. The two shocks can be distinguished by their respective impact on employment levels. During the first shock, no measures were taken to deal with fluctuations in employment. As a result, unemployment and employment rates showed considerable volatility. In contrast, the second shock led to the implementation of several measures aimed at stabilizing employment levels. I then exploit the Covid-19 crisis as a placebo treatment in the robustness tests.

Second, I used a confidential plant-level dataset from Istat Laboratorio Adele. This dataset was originally at the plant level. I constructed aggregate measures to gauge the manufacturing specialization of each LMA. These data cover the period 2007-2020. However, for the end of this paper, I use only the 2007 data. This way, there is no risk of such measures being contaminated by the shocks.

Third, I use the Istat shapefile to set the spatial dimension of the dataset[3]. As in my case, a DiD estimator must be adjusted for spatial and serial correlation in the error term. The OLS estimator, once the possible sources of endogeneity are dealt with, is consistent but may be

[2] https://www.istat.it/tavole-di-dati/occupati-residenti-e-persone-in-cerca-di-occupazione-nei-sll/

[3] https://www.istat.it/statistiche-per-temi/focus/informazioni-territoriali-e-cartografiche/statistiche-sul-territorio/sistemi-locali-del-lavoro-e-distretti-industriali

Table 5.2: **Trade between manufacturing and services in Italy (2010)**

	Manufacturing	Non-Manufacturing
Manufacturing	58.06%	8.80%
Non-Manufacturing	17.02%	16.11%

biased. The bias comes from the standard error, which needs to be corrected for spatial and serial correlation. Therefore, I use the HAC (heteroskedasticity- and autocorrelation-consistent standard errors). Accounting for such correlation is necessary to avoid possible spatial spillovers between LMAs. The main point is that possible spillovers between LMAs could bias the coefficient. For example, if one is unemployed in LMA (a) and a job is advertised in LMA (b), which is close to the second, then there could be a bias in the effect of the crisis on unemployment due to average commuting distances, even after controlling for housing market tightening. I then use HAC standard errors and a distance cutoff of 200 km to control for such potential endogeneity.

Fourth, I use national symmetric input-output tables to construct a proxy for the strength of input-output linkages. Since data for symmetric input-output tables are not available in the current version of ATECO at the time of the shock, I rely on the 2010 IO tables. From this data source, I have extrapolated information on the structure of national trade between 2-digit sectors[4]. From such data source it is also possible to measure the importance of manufacturing input-output in the national economy (see table 5.2). This motivates the decision to focus on manufacturing IO linkages: manufacturing accounts for the largest share of intersectoral intra-country trade ($\approx 58\%$).

5.4 The model

I exploit a DiD setting to assess the impact of IO linkages on unemployment. In particular, to assess the additional effect on unemployment, I estimate the following versions of the same model.

$$Unemployment_{rt} = \beta_{fe} Crisis_t \times IO_r + \boldsymbol{X}_{rt}\boldsymbol{\beta} + \alpha_r + \tau_t + \delta_{mt} + \epsilon_{rt} \tag{5.1}$$

where $Unemployment_{rt}$ is the log transformation of the unemployment rate, which varies at the LMA and year level. $Crisis_t$ is the common shock. I use the year 2008 according to the

[4]There are 63 sectors in these tables. Some of these are aggregated into industry groups. In the case of manufacturing, all but the following sectors are not aggregated. Sectors $10, 11, 12$, Sectors $13, 14, 15$, Sectors $31, 32$

classification of recessions implemented by FRED[5] in the case of the financial crisis. I use the year 2019 in the case of the Covid-19 shock. So, I have that variable $Crisis_t$ is equal to:

$$\text{Financial Crisis}_t = \begin{cases} 0, & \text{if } t \in [2006, 2007] \\ 1, & \text{if } t \in (2007, 2016] \end{cases} \tag{5.2}$$

and to:

$$\text{Covid Pandemic}_t = \begin{cases} 0, & \text{if } t \in [2013, 2018] \\ 1, & \text{if } t \in (2018, 2022] \end{cases} \tag{5.3}$$

I use them in two separate regressions. In the full model, I also include: α_r that is a vector of LMA fixed effects; τ_t that is is the vector of year fixed effects and δ_{mt} that is a special vector of fixed effects that vary over time. Due to the aforementioned North-South divide, I include these $South \times Year$ fixed effects to condition on the two different speeds of adjustment. ϵ_{rt} is the error term.

I also estimate an event study setup of the same model, which can be written as

$$\begin{aligned} Unemployment_{rt} = \sum_{\tau \in (-2.7), \tau \neq 0} \beta_\tau IO_r \times \boldsymbol{F}(t+\tau) + \\ + \boldsymbol{X}_{rt}\boldsymbol{\beta} + \alpha_r + \tau_t + \delta_{mt} + \epsilon_{rt} \end{aligned} \tag{5.4}$$

In this case, I do not pool observations between the pre- and post-treatment. Rather, I interact IO_r with an indicator variable F for each year before and after the treatment in a range of ten years $(t + \tau)$. In particular, in the case of the financial crisis, due to data limitations, I have 2 years of pre-treatment (2006 and 2007), I set the treatment to the year 2008, which has to be excluded from the model to center the regression, and 7 years of post-treatment (from 2009 to 2016).

On the other hand, in the case of Covid-19, I set the model differently:

$$\begin{aligned} Unemployment_{rt} = \sum_{\tau \in (-6.3), \tau \neq 0} \beta_\tau IO_r \times \boldsymbol{C}(t+\tau) + \\ + \boldsymbol{X}_{rt}\boldsymbol{\beta} + \alpha_r + \tau_t + \delta_{mt} + \epsilon_{rt} \end{aligned} \tag{5.5}$$

In this case, I have a data constraint for the post-treatment period, which I have to cut at the

[5] https://fred.stlouisfed.org/series/ITARECD

year 2022. For the pre-treatment, I started at year 2013. Again, to center the model, I exclude the interaction term between the indicator variable for year 2019 and IO_r.

5.4.1 Local Input-Output Linkages

IO_r is the source of the cross sectional variation. It is derived from the symmetric IO tables as follows. Following Ellison et al. (2010), I defined $input_{j \leftarrow i}$ as the fraction of input that goes from i to j, while $output_{j \leftarrow i}$ is the fraction of output that goes from i to j. Then I set

$$input_{ij} = \max(input_{j \leftarrow i}; input_{i \leftarrow j}) \tag{5.6}$$

which means that I take $input_{ij}$ to be the maximum value of the input flows between i and j. Similarly, for the output I set

$$output_{ij} = \max(output_{j \leftarrow i}; output_{i \leftarrow j}) \tag{5.7}$$

Finally, I built a statistic for IO flows that takes the maximum value between them:

$$IO_{ij} = \max(input_{ij}; output_{ij}) \tag{5.8}$$

This is an aggregate measure at the level of each pair of two-digit sectors (both manufacturing and non-manufacturing). I regionalize this value by using data on the co-occurrence of employees in each LMA. That is, if I observe that, say, sector 21 has a high value of IO_{ij} with sector 22, and in LMA (a) there is a high share of employment in both sectors relative to total employment, LMA (a) will have a high value of $IO_{21,22}$. LMAs with strong IO will be those with a higher co-occurrence in those sectors with higher values of IO_{ij}. The logic then is that LMAs with high levels of relative employment in sectors that turn out to be strongly interdependent according to IO_{ij} will be strongly IO dependent.

Such steps can be synthesized as follows. In the first step, I generate a weighted average over sector j of the value for each pair IO_{ij}. This results in a value of IO_{rj} for each sector j belonging to LMAs r. This is higher in LMAs where the sector j has a higher value IO_{ij} and higher values in the employment share of sector i, which is the weight.

$$\overline{IO_{rj}} = \frac{\sum_{rj=1}^{n} e_{rj} IO_{ij}}{\sum_{rj=1}^{n} e_{rj}} \tag{5.9}$$

Second, since I want a measure at the level of LMA r, I generate another weighted average. In this case, again, the value IO_r will be higher in those LMAs where IO_{rj} is higher and there are many sectors i (measured as their local employment share e_{ri}) having high values of IO_{ri}.

$$\overline{IO_r} = \frac{\sum_{i=1}^{n} e_{ri} IO_{ri}}{\sum_{i=1}^{n} e_{ri}} \tag{5.10}$$

This measure varies only at the LMA level and is a proxy for local IO dependency. I computed three different variations of this measure, depending on the sectors considered. The main independent variable is IO_r^{MAN}, which is computed considering only the IO linkages between manufacturing sectors. However, as a robustness test, I generate two more variables, one including all sectors and one including all non-manufacturing sectors.

Finally, I set

$$IO_r^{treated} = \begin{cases} 1, & \text{if } q^{IO} \in (q_2, q_{\max}] \\ 0, & \text{if } q^{IO} \in [q_{\min}, q_2] \end{cases} \tag{5.11}$$

where q is the tertile of the distribution. Essentially, observations with values of IO_r that fall in the upper third of the distribution are classified as treated (for a visual representation of this distribution, see figure 5.2[6]).

5.4.2 Control variables

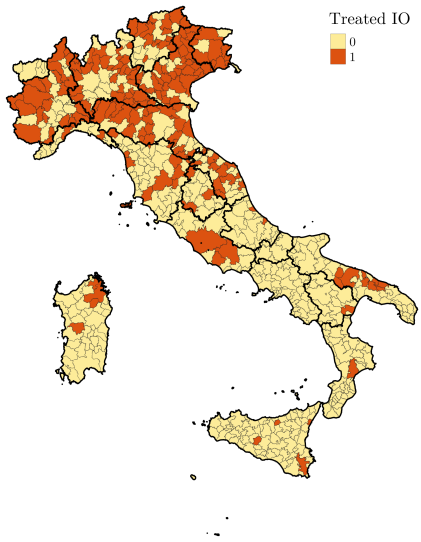
The full model also includes a vector of control variables X_{rt}. Each control variable is set to the base year (2007) - I have no variables for the previous year - and interacted with the indicator variable for each year. In this way, I am controlling for trends given the initial level of the local economic structure and avoid the potential contamination of the common shocks (Cinelli et al., 2022).

The variables included as controls are

- a dummy equal to 1 whether the LMA is an **industrial district** (2011 classification);
- a categorical variable that divides the national territory into three classes according to the level of **urbanization**;

[6]Here we can see that most of the industrial districts in Tuscany, traditionally specialized in light industry (textiles and clothing), are not included in the treated group. This may sound strange (and it is), but the main reason is that the IO tables offered by Istat group together the 2-digit Ateco sectors 13, 14, 15. Therefore, by definition, all intermediate flows between these sectors are not accounted for.

Figure 5.2: **Treated and Non-Treated Italian Local Labor Market Areas**



Notes. The map shows a categorical fill: Orange for *treated* LMAs and yellow for *not-treated* LMAs.

Source. My own elaboration

- a location quotient for **manufacturing concentration** calculated as the local ratio between manufacturing and total activities to the same ratio calculated at national level in 2007;
- the relative number of graduates on the total population as a proxy for **human capital** endowment, averaged between 2001 and 2011, since the only available data are the permanent population censuses in these two years;
- a proxy variable for **housing supply**, which is the rate of change in the number of housing units between 2011 and 2001;
- a **variety** measure computed as an entropy index among 3-digit sectors in each LMA in 2007;
- the **population density** computed using the population in 2007.

Briefly, the logic behind the inclusion of control variables is as follows. Industrial districts are manufacturing oriented areas in which small and medium sized firms are interconnected (Bellandi, 2016). However, if I included the district dummy as the main regressor, many overlapping

mechanisms would produce an unbiased estimate of the coefficient β_{fe}. Among them, the fact that industrial districts are computed in base year 2011 would suggest contamination from the common shock of 2007. Therefore, I partial-out all these other possible sources of endogeneity by including a dummy for industrial district as a control variable. One other most relevant source of endogeneity is the manufacturing specialization (Diamond & Simon, 1990). For this I add another control variable, the manufacturing location quotient. After removing manufacturing specialization, the residual variance of unemployment during recessions is potentially due to the *network* effect because of strong IO linkages (Acemoglu et al., 2016). The urbanization of an LMA is again a possible source of endogeneity bias, whether the 'city' phenomenon is compared with other LMAs. Cities are likely to be less volatile during recessions due to the mechanisms described by Lucas (1977) and then by Frenken et al. (2007). Even though the LMA fixed effect partially addresses this source of endogeneity, I include this variable, population density, and a proxy for the diversity of economic structure to address the hypothesis of portfolio diversification (Lucas, 1977; Simon, 1988; Frenken et al., 2007). Finally, I have two other main controls. Human capital is a necessary control because more educated workers are likely to move more (Faggian et al., 2019). During recessions, the movement of workers could be a relevant source of bias. I maintain that the inclusion of this variable and the spatially correlated standard errors are sufficient to estimate an unbiased effect of manufacturing IO linkages on unemployment. Finally, I include the trend for housing supply. This is again a relevant source of endogeneity whether the housing market is a constrain to the migration of workers (Evans and McCormick, 1994; Audas and MacKay, 1997).

5.4.3 Identification strategy: DiD estimator and parallel trends

The 2-group, 2-period pooled DiD estimator compares the evolution of the outcome between period 1 (pre-treatment) and period 2 (post-treatment) between a group g that goes from untreated in period 1 to treated in period 2 and a control group s that is *never treated* (De Chaisemartin & d'Haultfoeuille, 2023).

$$DID = Y_{g,2} - Y_{g,1} - (Y_{s,2} - Y_{s,1}) \tag{5.12}$$

Such a model relies on the *parallel trend assumption*, which means that without the treatment, the two groups being compared should have the same outcome *development*. This leads to the identification of the ATE (average treatment effect) for group g at time 2. The result of such a model is the unbiased coefficient β_{fe} of eq. 5.1.

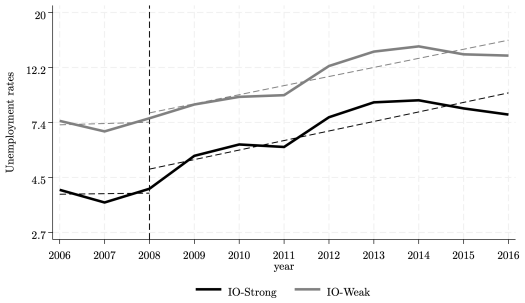
I test the parallel trend assumption in figure 5.3. Figure 5.3-a basically plots the evolution of unemployment in the two groups before and after the financial crisis. The vertical dashed line is the time of the shock (2008). From the visual representation, the parallel pre-treatment trends seem to be guaranteed. Rather, it is clear that there are relevant differences in average levels, which we remove with LMAs fixed effects. Figure 5.3-b shows that the parallel trend (pre-trend) assumption holds for this framework. On the other hand, figure 5.3-c and figure 5.3-d do the same for the Covid-19 shock. Again, the parallel trend assumption holds. Since the parallel trend assumption holds in this framework, there is no need to balance the treated and control groups of LMAs in terms of *observable characteristics*.

Returning to the model presented in eq. 5.1, I rely on traditional two-way fixed effects to deal with possible sources of endogeneity. In such a causal framework, β_{fe} captures the differences in unemployment rates between the comparison groups after the financial and covid crisis. At the national level, the effect of the financial crisis had a negative impact on unemployment rates (see figure 5.4). The coefficient β_{fe} should then be compared with such an effect. A positive coefficient means that the unemployment rate increases more in LMAs with strong IO linkages than in the control group. Conversely, a negative effect implies a flattening of such a negative trend. While unemployment rates fluctuated dramatically during the financial crisis, the effect of Covid-19 on employment was less pronounced (see figure 5.4). In fact, during the Covid-19, firms respond to the crisis by reducing the amount of vacancies rather than firing workers because of the implementation of the 'CIGS'. In general, figure 5.4 show that firms react through the reduction of job posting during shock while the unemployment response is lagged.

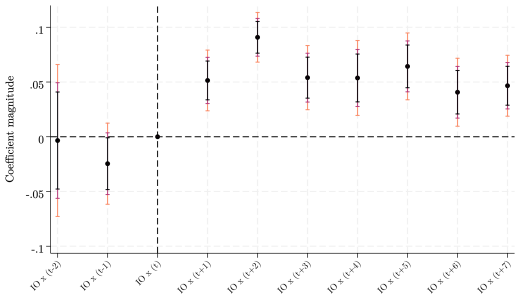
The two-way fixed effects model allows to deal with many possible sources of endogeneity. First, there are systematic differences in unemployment levels across LMAs that depend on their economic structure (see again figure 5.3-a and figure 5.3-c). By including the LMA fixed effect, I partial out such systematic differences. For example, it can be argued that some local characteristics affect both unemployment and input-output linkages (e.g. the presence of efficient infrastructure for firms). Controlling for LMA fixed effects delete such bias. In general, the inclusion of LMA fixed effects should be able to address concerns about omitted variable bias. The two-way fixed effect is also able to deal with common annual changes. Changes in national law, government intervention, changes in monetary policy, and so on, are controlled for by the year fixed effects. A possible bias could come from place-based policies implemented to deal with local peculiarities over the sample. In this case, if such policies are systematic, they may bias the results. However, to partially account for such place-based policies, I include time-varying

Figure 5.3: **Test for parallel trends assumption**

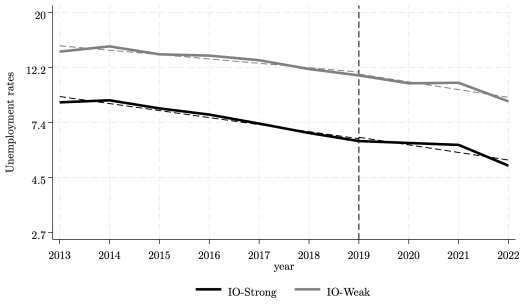
(a) Financial Crisis plot



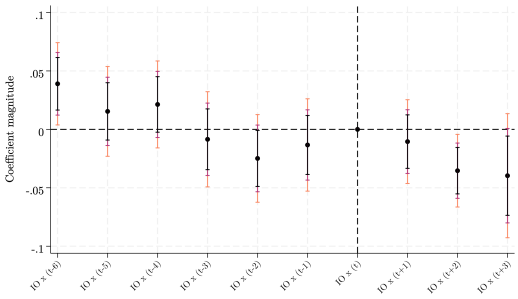
(b) Financial Crisis Event Study



(c) Covid-19 plot



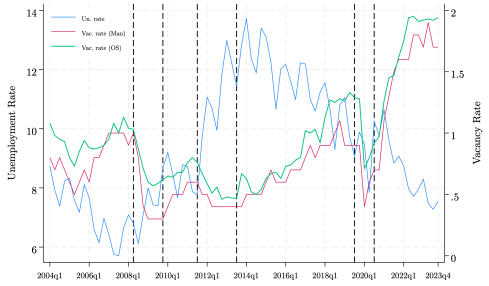
(d) Covid-19 Event Study



Notes. Panels (a) and (c) show the annual change in the unemployment rate. Panel (a) uses the period from 2006 to 2016, while panel (b) uses the Covid-19 crisis from 2013 to 2022. They also plot the unemployment trend before and after the crisis. The Y-axes are in natural levels, but were originally in logarithms. They are transformed for ease of reading. Panels (b) and (d) plot the event study setup in eq. 5.4 and eq. 5.5 but without the control variables. The result shows the magnitude of the coefficient for the terms $IO \times F(t+\tau)$ and $IO \times C(t+\tau)$ along with 90% (black), 95% (purple), and 99% (orange) confidence intervals. Standard errors are spatially (200 km) and serially (11 years) correlated consistent (HAC).

Source. My own elaboration on Istat data.

Figure 5.4: **Vacancy and unemployment rates in Italy (2006-2022)**



Notes. Blue line is the unemployment rate change. Red line is the vacancy rate in manufacturing while green is in other sectors. Left Y-axis refers to unemployment while right-hand Y-axis refers to vacancy rate.

Source. My own elaboration on Istat data.

macro-region fixed effects. If, during the period under study, policies were implemented to address the North-South divide in structural development, then the inclusion of such time-varying fixed effects removes this bias.

5.5 Results

Table 5.3 reports the OLS estimates of equation 5.1. There are 5 columns reporting different specifications with the logarithmic transformation of unemployment rates as the dependent variable. Column (1) controls for LMA FE and pools observations before and after the treatment. Column (2) includes year FE. Column (3) includes the dummy for South, interacted with year. Column (4) includes control variables × indicator variables for years and no south × years FE. Column (5), which is the preferred specification, includes LMA, year, South × year FE, and control variables × year. It estimates the coefficient β_{fe} on the interaction between IO and crisis using HAC standard errors. The spatial lag is set to 200 km and the temporal lag to 10 years.

The result suggests that LMAs with strong input-output linkages experience a larger increase in unemployment rates after the crisis compared to LMAs with weaker IO linkages. It is interesting to note that the effect of the IO linkages decreases from column (1) to column (5) due to the introduction of control variables. In fact, in columns (1), (2), and (3), we expect the coefficient on the interaction terms to be upwardly biased, capturing some of the variation due to manufacturing specialization. Once manufacturing specialization is partialled-out, the effect of the coefficient is greatly reduced. I maintain this is exactly the 'indirect effect' due to the

Table 5.3: **Input Output and unemployment changes**

	1. Unemployment	2. Unemployment	3. Unemployment	4. Unemployment	5. Unemployment
IO × Crisis	0.15**	0.15***	0.06***	0.09***	0.04**
	(0.06)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	6,100	6,100	6,100	5,860	5,860
R2-Within	0.01	0.06	0.23	0.17	0.27
LMA FE	YES	YES	YES	YES	YES
Year FE	NO	YES	YES	YES	YES
South × Years FE	NO	NO	YES	NO	YES
Controls × Years	NO	NO	NO	YES	YES

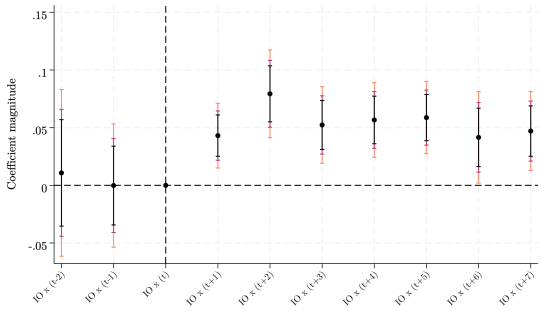
Notes. In all columns the panel identifier is the couple LMA and year. The dependent variable is the log transformation of the unemployment rate. Column (1) pooles observations prior to and after treatment and includes LMA FE. Treatment is set at the year 2008. All observations from 2009 to 2014 are post-treatment. Column (2) includes Year fixed effects rather than pooles before and after treatment and LMA FE. Column (3) includes a dummy South × Year to partial-out differential in speed of growth between northern and southern LMAs. Column (4) includes some control variables - trends and no South × Year FE. Control variables are: a dummy for industrial district, a dummy for urbanization, the manufacturing location quotient in 2007, human capital (the ratio of tertiary educated people on total population) that is the mean between 2011 and 2001, the growth rate in the number of real estates between 2011 and 2001. Control variables are interacted with indicator variables for each year from 2006 to 2016. Standard errors are HAC (heteroskedasticity and autocorrelation consistent) to take into consideration spatial spillovers as well as serial correalation.
∗ ∗ ∗ p<.01, ∗∗ p<.05, ∗ p<.1

propagation of the shock in the local industry. It drops from 15% in column (1) to 4% in column (5), which is the more parsimonious specification. Considering column (5) as the full model, LMAs with strong IO linkages experienced a 4 percent larger increase in unemployment rates after the crisis.

In the appendix (section A), I test the robustness of the results using a number of different indicators. First, I use the change in employment instead of unemployment. I find a negative effect on employment in LMAs with strong IO linkages of 0.8% (see column 5 of table 1). I also look at the subset of industrial districts to show that the result is not driven by manufacturing specialization. In fact, there is a 5.1% increase in unemployment in treated industrial districts (strong IO) compared to untreated industrial districts (see column 5 of table 2). The same result using only the subset of industrial districts is obtained by using employment instead of employment (see column 5 of table 3). Finally, I also use a different reference threshold to identify treated and non-treated LMAs. Using quartiles instead of tertiles, the result for unemployment is still the same. The quartile of LMAs with stronger IO linkages suffers a 3.5% increase in unemployment relative to the comparison group (from the first to the third quartile).

In figure 5.5, I show the result for the event study based on eq. 5.4. It includes all the control variables presented in column (5) of table 5.3. It reports the coefficients on the interaction terms between IO and year. The coefficients in $IO \times (t-2)$ and $IO \times (t-1)$ are zero and statistically insignificant. This suggests that the parallel trend assumption holds conditional on the control variables. The higher effect of the crisis is in the year $IO \times (t+2)$ (2010). Here, the increase in unemployment is about 8% higher in LMAs with strong IO compared to those with weaker IO.

Figure 5.5: **Input output and unemployment - Event Study**



Notes. The picture represents the timing of the shock and the responses over time of IO linkages. The unemployment rate is still the main dependent variable. The variables $IO \times (t + \tau)$ are interaction terms of the variable gauging thickness of IO, an dummy equals to one for LMAs within the third tertile of the continuous local IO variable, with indicator variables for each year. Year t identifies the starting point of the crisis. The model in the figure is the same used in column (5) of table 5.3. The figure reports the coefficient of the interaction between year and IO together with the 90% (black), 95% (purple) and 99% (orange) confidence intervals. Standard errors are HAC: spatially (200 km) and serially (10 years) correlated.

Source. My own elaboration

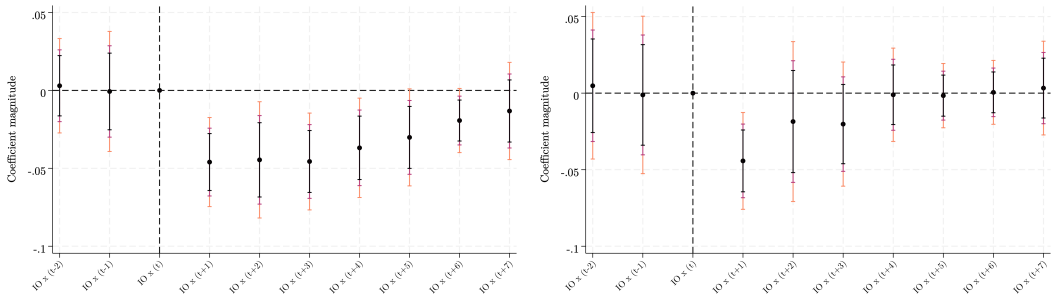
Figure 5.6-a symmetrically estimates the same coefficients but using a different independent variable. In this case, I use the thickness of the IO linkages between the non-manufacturing sector. The result suggests that LMAs with strong IO linkages experience a less severe increase in unemployment rates after the crisis compared to LMAs with weaker IO linkages in services. This is particularly relevant because the IO linkages in services acts as a moderator of crises, while manufacturing amplifies them. On the other hand, 5.6-b estimates the same model with all IO linkages. Again, the strength of local inter-sector networks seems to be a relevant mediator of the crisis in the year immediately following the shock. However, the negative effect on unemployment disappears at $t + 2$ (2010). The results obtained in this specification overlaps with the narrative about the role of sectoral diversification in cities. Once partialled out all possible sources of endogeneity, the effect of strong services IO linkages suggests a negative effect on unemployment as reported in previous paper about service specialization (Lagravinese, 2015).

5.5.1 The effect of COVID-19 as a placebo treatment

In this section, I use the Covid-19 crisis as a placebo treatment. Due to the state intervention to fix the level of employment through the 'cassa integrazione guadagni straordinaria' (CIGS) as a wage subsidy for those workers who experience a reduction in their working hours, we expect

Figure 5.6: **Input Output and Unemployment**

(a) Effect of non-manufacturing IO (b) Effect of total IO



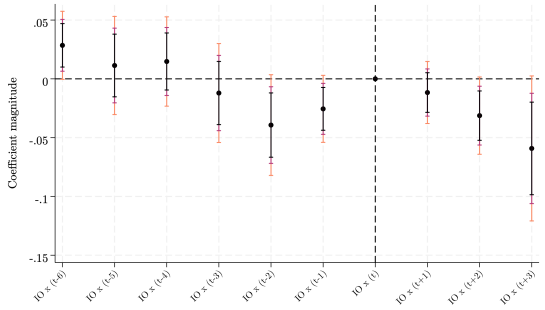
Notes. Panel (a) shows the same coefficients as in column (5) of table 5.3, but using a measure of IO only for non-manufacturing sectors. Panel (b) includes all sectors.

Source. My own elaboration on Istat data.

no effect on unemployment here. Basically, the research design is the same as in the previous application, but the shock is a 'fake' shock to unemployment. The results are shown in figure 5.7. As expected, there is no effect of the manufacturing IO linkages on unemployment. However, there is a statistically significant negative pre-trend in the 2 years prior to the crisis. This is due to the recovery period, during which unemployment falls more in LMAs with a thick IO linkages compared to the others.

As for the financial crisis, I again compare the results for manufacturing IO with those for services and total IO. The results are shown in figure 5.8. In the case of the services figure 5.8-a, we can see that the process of 'convergence' is now working. A positive pre-trend in unemployment suggests that places where service sectors are strongly interlinked were experiencing a higher increase in unemployment than other places ($IO \times (t-1)$) (2018). This is a convergence trend from the result obtained for the previous figure 5.6. While the interconnectedness of services acts as a moderator of unemployment during the financial crisis, a few years after the crisis, those LMAs that experienced a smaller reduction in unemployment faced an increase in their unemployment levels. On the other hand, figure 5.8-b shows no pre-trends during the pre-treatment period and a positive effect on unemployment in the year of the closure (2020).

Figure 5.7: **Input output and unemployment during Covid-19**

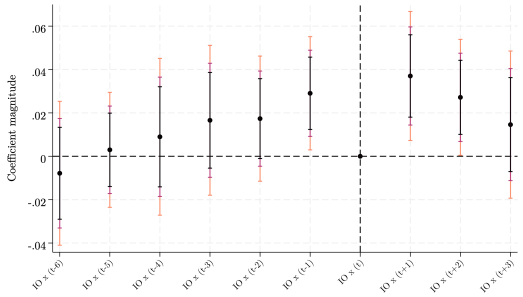


Notes. The picture represents the timing of the shock and the responses over time of IO linkages. The unemployment rate is still the main dependent variable. The variables $IO \times (t + \tau)$ are interaction terms of the variable gauging thickness of IO, an dummy equals to one for LMAs within the third tertile of the continuous local IO variable, with indicator variables for each year. Year t identifies the starting point of the crisis (2019). The model in the figure is the same used in column (5) of table 5.3 but changes the timing of the crisis. In this case, I use the Covid-19 crisis as a common shock. The figure reports the coefficient of the interaction between year and IO together with the 90% (black), 95% (purple) and 99% (orange) confidence intervals. Standard errors are HAC: spatially (200 km) and serially (10 years) correlated.

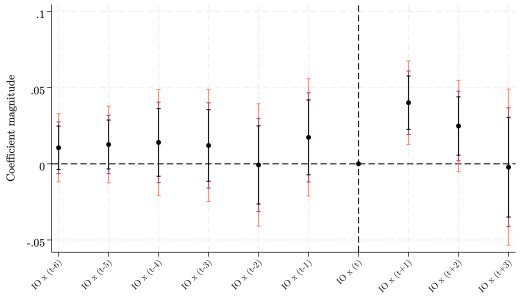
Source. My own elaboration

Figure 5.8: **Input Output and Unemployment during Covid-19**

(a) Effect of non-manufacturing IO



(b) Effect of total IO



Notes. Panel (a) shows the same coefficients as in column (5) of table 5.3, but using a measure of IO only for non-manufacturing sectors. Panel (b) includes all sectors.

Source. My own elaboration on Istat data.

5.6 Conclusions and policy implications

This paper is the first attempt to estimate the additional effect on unemployment of strong local input-output linkages in manufacturing. While manufacturing is mostly export-oriented, it is also highly localized. A large part of Italian manufacturing production is located in industrial districts, which account for a quarter of the total local labor market areas in Italy (Bellandi, 2016). This happens because of the incentive of firms to locate close to their customers/suppliers (Ellison et al., 2010). Proximity reduces transportation and transaction costs between firms and generates localized knowledge spillovers (Bellandi, 1995; Diamond and Simon, 1990). I exploit this regularity to generate a measure of local input-output linkages using symmetric national IO tables and a confidential plant-level dataset obtained from the Istat Laboratorio Adele. The proxy allows me to investigate the additional effect on unemployment due to the propagation of shocks through the local value chain.

In general, manufacturing is expected to be more volatile than other sectors when a global shock hits the economy. However, manufacturing also relies on "national" local transactions to produce its total output. 58% of total national trade flows are within the manufacturing sector. For this reason, the effect of a shock on manufacturing is not limited to the shock itself. Rather, it propagates through the local input-output linkages to produce larger fluctuations (Acemoglu et al., 2016). I estimate this effect using a DiD approach over the period 2006-2022. The period under study is particularly useful for estimating such an effect because of the presence of two common nationwide shocks. The first is the financial crisis that started in 2007 and spread in Italy over the next 5 years. On the other hand, the second crisis (Covid-19) is used as a placebo treatment because unemployment was not free to fluctuate due to government intervention. I found that during the financial crisis, LMAs with strong manufacturing IO linkages suffer an additional increase in unemployment compared to the control group equal to 4 points percent. Also, the Covid-19 crisis generates, as expected, no significant differences between the treated and control groups of LMAs. The placebo test provides robust confirmation that the results are not due to improper specification of the model.

The identification of the causal effect of IO linkages on unemployment is supported by a theoretical framework that merges the literature on the network effect due to Acemoglu et al. (2016) and the literature on the (de)centralized bargaining process (Boeri et al., 2021). The performance of the national economy during recessions is linked to the ability of different places to respond to economic cycles. While the need to fix employment levels during the crisis is

a desirable policy, the econometric exercise carried out in this paper shows that places where manufacturing sectors are locally highly interlinked are those to experience larger fluctuations in unemployment during crises. This calls for more place-based counter-cyclical unemployment policies targeted at specific locations. In fact, southern LMAs, where few report high levels of manufacturing IO as well as strong manufacturing specialization, had very low unemployment fluctuations during the financial crisis. This led to a tendency towards convergence during crises, which reversed in good times.

Some limitations remain. First, the econometric exercise used symmetric national IO tables. These are only available for 2010 and may have been altered by the previous crisis. Second, the measure used for IO is a proxy, and even if the DiD estimator is unbiased, it is not able to deal with the real level of IO linkages at the local level. This is also an invitation to the national statistical office to update its dataset to accurately measure such variation at the local level. This is very important from both an academic and policy point of view. Finally, this paper discusses the relevance of intra-local IO linkages for the propagation of global crises at the local level. Another relevant mechanism occurs in the case of trans-local IO linkages (between different LMAs that might also belong to the same NUTS-2 region). In the same way that local IO linkages amplify fluctuations at the level of the LMA, trans-local IO linkages do so at the level of a group of LMAs. This is beyond the scope of this paper, but provides an insight to further analyze such a direction.

Besides the limitation, it is important to emphasize the real contribution of this paper. First, there is an academic contribution that comes from the empirical side. Here, I test theories of aggregate fluctuations arising from the presence of localized network effects, which have often been overlooked from a macro perspective. Second, there is a real empirical contribution with political returns. This is of interest to Italian policymakers because it gives an idea of the extent to which places react differently to economic shocks and how much local structures are relevant in mitigating such shocks. An intelligent policy could differentiate policies in terms of local structures to deal with aggregate fluctuations.

Appendices

A Robustness Tests for Financial Crisis

This section provides several robustness tests by replicating the pooled regression as in equation 5.1. The replication here is for the global shock caused by the financial crisis. All tables replicate table 5.3.

A.1: **Input Output and Employment Changes**

	1. Employment	2. Employment	3. Employment	4. Employment	5. Employment
IO × Crisis	0.016**	0.016***	-0.010***	0.008	-0.008***
	(0.007)	(0.006)	(0.002)	(0.005)	(0.003)
Observations	6,100	6,100	6,100	5,860	5,860
R2	0.007	0.011	0.229	0.093	0.298
LMA FE	YES	YES	YES	YES	YES
Year FE	NO	YES	YES	YES	YES
South x Year FE	NO	NO	YES	NO	YES
Controls x Year FE	NO	NO	NO	YES	YES

Note. In all columns the panel identifier is the couple LMA and year. The dependent variable is the log transformation of the employment rate. See Notes to table 5.3. *** p<.01, ** p<.05, * p<.1

A.2: **Input Output and Unemployment Changes (subset of IDs)**

	1. Unemployment	2. Unemployment	3. Unemployment	4. Unemployment	5. Unemployment
IO × Crisis	0.076	0.076***	0.055**	0.063**	0.051*
	(0.055)	(0.024)	(0.026)	(0.029)	(0.030)
Observations	1,410	1,410	1,410	1,380	1,380
R2	0.004	0.026	0.106	0.099	0.156
LMA FE	YES	YES	YES	YES	YES
Year FE	NO	YES	YES	YES	YES
South x Year FE	NO	NO	YES	NO	YES
Controls x Year FE	NO	NO	NO	YES	YES

Note. In all columns the panel identifier is the couple LMA and year. The dependent variable is the log transformation of the unemployment rate. See Notes to table 5.3. *** p<.01, ** p<.05, * p<.1

A.3: **Input Output and Employment Changes (subset of IDs)**

	1. Employment	2. Employment	3. Employment	4. Employment	5. Employment
IO × Crisis	-0.005	-0.005	-0.010***	-0.005	-0.009**
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	1,410	1,410	1,410	1,380	1,380
R2	0.001	0.002	0.056	0.242	0.307
LMA FE	YES	YES	YES	YES	YES
Year FE	NO	YES	YES	YES	YES
South x Year FE	NO	NO	YES	NO	YES
Controls x Year FE	NO	NO	NO	YES	YES

Notes. In all columns the panel identifier is the couple LMA and year. The dependent variable is the log transformation of the Employment rate. See Notes to table 5.3. *** p<.01, ** p<.05, * p<.1

A.4: **Input Output and Uneployment Changes (Quartiles)**

	1. Unemployment	2. Unemployment	3. Unemployment	4. Unemployment	5. Unemployment
IO × Crisis	0.143**	0.143***	0.056***	0.083***	0.035**
	(0.057)	(0.027)	(0.018)	(0.021)	(0.017)
Observations	6,100	6,100	6,100	5,860	5,860
R2	0.010	0.048	0.223	0.164	0.265
LMA FE	YES	YES	YES	YES	YES
Year FE	NO	YES	YES	YES	YES
South x Year FE	NO	NO	YES	NO	YES
Controls x Year FE	NO	NO	NO	YES	YES

Notes. In all columns the panel identifier is the couple LMA and year. The dependent variable is the log transformation of the unemployment rate. In this table, treated and non-treated LMAs are built using quartile rather than tertile. *** p<.01, ** p<.05, * p<.1

Part III

Conclusive Part

Chapter 6

Conclusions

6.1 Brief Summary and Main Contributions

This thesis focused on the effect of external economies due to the geographical concentration of manufacturing on several economic indicators that reveal the economic performance of places. The interest in manufacturing as the main engine of local and national growth and in the Italian case has had the effect of guiding my analysis to a specific unit of analysis. If the geographical concentration refers to the Italian case, industrial districts become the natural unit of investigation, since most of the manufacturing activity is concentrated in them (Becattini, 1979; Becattini, 1989; Bellandi, 1989).

Recently, these areas have experienced dramatic changes in their industrial structure due to the influx of large firms (see chapter 3). While this is not a problem per se, since large firms bring with them higher levels of own efficiency relative to smaller firms, it is a potential threat to paths of self-sustaining growth. As suggested by Bellandi (2009), industrial districts thrive when some systemic conditions are realized. The presence of industry-specific public goods, a cooperative nexus among a set of producers organized in phases of production, and their limited size are conditions that are necessary in industrial districts to join external economies (Becattini & Musotti, 2003). This is an emerging challenge for both the Italian industrial organization and the model of industrial districts (Becattini et al., 2009). Even if this work does not properly exploit the interdisciplinary lens that is necessary for the study of industrial districts, it brings some relevant empirical insights from the proper point of view of the economic discipline. This is one of the main limitations of these studies.

However, the scope of this dissertation is also to bridge the traditional literature on regional and urban economics with the literature on industrial districts. Once the perspective of this dissertation is defined, it is also possible to deal with the related tools. Among the set of systemic conditions that need to be realized in industrial districts, this thesis focuses on those that arise from local industrial structures. These are the ways in which places, cities and regions organize their production processes. This is well developed in the urban economics literature, which has the advantage of being internally consistent. I draw on this literature to present the main stylized facts and economic rationale of the thesis. Here, models of spatial equilibrium are necessary to draw meaningful conclusions. This requires assumptions about the behavior of firms and workers and about optimization processes. One can be concerned that the analytical conclusions derived are simply the logical consequences of overly strict and implausible assumptions. Nevertheless, it is a way of isolating human behavior (when acting in economic contexts) when constrained by certain conditions.

Moreover, theoretical derivations provide a foundation for developing empirical approaches that align with the data. Empirical tools come from the quantitative point of view. While case studies often focus on the specificity of places and their organic interactions to provide insightful conclusions, econometric analysis tends to isolate specific phenomena to measure their causal effects. The latter has the advantage of internal and (often) external validity, whereas the former offers at most internal validity. I also use the entirety of local labor market areas in Italy (610 local labor market areas - LMAs) rather than focusing only on industrial districts (141 LMAs). In this way, the presence of a counterfactual makes the econometrics more robust. In each econometric design, the district model was the reference unit, but I prefer to decompose its structure into industrial specialization, input-output linkages, labor pooling, and knowledge spillovers to avoid the use of a simple dummy for industrial districts, which covers many aspects that I could not control for.

The structure of this conclusion is based on three blocks. The first block summarizes and provides an overview of the main contributions of the three original chapters of the thesis, respectively chapter 3, chapter 4 and chapter 5. The perspective is on the main dependent variables of each chapter: respectively, employment, productivity, unemployment. The second block retrieves the main estimates obtained in each chapter to document the presence of a trade-off between employment and productivity growth when looking at the national effect of place-based policies. While policy implications are not really discussed in each chapter of the thesis, here I take advantage of the space provided by the more extensive format of the thesis to

discuss policy implications for the spatial organization of production in the case of Italy. It relies on the theoretical framework proposed in chapter 2.2. Finally, the third block is also a traditional one. It basically offers a perspective on my future research. This works as a concluding section for the thesis, hoping that this is the starting point for future detailed studies.

6.1.1 Employment

In chapter 3, I use the influx of large firms into industrial districts to see to what extent the movement of workers from smaller to larger firms can lead to higher levels of total employment in the region. I use the basic to non-basic multiplier to depict a causal mechanism from tradable activities (manufacturing + extraction activities) to non-tradable activities (all goods and services devoted to local consumption). It has been argued that industrial districts produce a particular form of spatial equilibrium that tends toward full employment. This was ensured by the independence of small firms from large corporations. Even if small firms paid lower wages than large one, they employed a larger number of workers in the aggregate. Then, while wages were lower, the income available to households was higher because of overall higher levels of employment (Graziani, 1998). However, the chapter questions whether the influx of large firms can offset such a peculiar equilibrium. This is driven by a key stylized fact that is the *pouring out* effect that is workers are increasingly moving from smaller to larger firms, being the same level of tradable employment. Given the level of jobs in tradable sectors, the number of jobs in non-tradable sectors increases over the period under study (2012-2020).

I propose two main hypotheses based on pecuniary externalities (Ottaviano & Thisse, 2001). First, while larger firms pay higher wages, the *pouring out* effect due to the movement of workers from smaller to larger firms is sufficient to increase non-tradable jobs due to the expansion of local demand, given the level of tradable activities. Second, in the counterfactual, since larger firms have less incentive to purchase local inputs because they trade off transportation costs more than smaller firms, the increase in the number and employment of larger firms has a negative impact on nontradable jobs because of the reduction in backward and forward linkages. The result is that larger firms have high levels of absolute job multipliers that are sufficient to account for the increase in non-tradable jobs over the period under investigation. Nevertheless, the entry of a tradable firm has a differential effect according to the place where it locates because of the presence of the negative *competition effect*. In general, the multipliers are higher outside the industrial districts. In industrial districts, however, the larger multipliers are those resulting from the entry of large firms. In non-districts, smaller firms have the larger multipliers that are

highest across all categories (see table 3.6). In the next section, I use this to draw some policy implications.

Synthesis - Are there local multipliers from tradable (manufacturing) to non-tradable activities in Italy over the period 2012-2020? Can *pouring out* effects from smaller to larger firms explain the growth of non-tradable activities? The answer is yes and yes.

6.1.2 Productivity

In chapter 4, I still started from the same stylized fact. While an influx of larger firms potentially creates an equilibrium with a higher level of employment, it also reduces the level of local competition. As fewer firms account for an increasing share of total manufacturing employment, the Herfindal-Hirschman Index (HHI) of competition tends to rise, indicating lower levels of local competition. The interest of the chapter here is on productivity, and in particular on the elasticity of productivity with respect to specialization and competition. I built on theories of agglomeration externalities proposed by Glaeser et al. (1992) and theories on external economies in *perfect competition* proposed by Chipman (1970) to develop a model of partial equilibrium in the local market. The intuition is based on oligopsony in the labor market and the preference for large expanding and competitive industries. The equilibrium provides a functional form for local productivity shifter (the term A of the production function). This increases with the geographic concentration of an industry and its degree of local competition.

I test this by proxying local productivity with local total factor productivity extracted from the firm-level production function (Petrin & Levinsohn, 2012). After accounting for endogeneity leveraging on the most recent literature on estimating agglomeration externalities (Combes et al., 2010), I estimate the effect of specialization, competition, and their interaction on this local component of industrial TFP (LITFP). The results confirm that competition positively affects the effect of specialization on LITFP. However, the effect of geographic concentration of manufacturing is never positive when considering 3-digit industries, also when competition is very fierce (see figure 4.2). I argue that when considering 3-digit industries as industrial unit of analysis, the assumption of the econometric model is that labor pooling and knowledge spillovers take palce only within the same industry. This assumption is about the degree of skill substitutability between workers in different industries. Once such an assumption is relaxed and total manufacturing specialization is used as the independent variable, the model suggests a positive effect of specialization at certain levels of competition, and the higher the competition,

the higher the effect of specialization on LITFP. This positive effect disappears at low levels of competition. I also suggest some thresholds above which external economies disappear. Again, this has relevant policy implications, which are discussed in the next section.

Synthesis - Do external economies in manufacturing promote productivity growth in Italy in the period 2012-2020? Can external economies in manufacturing emerge in a context of low local competition? The answer is yes and no.

6.1.3 Unemployment

Chapter 5 took a different perspective. It still discussed some of the advantages of regions that are highly specialized in manufacturing activities, but it looked at fluctuations over business cycles, particularly in unemployment. The stylized fact from which I started was that the financial and sovereign debt crises affected LMAs differently. Places with very low levels of unemployment - which correlate with the degree of specialization in manufacturing - suffered large increases in unemployment, while places with higher levels of 'structural unemployment' fluctuated less (see figure 5.1). Certainly, places with high levels of manufacturing specialization are more exposed to export activities resulting in procyclical tendencies (Caivano et al., 2011). However, shocks to specific industries may be washed out at the aggregate level (Lucas, 1977). The rationale for this is that if some industries have to lay off workers, some others can hire them (Simon, 1988). Thus, at the aggregate level, industry-specific shocks are negligible. I question this view. In places where industries are strongly interlinked through input-output linkages, the effect can be amplified. The direct effect of a shock is amplified by an indirect effect when there are strong input-output linkages. The reduction in global demand for export-oriented activities is reflected in their backward linkages and reduces local demand for intermediate goods. Through multiple feedbacks, the initial shock is amplified at the level of the local economy.

I estimated this effect using a difference-in-differences estimator. After controlling for several pretreatment confounding variables and conditioning on manufacturing specialization, I find that in places where IO linkages are stronger, there is a significant reduction in unemployment that is larger than that of the comparison group by 4 percentage points. This is also consistent within the subsample of industrial districts only. I also used the Covid 19 crisis as a placebo test. Indeed, during this period there was a large use of subsidies to fix the level of employment. The effect during Covid-19 is actually negligible. Again, this has relevant policy implications, which I suggest in the next section.

Synthesis - Does unemployment fluctuate less during economic turbulence in local labor market areas with strong input-output linkages? The answer is no.

6.2 Policies implications

The results of the previous chapters are useful for thinking about policy. Place-based policies are efficient if the benefits of their implementation exceed their costs. Specifically, they are efficient if they are able to improve national economic indicators[1]. In the following, I present my results in the settings proposed by Glaeser and Gottlieb (2008), Kline and Moretti (2014a), Austin et al. (2018), and Bartik (2020). In the next parts, I also show that there are a couple of trade-offs when we look at place-based policies. First, there is a trade-off when policymakers are willing to reallocate manufacturing jobs and plants across space. Second, there is another trade-off when the policy maker's goal is to encourage firms to grow internally. In both cases, there is a positive effect on employment, but the effect on productivity is negative in the first case, especially in the short run, and to some extent limited in the second.

With respect to spatial reallocation, the trade-off arises from the fact that the geographic concentration of manufacturing employment has positive returns to aggregate productivity, making reallocation to low-density areas inefficient and costly. On the other hand, reallocating jobs from high-density to low-density areas increases national employment. Similarly, there is a trade-off when industrial policies aim to increase the size of firms or encourage the entry of larger firms and mergers and acquisitions. While shifting jobs from smaller to larger firms has a positive effect on national employment (via higher local multipliers), the effect of increasing size in LMAs is to reduce competition with a relatively negative effect on productivity. Finally, I briefly discuss the possibilities for pro-cyclical policies in the presence of localized external economies. I discuss this in more detail below.

6.2.1 Policies for Place-Based Jobs

When a manufacturing firm locates in an LMA, it creates additional jobs in non-tradable sectors because of the local multiplier effect through increased demand for intermediate inputs and the labor demand effect through the expansion of the local wage bill. The rationale for this section

[1] Although this is the setting followed in this chapter, it is worth noting that a district-based approach to place-based policy could also focus on welfare gains rather than just employment and productivity (Becattini, 2015). However, as discussed above, this paper is limited to focusing on measurable and easily operationalized indicators.

is that the reallocation of jobs from high-density (highly competitive) areas to low-density (less competitive) areas can promote national employment growth. A related question, which I answer in chapter 3, is the extent to which shifting jobs *within* an LMA from smaller to larger firms can create additional jobs overall - given the level of tradable jobs. I answer such questions by drawing on the estimate presented in chapter 3. The relevant concept here is the local job multiplier. The job multiplier can be thought of as the increase in the number of non-tradable jobs due to one additional tradable job.

Place-Based policies for Spatial Inequalities - Main findings of chapter 3 suggests that moving a manufacturing establishment from dense markets such as industrial districts to other non-district areas is likely to produce a greater increase in non-tradable activities[2]. The job multiplier in industrial districts is 2.2, while that in non-districts is ≈ 3 (see table 6.1, columns 2 and 3). An increase of 100 jobs in tradable sectors creates 35% more jobs in non-tradable sectors in non-district areas than in district areas. I argue in the chapter that this is due to a reduced *competition effect* in non-district areas. Replication with several other types of areas yields similar results. For example, the job multiplier in high-unemployment areas (where the unemployment rate is $\approx 20\%$) is about twice that of low-unemployment areas (where the unemployment rate is $\approx 6\%$) (see columns 4 and 5 of table 6.1). Similarly, the job multiplier in low-employment areas (employment rate $\approx 31\%$) is almost 50% higher (up to ≈ 4) than that (≈ 2.7) in high-employment areas (employment rate $\approx 51\%$) (see columns 6 and 7 of table 6.1). A different result is obtained if we look at the degree of urbanization, taking it as a proxy for productive amenities. One additional tradable job generates 2.8 and 2.3 jobs in large and rural LMAs respectively (see table 6.1, column 8 and 9). The effect of moving manufacturing plants from high density areas to low density areas has positive effect for national employment growth.

Local Industrial Policies for Employment Growth - Returning to the core of the result obtained in chapter 3, I examine the extent to which a *pouring out* effect from smaller to larger firms leads to an increase in total employment. In this case, such a *pouring out* effect risks being washed out by a negative *cost-linkages effect* if large firms rely less on local inputs. Here, the results suggest that the worker demand effect due to increased employment by larger firms (via higher wages) is higher than the negative *cost-linkage* effect that is documented in table 3.4. In

[2]If the idea of moving the establishment does not appeal to the reader thinking about a growth process, the same reasoning can be made in terms of winning or losing entry establishments. That is, it can be thought of as a trade-off between locating such an establishment in one area versus another.

Table 6.1: **Jobs Multipliers**

	Full Sample (1)	Non-Districts (2)	Districts (3)	Low-Unemp. (4)	High-Unemp. (5)	Low-Emp. (6)	High-Emp. (7)	Large Cities (8)	Rural Areas (9)
Jobs Multipliers	2.835***	2.975***	2.200***	2.013***	4.079***	3.983***	2.659***	2.788***	2.311***
	(0.167)	(0.215)	(0.466)	(0.304)	(0.180)	(0.215)	(0.112)	(0.188)	(0.239)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
LMA FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	3,606	2,763	843	1,335	1,115	1,129	1,292	126	2,961
N. LMAs	610	469	141	271	223	206	237	21	502

Notes. The main dependent variable is the 3-years change in the level of non-tradable jobs. The main independent variable is the 3-years change in the level of tradable jobs. The instrument used is the same as in chapter 3. LMA and Year fixed effects (FE) are included in all specifications. Standard errors are clustered at the LMA level.
*** p<.01, ** p<.05, * p<.1

general, equilibria with large tradable firms have higher levels of local non-tradable employment in comparison to those with micro and medium, but smaller than that with small firms (see table 3.3 in chapter 3). Surprisingly, this effect is stronger in industrial districts where the *cost-linkage effect* is expected to be higher (see column 8 in table 3.6 of chapter 3).

Overall, these results suggest that policies that encourage the entry of large firms into industrial districts are not detrimental to national growth. However, while this effect is positive in industrial districts, the effect of large firm entry is weaker in non-district areas (see column 7 in table 3.6 of chapter 3). Here, the movement of workers from small to large firms is detrimental to national growth, while the movement of workers from micro and medium to large firms promotes employment growth. A policy mix that encourages the entry of small manufacturing firms in non-district areas to protect them from the strong competition that exists in industrial districts, while providing incentives for large tradable firms to locate in industrial districts, is the way in which the policy maker could maximize employment growth. The effect of the entry of small tradable firms could also have important externalities in terms of reducing crime rates, social spillovers and fiscal costs if these firms (re-)locate in areas of high unemployment.

6.2.2 Place-Based Policies for Productivity

If the policy implications due to results obtained in chapter 3 are optimistic, the results in chapter 4 shed some doubts about the possibility of positive place-based policies. In this section, I challenge the idea that the reallocation of manufacturing jobs or plants across space (or between firms of different sizes) can lead to an overall increase in productivity. The main concept on which I base this chapter is that of elasticity, or the extent to which productivity responds to changes in the degree of specialization. Chapter 4 relies on the role of competition for productivity gains. However, there are different elasticity coefficients depending on the presence or absence of non-

linearities. This will be discussed in the following paragraphs. I begin by explaining a scenario with a linear model of specialization to move to nonlinearities due to the degree of specialization and finally to competition. In the last part, I also try to discuss the effect of increasing size and decreasing competition, although this is not a direct topic of chapter 4.

Constant Elasticity - Let's take an average LMA with a low level of manufacturing activity. In this environment, what is the impact on Region B of a plant moving from Region A? Assuming that the level of competition remains constant, the effect of a 1 p.p. increase in manufacturing specialization is a 0.067 p.p. increase in productivity (see table 6.2, column 1). Here, the point estimate for specialization is the same reported in table 4.3, column 7. Since the model does not assume nonlinearities in the elasticity, the total national effect on productivity is zero. That is, the positive effect of a 1 p.p. increase in specialization in region B is offset by the same negative effect in region A. In what follows, I test if there exist nonlinearities in the elasticity of productivity with respect of specialization.

Non-Linearities in Elasticity due to Specialization - What happens if we assume that the geographic concentration of manufacturing is nonlinear in the level of specialization? In other words, is the effect of increasing manufacturing specialization higher or lower in low-manufacturing regions than in high-manufacturing regions? The result can be obtained by running a regression such as the one in chapter 4, equation 4.10, including, say, two levels of specialization (as below and above the median level of specialization) interacted with the variable for specialization rather than the HHI for competition. The point estimate for low-manufacturing areas, in column 2, is .150, and there are no differences with respect to the same value obtained for the high-manufacturing areas (see *p-value* for equal slope accepting null hypothesis of equal slopes). The coefficient for high specialization must be interpreted as the difference with respect to low specialization. As in Kline and Moretti (2014a), there is a constant elasticity of manufacturing productivity with respect to specialization across Italian LMAs. This is approximated by a logarithmic function. Again, moving a manufacturing plant from Region A to Region B has no effect on productivity.

Non-Linearities in Elasticity due to Competition - What if the effect of specialization depends on that of competition? In general, when competition is included, there are direct and indirect effects on productivity. Let's consider a country with 2 regions. Region A has a high concentration of manufacturing activity with a high level of competition (i.e. industrial districts).

Table 6.2: **Nonlinearities in Productivity Elasticities**

	Constant (1)	Low-Spec (2)	High-Comp (3)	Small Size (4)	Large (5)	Medium (6)	Small (7)	Micro (8)
Elasticity	0.067***	0.150**	0.109***	0.099**	0.067***	0.040***	0.049***	0.076***
	(0.026)	(0.076)	(0.040)	(0.040)	(0.023)	(0.012)	(0.017)	(0.029)
vs High Spec		-0.034						
		(0.071)						
vs Low Comp			-0.004*					
			(0.002)					
vs Large Size				-0.051*				
				(0.031)				
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
3-Digit FE	YES	YES	YES	YES	YES	YES	YES	YES
Large Cities FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,357	6,357	6,357	6,357	6,363	6,363	6,363	6,363
p-value equal slopes		[0.630]	[0.073]	[0.098]		[0.035]		

The main independent variable for specialization is the total count of plants in all the others 3-digit local industries. *vs* High spec represents the differential in point estimate below and above the median value of specialization given by the coefficient of variable elasticity in column 2. *vs* Low Comp reports the same estimate of table 4.3. *vs* Large Size represents the differential in point estimate below and above the median value of size given by the coefficient of variable elasticity in column 4. All columns include the average level of human capital, the surface of the LMA, the average plants' size in the relative 3-digit local manufacturing industry, and the total number of employees in each local 3-digit industry as control variables. Their coefficients are not reported. First-stage f statistics are not reported here; however, they are always higher than 10. The instruments used are the same reported in table 4.2. The *HHI* is measured in level (0-100) where 0 means perfect competition and 100 monopoly. It is the total average across all the 3-digit local industries. Standard errors are in parentheses, *p-values* in brackets. Standard errors are clustered at the 3-digit local industry.
*** p<.01, ** p<.05, * p<.1

Region B has a low concentration of manufacturing activity with a low level of competition (i.e. other non-urban LMAs). The relocation of a manufacturing plant from A to B has a negative direct effect on Region A equal to the elasticity of productivity with respect to agglomeration. Region A also suffers another negative effect, which is the indirect effect of a reduction in competition on the effect of agglomeration on productivity. This corresponds to the elasticity of agglomeration with respect to competition. On the other hand, region B experiences a positive direct effect of agglomeration and a positive indirect effect of competition. National productivity is increased if the sum of the two negative effects is less than the sum of the two positive effects.

According to the estimation that I include in chapter 4, and that is reported for easing the reading in table 6.2 column 3, there are heterogeneous effects of agglomeration on productivity at different levels of competition. The elasticity of productivity with respect of specialization is 0.109 when high competition manufacturing areas are considered. The interaction term suggest a differential effect in low competitive areas equal to -0.004. Obviously, the higher the geographical concentration of plants and workers, the higher the local competition. In this case, we obtain a positive effect at the national level if the receiving region has a higher level of competition. Since high manufacturing locations always have higher levels of competition, the effect of moving a production facility from region A (high concentration, high competition) to region B (low

concentration, low competition) has a negative effect on national manufacturing productivity. Since the elasticity of the receiving region is zero, and that is the proper case for Italian low manufacturing LMAs (having levels of competition below the threshold found in chapter 4), the overall national effect of manufacturing is equal to the reduction in the elasticity in the high manufacturing regions. Therefore, moving a facility from Region A to Region B has a negative effect.

Non-Linearities in Elasticity due to Size - However, the question raised at the beginning of the chapter 4 was about the entry of large firms. Here I separate the results into two different scenarios. These are summarized by the elasticities reported in columns 4 through 8. The entry of larger firms reduces competition by concentrating more manufacturing employment among a few employers. Again, we have two effects when larger firms enter the local market. First, there is a positive elasticity of productivity with respect to the size of firm entry. Column 5 reports the elasticity of LITFP with respect to large firms, column 6 with respect to medium firms, column 7 with respect to small firms, and column 8 with respect to micro firms. The largest effect is for micro, followed by large, small, and medium. If the entry of a firm does not change the level of competition, then the entry of micro firms maximizes productivity. In general, the entry of firms of any dimensional class tends to increase the level of productivity.

However, there is a related negative effect on productivity due to reduced competition when a larger firm enters the market. A simple way to visualize this case is to repeat the equation 4.10 with average size as the interacting factor instead of competition. The coefficient is reported in table 6.2, column 4. In this case, competition is a control variable. As for the interaction term with competition, the point estimate for the interaction term is negative, suggesting that the effect of 'winning a plant' is reduced the larger the average firm in the LMA is[3]. The results also suggest that there is a size threshold above which external economies peter out, which is equal to 16.5.

There is a threshold above which the elasticity of productivity becomes 0, that is 16.5 employees per firm. Thus, according to the average size of each class of firms, the only category of firms that is below the average size is the micro (2.3 employees on average). Certainly, as the number of firms within the local manufacturing sector increases, the marginal effect on competition and size of the entry of a micro firm becomes smaller. Small, medium and large firms

[3]This result must not be confounded with the effect of own-firm growth. The estimated residual (the LITFP) from the production function cleans up the effect of own-firm growth. Thus, it must be seen as the effect that an increase in the average size of firms has on the productive capacity of local manufacturing.

have the negative effect of raising the average size of the local manufacturing sector above the threshold. Accordingly, the same policy mix formulated in the previous section is inefficient in this case. There are several reasons for this.

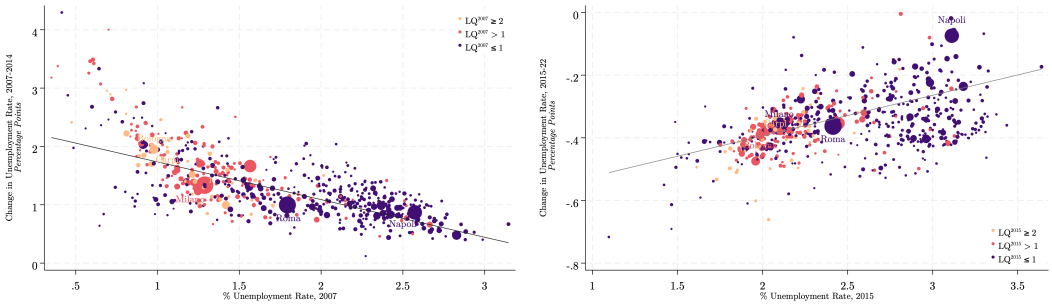
Policy Mix - In general, policies here can be discussed in terms of *within* LMA reallocation of employment from smaller to larger firms and *between* LMA reallocation of firms (also according to their size). Even if the policy maker can encourage the entry of large firms, mergers and acquisitions, and own-firm growth, the average level of local competition/size is beyond his control. In general, the entry of small, medium and large firms tends to reduce the level of competition and increase the average size. This has a negative impact on LITFP. However, there is the direct effect of firms' own productivity growth as they grow larger. This is not included in the estimates, but it is very relevant in a scenario of global competition; it is well reported in the literature. And all the more so given the average size of Italian manufacturing firms (≈ 4.4). There is room for optimal policies that encourage firms to grow larger and that set levels of competition and size, provided it is feasible; the threshold for still benefiting from external economies is 16.5 employees per firm, even if the effect is decreasing. That is, the effect of specialization is higher at size 10 than at size 12. However, a proper model should take into account the extent to which external and internal economies affect aggregate productivity differently. Here, I document a trade-off between competition/size and the existence of localized external economies. On the other hand, the relocation of manufacturing firms to low-density areas generally has no effect. Controlling for the effects of competition and size, the relocation of small firms from high to low density areas has an overall negative effect on productivity.

6.2.3 Afterthought on Pro-cyclical Place-Based Policies

In this last section, I briefly sketch some ideas about policies in light of the results obtained in chapter 5. First of all, findings in chapter 5 suggests that places where IO linkages are stronger fluctuate more in terms of unemployment. This is so because of a network effect between industries. Let's start with an empirical regularity. On the one hand, during the economic downturn that occurred in Italy between 2007 and 2014, places with strong specialization in manufacturing and also low levels of unemployment experienced dramatic increases in unemployment rates (see figure 6.1-a). On the other hand, in the period of economic recovery, the effect is reversed; places with low levels of unemployment experiences a relevant reduction in unemployment rates (see figure 6.1-b).

Figure 6.1: **Unemployment Change in Italian LMAs**

(a) Downturn (b) Recovery



Notes.

Source. My own elaboration on Istat data.

So what are the reasons to think about pro-cyclical place-based policies? During recessions there are two effects: the *cleansing* and the *sullying* effect. The *cleansing* effect refers to the squeezing out of unproductive routines and firms that occurs during the crisis. This frees labor and capital from old and unproductive arrangements to be better allocated. The *sullying effect* refers to the fact that the quality of matching of labor in the market is procyclical. During economic downturns, firms create fewer vacancies and workers are less likely to move from job to job; accordingly, jobs created during recessions are temporary and low-paid. If the *cleansing effect* is higher than the *sullying effect*, then the healing period will drive the LMA to a faster growth rate in terms of employment and productivity.

Now, to return to the example in the previous section of Region A and Region B, the former is highly productive and highly competitive because it enjoys agglomeration economies, while the latter is a lagging region. In region A, which is highly specialized in manufacturing and benefits from external economies, labor pooling and strong input-output linkages accentuate the *cleansing effect* during downturns, leading to larger initial increases in unemployment but also to faster recoveries due to the availability of skilled and specialized labor. This is documented in chapter 5 and figure 6.1-b. Here, the elasticity of labor supply relative to demand will be greater because of the rise in unemployment. This dynamics supports the rationale for creation incentives à-la Caballero and Hammour (1996) specifically targeted at these regions. Creation incentives directly encourage creation of new arrangements via innovation, e.g. investment tax credits, while production incentives encourage production, e.g. corporate tax cuts. In contrast to other

less procyclical regions, manufacturing regions can benefit more from creation incentives during periods of economic downturn due to their pronounced cyclical volatility, which increases the impact of such policies on regional and potentially national productivity. In addition to creation incentives, the use of household unemployment benefits will help to sustain local demand and reduce the negative social impact of any prolonged unemployment.

However, the use of place-based countercyclical policies in region A with high manufacturing specialization exacerbates regional disparities. While these policies are effective in catalyzing faster recoveries in targeted areas, they do not necessarily promote balanced national growth. Instead, they may concentrate growth in already specialized regions, thereby widening regional economic disparities. The challenge for the efficient use of resources is therefore to design these policies in such a way that they can be turned on and off depending on the business cycle. Because they are place-based, these policies will be less costly than national policies.

On the other hand, region B benefits more from production incentives during economic booms. Since high unemployment produces negative social and economic effects, the use of this measure is also justified from a fiscal point of view (see chapter 2.2). Accordingly, the level of unemployment in these regions is reduced at the expense of subsidizing less productive arrangements. The overall effect of such a policy must be evaluated from the point of view of both job creation and productivity growth. As shown in the previous section, incentives such as corporate tax cuts could increase the demand for manufacturing labor in region B, which will have a positive impact on national employment rates but a negative impact on productivity growth. Overall, benefits and costs need to be at least balanced for such a policy to be efficient. The implementation of countercyclical place-based policies targeting firms in strong economic areas, as well as procyclical place-based policies targeting firms in depressed areas, could have the effect of increasing both overall productivity by sustaining creation in strong regions and employment through income tax cuts in lagging regions.

Chapter 7

Future Research Perspective

7.1 Working papers

After working on these topics for several years, I have complemented the Ph.D. research with other research activities to broaden my knowledge of economic phenomena.

Social Innovation The first topic of interest is the mechanism of external economies, which is strictly related to agglomeration externalities. Once the working mechanism of agglomeration and external economies is understood, there are many areas where it can be applied. I am working on a project about social innovation and how agglomeration externalities promote its emergence. While the traditional literature on this topic assumes that social innovation occurs in rural and low-income areas, this working paper documents that social innovation occurs primarily in high-income and high-density areas[1].

Demographics In the same line of research, I am working on a project about the labor market in regions that enjoy external economies. In particular, this paper argues about the mitigating effect of aging on external economies. The more the population ages, the less the advantages firms gain in the local labor market, since knowledge spillovers and labor pooling require fluidity. Such fluidity decreases with age. The results confirm this hypothesis. This paper is now under review in Industrial and Corporate Change after a first round of major revisions[2].

[1] It is co-authored by Roberto Dellisanti of the Politecnico di Milano and Amir Maghssudipour of the University of Padova.

[2] The paper is co-authored by Amir Maghssudipour.

Labor Hoarding The labor market in manufacturing densely populated areas generate external economies and different agent behavior. This idea stems from the development of the third chapter. However, the third chapter was not able to explain all the dynamics that I had in mind, mainly because of the lack of data. In particular, a key point concerns the procyclical tendency of productivity; it rises during booms and collapses during busts. Among the reasons given in the literature, one is particularly relevant in the case of a thick labor market. This is the hypothesis of labor hoarding. Since firing, hiring and training workers is costly, firms retain workers during crises, making productivity procyclical. In a thick labor market, the costs of firing, hiring and training are lower, so the main hypothesis of the paper is that *labor hoarding* is lower in thick labor markets[3].

Tourism The second line of research concerns manufacturing in general. It is the engine of local and national growth and creates the conditions for external economies. While in Italy there is a tendency towards a spatial concentration of manufacturing activities, along with a partial reduction of the share of manufacturing in the national economy, the tourism sector is becoming increasingly relevant. The idea behind this paper is that increases in the share of tourism-related sectors crowd out manufacturing, this is called *beach disease*. One reason for this is the rising cost of housing that many Italian cities are experiencing. Manufacturing firms trade off the cost of housing in the city of art and move to other cities with related low cost of housing[4].

7.2 Research projects

While the previous section described concrete projects that I will start working on once I finish the dissertation, or that are just working papers, there are some other relevant topics that I would like to explore.

Fertility First, Italy's population decline poses significant challenges for economic growth, debt sustainability, and welfare costs. Recent studies, such as Coskun and Dalgic (2024), examine the impact of 'breadwinner women' on fertility rates and find a shift from traditional countercyclical fertility trends to a procyclical pattern. Traditionally, fertility tended to increase during economic

[3] I have a project on this using the German linked employer-employee dataset, co-authored by my friend and colleague Maximilian Günnewig-Mönert from the University of Cologne, which is now patiently waiting for me to write the dissertation.

[4] This research project is co-authored with my friend and colleague Vieri Calogero, from the University of Milano Bicocca.

downturns due to lower employment and thus lower opportunity costs associated with pregnancy (Butz & Ward, 1979). However, this trend has reversed as economic cycles increasingly influence sectoral employment. Men, who are more likely to be employed in cyclical sectors such as manufacturing, face greater job instability during downturns, while women, who are more likely to be employed in counter-cyclical sectors such as health and education, increasingly assume the role of primary breadwinners. Consequently, the economic need for women's wages during downturns aligns fertility patterns with the business cycle, making them procyclical. At the local level, in LMAs highly concentrated in cyclical activities, three main effects influence fertility: an income effect, where higher wages increase the opportunity cost of childbearing; an amenities effect, where more fertility-related services are available; and a composition effect, where the higher proportion of laid-off men intensifies the breadwinner role for women. This suggests that fertility decline will be more pronounced in industrial districts (or, more generally, in regions with a high density of manufacturing) than in less specialized regions due to a stronger 'breadwinner effect'. That is, since industrial regions are more specialized in pro-cyclical industries, they end up laying off more working men, with women more likely to take on the breadwinner role during economic turbulence.

Labor market Second, I want to work on a follow-up to chapters 3 and 4. The idea here is to look at different segments of the labor market when looking at competition. Let's consider what happens when a large company moves into a local manufacturing area. It will have to hire some workers, both from unemployment and from other firms. Through selection, large firms will tend to hire more productive workers because they can take advantage of higher wages. This leads to an increase in the productivity of large firms and a decrease in the productivity of small firms. This is what the literature defines as *labor poaching* (Combes & Duranton, 2006). This is increasingly the case for firms in the ICT and digital marketing sectors. Companies such as Google and Meta have statistics on the productivity of workers as they work on their platform to complete their tasks. They can hire them knowing their productivity ex ante. As a result, knowledge spillovers are directed from smaller to larger firms and from low to high productivity firms. Job-to-job movement is increasingly based on different segments of the local market, i.e. workers hired in large firms will move to other large firms. This can be confirmed by looking at the data, and then spillovers can be measured using available Italian data on plants and firms.

Spatial inequalities Third, I am increasingly interested in the econometrics of spatial inequality. Today, there is little evidence on the effect of increasing agglomeration on national economic performance. This would contribute to the efficiency-equity puzzle of agglomeration (Austin et al., 2018). The idea here is to use regional data to construct national indicators of spatial concentration. Then, by comparing countries with different levels of agglomeration, we provide evidence on the role of geographic concentration for national growth. This is related to the literature on place-based policies and their implementation. In particular, this could help to assess the effectiveness of the regional cohesion policies implemented by the European Community.

All in all, this is a rather large research agenda from which I will probably draw relevant ideas and discard those that are inconsistent.

Bibliography

Abdel-Rahman, H., & Fujita, M. (1990). Product variety, marshallian externalities, and city sizes. *Journal of regional science*, *30*(2), 165–183.

Acemoglu, D., Akcigit, U., & Kerr, W. (2016). Networks and the macroeconomy: An empirical exploration. *Nber macroeconomics annual*, *30*(1), 273–335.

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., & Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica*, *80*(5), 1977–2016.

Arrighetti, A., de Nardis, S., & Traù, F. (2024). Il falso mito della manifattura inefficiente. *Working Paper*.

Arrighetti, A., & Traù, F. (2007). La" questione dimensionale" come problema organizzativo. natura e logica evolutiva del medium business sector nell'industria italiana. *L'industria*, *28*(3), 529–570.

Audas, R. P., & MacKay, R. R. (1997). A tale of two recessions. *Regional Studies*, *31*(9), 867–874.

Austin, B., Glaeser, E., & Summers, L. (2018). Jobs for the heartland: Place-based policies in 21st-century america. *Brookings Papers on Economic Activity*, *2018*(1), 151–255.

Autor, D. H., Dorn, D., & Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the united states. *American economic review*, *103*(6), 2121–2168.

Azar, J., Marinescu, I., & Steinbaum, M. (2019). Measuring labor market power two ways. *AEA Papers and Proceedings*, *109*, 317–321.

Barlevy, G. (2002). The sullying effect of recessions. *The Review of Economic Studies*, *69*(1), 65–96.

Barrios, S., Bertinelli, L., & Strobl, E. (2006). Geographic concentration and establishment scale: An extension using panel data. *Journal of Regional Science*, *46*(4), 733–746.

Bartik, T. J. (2020). Using place-based jobs policies to help distressed communities. *Journal of Economic Perspectives*, *34*(3), 99–127.

Basu, S., & Fernald, J. G. (1995). Are apparent productive spillovers a figment of specification error? *Journal of Monetary Economics*, *36*(1), 165–188.

Beaudry, C., & Schiffauerova, A. (2009). Who's right, marshall or jacobs? the localization versus urbanization debate. *Research policy*, *38*(2), 318–337.

Becattini, G. (1962). *Il concetto d'industria e la teoria del valore*. P. Boringhieri.

Becattini, G. (1979). *Dal settore industriale al distretto industriale. alcune considerazioni sull'unità di indagine dell'economia industriale*. Il mulino.

Becattini, G. (1989). Riflessioni sul distretto industriale marshalliano come concetto socio-economico. *Stato e mercato*, 111–128.

Becattini, G. (2002). Industrial sectors and industrial districts: Tools for industrial analysis. *European planning studies*, *10*(4), 483–493.

Becattini, G. (2015). Beyond geo-sectoriality: The productive chorality of places. *Investigaciones Regionales-Journal of Regional Research*, (32), 31–41.

Becattini, G., Bellandi, M., & De Propris, L. (2009). Critical nodes and contemporary reflections on industrial districts: An introduction. In *A handbook of industrial district* (pp. xv–xxxv). Edward Elgar.

Becattini, G., & Coltorti, F. (2006). Areas of large enterprise and industrial districts in the development of post-war italy: A preliminary survey. *European Planning Studies*, *14*(8), 1105–1138.

Becattini, G., & Dei Ottati, G. (2006). The performance of italian industrial districts and large enterprise areas in the 1990s. *European Planning Studies*, *14*(8), 1139–1162.

Becattini, G., & Musotti, F. (2003). Measuring the district effect. reflections on the literature. *PSL Quarterly Review*, *56*(226).

Bellandi, M. (1989). The industrial district in marshall. *Small firms and industrial districts in Italy*, 136–152.

Bellandi, M. (1995). *Economie di scala e organizzazione industriale*. Angeli.

Bellandi, M. (2001). Local development and embedded large firms. *Entrepreneurship & Regional Development*, *13*(3), 189–210.

Bellandi, M. (2002). Italian industrial districts: An industrial economics interpretation. *European Planning Studies*, *10*(4), 425–437.

Bellandi, M. (2006). A perspective on clusters, localities, and specific public goods. *Clusters and Globalisation. The Development of Urban and Regional Economies. Cheltenham: Edward Elgar*, 96–113.

Bellandi, M. (2009). External economies, specific public goods and policies. In G. Becattini, M. Bellandi, & L. De Propris (Eds.), *A handbook of industrial districts*. Edward Elgar Publishing.

Bellandi, M. (2016). The role of small firms in the development of italian manufacturing industry. In E. Goodman, J. Bamford, & P. Saynor (Eds.), *Small firms and industrial districts in italy* (pp. 31–62). Routledge.

Bellandi, M., et al. (2020). Some notes on the impacts of covid-19 on italian sme productive systems. *Symphonya*, *2*, 63–72.

Bellandi, M., & De Propris, L. (2015). Three generations of industrial districts. *Investigaciones Regionales-Journal of Regional Research*, (32), 75–87.

Bellandi, M., & De Propris, L. (2017). New forms of industrial districts. *Economia e Politica Industriale*, *44*, 411–427.

Bellandi, M., & Di Tommaso, M. R. (2006). The local dimensions of industrial policy. In P. Bianchi & S. Labory (Eds.), *International handbook on industrial policy* (pp. 342–361). Edward Elgar Publishing.

Bellandi, M., & Santini, E. (2019). Territorial servitization and new local productive configurations: The case of the textile industrial district of prato. *Regional Studies*, *53*(3), 356–365.

Biddle, J. E. (2014). Retrospectives: The cyclical behavior of labor productivity and the emergence of the labor hoarding concept. *Journal of Economic Perspectives*, *28*(2), 197–212.

Bishop, P., & Gripaios, P. (2010). Spatial externalities, relatedness and sector employment growth in great britain. *Regional Studies*, *44*(4), 443–454.

Blanchard, O. (2006). European unemployment: The evolution of facts and ideas. *Economic policy*, *21*(45), 6–59.

Blanchard, O. J., Katz, L. F., Hall, R. E., & Eichengreen, B. (1992). Regional evolutions. *Brookings papers on economic activity*, *1992*(1), 1–75.

Boeri, T., Ichino, A., Moretti, E., & Posch, J. (2021). Wage equalization and regional misallocation: Evidence from italian and german provinces. *Journal of the European Economic Association*, *19*(6), 3249–3292.

Bohm, P. (2017). External economies. In *The new palgrave dictionary of economics* (pp. 1–5). Palgrave Macmillan UK. https://doi.org/10.1057/978-1-349-95121-5_266-2

Boix, R., & Trullén, J. (2010). Industrial districts, innovation and i-district effect: Territory or industrial specialization? *European Planning Studies*, *18*(10), 1707–1729.

Boldrin, M., & Canova, F. (2001). Inequality and convergence in europe's regions: Reconsidering european regional policies. *Economic policy*, *16*(32), 206–253.

Brunello, G., & Langella, M. (2016). Local agglomeration, entrepreneurship and the 2008 recession: Evidence from italian industrial districts. *Regional Science and Urban Economics*, *58*, 104–114.

Buciuni, G., & Pisano, G. (2018). Knowledge integrators and the survival of manufacturing clusters. *Journal of Economic Geography*, *18*(5), 1069–1089.

Butz, W. P., & Ward, M. P. (1979). The emergence of countercyclical us fertility. *The American economic review*, *69*(3), 318–328.

Caballero, R. J., & Hammour, M. L. (1994). The cleansing effect of recessions. *American Economic Review*, *84*(5), 1350–1368.

Caballero, R. J., & Hammour, M. L. (1996). On the timing and efficiency of creative destruction. *The Quarterly Journal of Economics*, *111*(3), 805–852.

Caballero, R. J., & Lyons, R. K. (1990). Internal versus external economies in european industry. *European Economic Review*, *34*(4), 805–826.

Caballero, R. J., & Lyons, R. K. (1992). External effects in us procyclical productivity. *Journal of Monetary Economics*, *29*(2), 209–225.

Caivano, M., Rodano, L., & Siviero, S. (2011). The transmission of the global financial crisis to the italian economy. *Giornale degli economisti e annali di economia*, 1–32.

Caragliu, A., de Dominicis, L., & de Groot, H. L. (2016). Both marshall and jacobs were right! *Economic geography*, *92*(1), 87–111.

Cerqua, A., & Pellegrini, G. (2020). Local multipliers at work. *Industrial and Corporate Change*, *29*(4), 959–977.

Chinitz, B. (1961). Contrasts in agglomeration: New york and pittsburgh. *The American Economic Review*, *51*(2), 279–289.

Chipman, J. S. (1970). External economies of scale and competitive equilibrium. *The Quarterly Journal of Economics*, *84*(3), 347–385.

Ciapanna, E., Formai, S., Linarello, A., & Rovigatti, G. (2024). Measuring market power: Macro- and micro-evidence from italy. *Empirical Economics*, 1–41.

Cinelli, C., Forney, A., & Pearl, J. (2022). A crash course in good and bad controls. *Sociological Methods & Research*, 00491241221099552.

Citino, L., & Linarello, A. (2022). The impact of chinese import competition on italian manufacturing. *Review of International Economics*, *30*(3), 702–731.

Coltorti, F., & Venanzi, D. (2017). Productivity, competitiveness, and territories of the italian medium-size companies. *International Journal of Economics and Finance*, *9*, 12.

Combes, P.-P., & Duranton, G. (2006). Labour pooling, labour poaching, and spatial clustering. *Regional Science and Urban Economics*, *36*(1), 1–28.

Combes, P.-P., Duranton, G., & Gobillon, L. (2008). Spatial wage disparities: Sorting matters! *Journal of urban economics*, *63*(2), 723–742.

Combes, P.-P., Duranton, G., & Gobillon, L. (2011). The identification of agglomeration economies. *Journal of economic geography*, *11*(2), 253–266.

Combes, P.-P., Duranton, G., Gobillon, L., Puga, D., & Roux, S. (2012). The productivity advantages of large cities: Distinguishing agglomeration from firm selection. *Econometrica*, *80*(6), 2543–2594.

Combes, P.-P., Duranton, G., Gobillon, L., & Roux, S. (2010). Estimating agglomeration economies with history, geology, and worker effects. In E. L. Glaeser (Ed.), *Agglomeration economics* (pp. 15–66). University of Chicago Press.

Combes, P.-P., & Gobillon, L. (2015). The empirics of agglomeration economies. In G. Duranton, V. Henderson, & W. Strange (Eds.), *Handbook of regional and urban economics* (pp. 247–348, Vol. 5). Elsevier.

Combes, P.-P., Magnac, T., & Robin, J.-M. (2004). The dynamics of local employment in france. *Journal of Urban Economics*, *56*(2), 217–243.

Coskun, S., & Dalgic, H. C. (2024). The emergence of procyclical fertility: The role of breadwinner women. *Journal of Monetary Economics*, *142*, 103523.

Cucculelli, M., & Micucci, G. (2008). Family succession and firm performance: Evidence from italian family firms. *Journal of Corporate Finance*, *14*(1), 17–31.

Cucculelli, M., & Storai, D. (2018). Industrial districts, district effect and firm size: The italian evidence. *Cambridge Journal of Economics*, *42*(6), 1543–1566.

Davis, S. J., & Haltiwanger, J. (1992). Gross job creation, gross job destruction, and employment reallocation. *The Quarterly Journal of Economics*, *107*(3), 819–863.

Davis, S. J., Haltiwanger, J., & Schuh, S. (1996). Small business and job creation: Dissecting the myth and reassessing the facts. *Small business economics*, *8*, 297–315.

De Blasio, G., & Menon, C. (2011). Local effects of manufacturing employment growth in italy. *Giornale degli Economisti e Annali di Economia*, 101–112.

De Chaisemartin, C., & d'Haultfoeuille, X. (2023). Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey. *The Econometrics Journal*, *26*(3), C1–C30.

De Dominicis, L., Arbia, G., & De Groot, H. L. (2013). Concentration of manufacturing and service sector activities in italy: Accounting for spatial dependence and firm size distribution. *Regional Studies*, *47*(3), 405–418.

Dekle, R., & Eaton, J. (1999). Agglomeration and land rents: Evidence from the prefectures. *Journal of Urban Economics*, *46*(2), 200–214.

Delgado, M., Porter, M. E., & Stern, S. (2016). Defining clusters of related industries. *Journal of Economic Geography*, *16*(1), 1–38.

Di Caro, P. (2015). Recessions, recoveries and regional resilience: Evidence on italy. *Cambridge Journal of Regions, Economy and Society*, *8*(2), 273–291.

Diamond, C. A., & Simon, C. J. (1990). Industrial specialization and the returns to labor. *Journal of Labor Economics*, *8*(2), 175–201.

Diodato, D., Neffke, F., & O'Clery, N. (2018). Why do industries coagglomerate? how marshallian externalities differ by industry and have evolved over time. *Journal of Urban Economics*, *106*, 1–26.

Dixit, A. K., & Stiglitz, J. E. (1977). Monopolistic competition and optimum product diversity. *The American economic review*, *67*(3), 297–308.

Drucker, J. (2011). Regional industrial structure concentration in the united states: Trends and implications. *Economic Geography*, *87*(4), 421–452.

Drucker, J., & Feser, E. (2012). Regional industrial structure and agglomeration economies: An analysis of productivity in three manufacturing industries. *Regional Science and Urban Economics*, *42*(1-2), 1–14.

Duranton, G., & Puga, D. (2001). Nursery cities: Urban diversity, process innovation, and the life cycle of products. *American Economic Review*, *91*(5), 1454–1477.

Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In V. Henderson & J.-F. Thisse (Eds.), *Handbook of regional and urban economics* (pp. 2063–2117, Vol. 4). Elsevier.

Ellison, G., & Glaeser, E. L. (1997). Geographic concentration in us manufacturing industries: A dartboard approach. *Journal of political economy*, *105*(5), 889–927.

Ellison, G., Glaeser, E. L., & Kerr, W. R. (2010). What causes industry agglomeration? evidence from coagglomeration patterns. *American Economic Review*, *100*(3), 1195–1213.

Evans, P., & McCormick, B. (1994). The new pattern of regional unemployment: Causes and policy significance. *The Economic Journal*, *104*(424), 633–647.

Faggian, A., Modrego, F., & McCann, P. (2019). Human capital and regional development. *Handbook of regional growth and development theories*, 149–171.

Faggio, G., Silva, O., & Strange, W. C. (2017). Heterogeneous agglomeration. *Review of Economics and Statistics*, *99*(1), 80–94.

Foster, L., Grim, C., & Haltiwanger, J. (2016). Reallocation in the great recession: Cleansing or not? *Journal of Labor Economics*, *34*(S1), S293–S331.

Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional studies*, *41*(5), 685–697.

Fujita, M., Krugman, P. R., & Venables, A. (2001). *The spatial economy: Cities, regions, and international trade*. MIT press.

Fujita, M., & Thisse, J.-F. (1996). Economics of agglomeration. *Journal of the Japanese and international economies*, *10*(4), 339–378.

Gaigné, C., & Sanch-Maritan, M. (2019). City size and the risk of being unemployed. job pooling vs. job competition. *Regional Science and Urban Economics*, *77*, 222–238.

Gerolimetto, M., & Magrini, S. (2014). Spatial analysis of employment multipliers in spanish labor markets. *Rivista Italiana di Economia Demografia e Statistica*, *68*(3/4), 87–94.

Giovannetti, G., Ricchiuti, G., & Velucchi, M. (2011). Size, innovation and internationalization: A survival analysis of italian firms. *Applied Economics*, *43*(12), 1511–1520.

Glaeser, E., Kallal, H. D., Scheinkman, J. A., & Shleifer, A. (1992). Growth in cities. *Journal of political economy*, *100*(6), 1126–1152.

Glaeser, E. L., & Gottlieb, J. D. (2008). The economics of place-making policies. *Brookings Papers on Economic Activity*, *2008*(1).

Glaeser, E. L., & Kerr, W. R. (2009). Local industrial conditions and entrepreneurship: How much of the spatial distribution can we explain? *Journal of Economics & Management Strategy*, *18*(3), 623–663.

Glaeser, E. L., & Maré, D. C. (2001). Cities and skills. *Journal of labor economics*, *19*(2), 316–342.

Gould, E. D. (2007). Cities, workers, and wages: A structural analysis of the urban wage premium. *The Review of Economic Studies*, *74*(2), 477–506.

Graziani, A. (1998). *Lo sviluppo dell'economia italiana: Dalla ricostruzione alla moneta europea*. Bollati Boringhieri.

Groenewegen, P. (2017). Division of labour. In *The new palgrave dictionary of economics* (pp. 1–13). Palgrave Macmillan UK. https://doi.org/10.1057/978-1-349-95121-5_675-2

Gutierrez-Posada, D., Kitsos, T., Nathan, M., & Nuccio, M. (2023). Creative clusters and creative multipliers: Evidence from uk cities. *Economic Geography*, *99*(1), 1–24.

Hall, R. E. (1988). The relation between price and marginal cost in us industry. *Journal of political Economy*, *96*(5), 921–947.

Haltiwanger, J., Hyatt, H., McEntarfer, E., & Staiger, M. (2024). Cyclical worker flows: Cleansing vs. sullying. *Review of Economic Dynamics*, 101252.

Heckman, J. J. (2000). Policies to foster human capital. *Research in economics*, *54*(1), 3–56.

Henderson, V. (1986). Efficiency of resource usage and city size. *Journal of Urban economics*, *19*(1), 47–70.

Henderson, V. (2003). Marshall's scale economies. *Journal of urban economics*, *53*(1), 1–28.

Henderson, V., Kuncoro, A., & Turner, M. (1995). Industrial development in cities. *Journal of political economy*, *103*(5), 1067–1090.

Holmes, T. J., & Stevens, J. J. (2002). Geographic concentration and establishment scale. *Review of Economics and Statistics*, *84*(4), 682–690.

Hsieh, C.-T., & Moretti, E. (2019). Housing constraints and spatial misallocation. *American economic journal: macroeconomics*, *11*(2), 1–39.

Kaldor, N. (1966). Causes of the slow rate of economic growth of the united kingdom: An inaugural lecture. *Cambridge Journal of Economics*.

Kazekami, S. (2017). Local multipliers, mobility, and agglomeration economies. *Industrial Relations: A Journal of Economy and Society*, *56*(3), 489–513.

Kline, P., & Moretti, E. (2013). Place based policies with unemployment. *American Economic Review*, *103*(3), 238–243.

Kline, P., & Moretti, E. (2014a). Local economic development, agglomeration economies, and the big push: 100 years of evidence from the tennessee valley authority. *The Quarterly journal of economics*, *129*(1), 275–331.

Kline, P., & Moretti, E. (2014b). People, places, and public policy: Some simple welfare economics of local economic development programs. *Annu. Rev. Econ.*, *6*(1), 629–662.

Knight, H., Frank. (1924). Some fallacies in the interpretation of social cost. *The Quarterly Journal of Economics*, *38*(4), 582–606.

Kolko, J. (2010). Urbanization, agglomeration, and coagglomeration of service industries (E. Glaeser, Ed.). *Agglomeration Economics*, 151–180.

Kozeniauskas, N., Moreira, P., & Santos, C. (2022). On the cleansing effect of recessions and government policy: Evidence from covid-19. *European Economic Review*, *144*, 104097.

Krugman, P. (1991). Increasing returns and economic geography. *Journal of political economy*, *99*(3), 483–499.

Lafourcade, M., & Mion, G. (2007). Concentration, agglomeration and the size of plants. *Regional science and urban economics*, *37*(1), 46–68.

Lagravinese, R. (2015). Economic crisis and rising gaps north–south: Evidence from the italian regions. *Cambridge journal of regions, economy and society*, *8*(2), 331–342.

Levinsohn, J., & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The review of economic studies*, *70*(2), 317–341.

Lindström, T. (2000). External economies in procyclical productivity: How important are they? *Journal of Economic Growth*, *5*, 163–184.

Lucas, R. E. (1977). Understanding business cycles. *Carnegie-Rochester Conference Series on Public Policy*, *5*(1), 7–29.

Malizia, E., Feser, E. J., Renski, H., & Drucker, J. (2020). *Understanding local economic development*. Routledge.

Malizia, E. E., & Ke, S. (1993). The influence of economic diversity on unemployment and stability. *Journal of Regional Science*, *33*(2), 221–235.

Manning, A. (2010). The plant size-place effect: Agglomeration and monopsony in labour markets. *Journal of economic geography*, *10*(5), 717–744.

Markusen, A. (1996). Sticky places in slippery space: A typology of industrial districts. *Economic Geography*, 293–313.

Marshall, A. (1890). *Principles of economics* (1st ed.). Macmillan; Co.

Marshall, A., & Marshall, M. P. (1879). *The economics of industry*. Macmillan; Co.

Martin, R., & Sunley, P. (2015). On the notion of regional economic resilience: Conceptualization and explanation. *Journal of economic geography*, *15*(1), 1–42.

Martin, R., Sunley, P., Gardiner, B., & Tyler, P. (2016). How regions react to recessions: Resilience and the role of economic structure. *Regional studies*, *50*(4), 561–585.

Mayer, T., & Ottaviano, G. I. (2008). The happy few: The internationalisation of european firms: New facts based on firm-level evidence. *Intereconomics*, *43*(3), 135–148.

McCombie, J. S., & Roberts, M. (2007). Returns to scale and regional growth: The static-dynamic verdoorn law paradox revisited. *Journal of Regional Science*, *47*(2), 179–208.

Merlo, E., et al. (2009). Apprenticeship and technical schools in the formation of industrial districts. In G. Becattini, M. Bellandi, & L. De Propris (Eds.), *A handbook of industrial districts* (pp. 32–42). Elgar.

Moretti, E. (2004). Estimating the social return to higher education: Evidence from longitudinal and repeated cross-sectional data. *Journal of econometrics*, *121*(1-2), 175–212.

Moretti, E. (2010). Local multipliers. *American Economic Review*, *100*(2), 373–377.

Moretti, E. (2021). The effect of high-tech clusters on the productivity of top inventors. *American Economic Review*, *111*(10), 3328–3375.

Moretti, E., & Thulin, P. (2013). Local multipliers and human capital in the united states and sweden. *Industrial and Corporate Change*, *22*(1), 339–362.

Neffke, F., Henning, M., Boschma, R., Lundquist, K.-J., & Olander, L.-O. (2011). The dynamics of agglomeration externalities along the life cycle of industries. *Regional studies*, *45*(1), 49–65.

Neffke, F., Otto, A., & Weyh, A. (2017). Inter-industry labor flows. *Journal of Economic Behavior & Organization*, *142*, 275–292.

Olley, G., & Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, *64*(6), 1263–1297.

Osman, T., & Kemeny, T. (2022). Local job multipliers revisited. *Journal of Regional Science*, *62*(1), 150–170.

Ottaviano, G. I., & Thisse, J. F. (2001). On economic geography in economic theory: Increasing returns and pecuniary externalities. *Journal of Economic Geography*, *1*(2), 153–179.

Overman, H. G., & Puga, D. (2002). Unemployment clusters across europe's regions and countries. *Economic policy*, *17*(34), 115–148.

Overman, H. G., & Puga, D. (2010). Labor pooling as a source of agglomeration: An empirical investigation. In *Agglomeration economics* (pp. 133–150). University of Chicago Press.

Panagos, P., Van Liedekerke, M., Jones, A., & Montanarella, L. (2012). European soil data centre: Response to european policy support and public data requirements. *Land use policy*, *29*(2), 329–338.

Pellegrino, B., & Zingales, L. (2017). *Diagnosing the italian disease* (tech. rep.). National Bureau of Economic Research.

Petrin, A., & Levinsohn, J. (2012). Measuring aggregate productivity growth using plant-level data. *The Rand journal of economics*, *43*(4), 705–725.

Porter, M. E. (2008). *Competitive advantage: Creating and sustaining superior performance*. simon; schuster.

Puga, D. (2010). The magnitude and causes of agglomeration economies. *Journal of regional science*, *50*(1), 203–219.

Romano, S. (2021). The 2011 crisis in italy: A story of deep-rooted (and still unresolved) economic and political weaknesses. *Financial Crisis Management and Democracy: Lessons from Europe and Latin America*, 173–184.

Romer, P. (1986). Increasing returns, specialization, and external economies: Growth as described by allyn young. *Rochester Center for Economic Research Working Paper*, *64*.

Romer, P. M. (1990). Endogenous technological change. *Journal of political Economy*, *98*(5, Part 2), S71–S102.

Romer, P. M. (1994). The origins of endogenous growth. *Journal of Economic perspectives*, *8*(1), 3–22.

Rosenthal, S. S., & Strange, W. C. (2001). The determinants of agglomeration. *Journal of urban economics*, *50*(2), 191–229.

Rosenthal, S. S., & Strange, W. C. (2004). Evidence on the nature and sources of agglomeration economies. In V. Henderson & J.-F. Thisse (Eds.), *Handbook of regional and urban economics* (pp. 2119–2171, Vol. 4). Elsevier.

Rosenthal, S. S., & Strange, W. C. (2020). How close is close? the spatial reach of agglomeration economies. *Journal of economic perspectives*, *34*(3), 27–49.

Rovigatti, G., & Mollisi, V. (2018). Theory and practice of total-factor productivity estimation: The control function approach using stata. *The Stata Journal*, *18*(3), 618–662.

Ruiz-Fuensanta, M. J., & Bellandi, M. (2019). Entrepreneurship dynamics and economic cycles: An analysis for local systems and industrial districts. *European Planning Studies*, *27*(9), 1727–1747.

Sachs, J. D., & McCord, G. C. (2016). Regional development, geography of. In *The new palgrave dictionary of economics* (pp. 1–6). Palgrave Macmillan UK. https://doi.org/10.1057/978-1-349-95121-5_2753-1

Sforzi, F., Openshaw, S., & Wymer, C. (1991). Le procedura di identificazione dei sistemi locali del lavoro. *ISTAT, I Sistemi Locali del Lavoro*, 235–247.

Sforzi, F. (2002). The industrial district and the'new'italian economic geography. *European Planning Studies*, *10*(4), 439–447.

Sforzi, F., & Boix, R. (2015). What about industrial district (s) in regional science? *Investigaciones Regionales-Journal of Regional Research*, (32), 61–73.

Silvestre, J. (2016). Economies and diseconomies of scale. In *The new palgrave dictionary of economics* (pp. 1–7). Palgrave Macmillan UK. https://doi.org/10.1057/978-1-349-95121-5_546-1

Simon, C. J. (1988). Frictional unemployment and the role of industrial diversity. *The Quarterly Journal of Economics*, *103*(4), 715–728.

Smith, A. (1776). *An inquiry into the nature and causes of the wealth of nations*. W. Strahan; T. Cadell, London.

Sraffa, P. (1926). The laws of returns under competitive conditions. *The economic journal*, *36*(144), 535–550.

Steijn, M. P., Koster, H. R., & Van Oort, F. G. (2022). The dynamics of industry agglomeration: Evidence from 44 years of coagglomeration patterns. *Journal of Urban Economics*, *130*, 103456.

Stigler, J., George. (1951). The division of labor is limited by the extent of the market. *Journal of political economy*, *59*(3), 185–193.

Van der Panne, G. (2004). Agglomeration externalities: Marshall versus jacobs. *Journal of evolutionary economics*, *14*, 593–604.

Van Dijk, J. J. (2017). Local employment multipliers in us cities. *Journal of Economic Geography*, *17*(2), 465–487.

Van Dijk, J. J. (2018). Robustness of econometrically estimated local multipliers across different methods and data. *Journal of Regional Science*, *58*(2), 281–294.

Venables, A. J. (1996). Equilibrium locations of vertically linked industries. *International economic review*, 341–359.

Viner, J. (1932). Cost curves and supply curves. *Journal of Economics*, *3*(1), 23–46.

Vipond, J. (1974). City size and unemployment. *Urban Studies*, *11*(1), 39–46.

Wang, T., & Chanda, A. (2018). Manufacturing growth and local employment multipliers in china. *Journal of Comparative Economics*, *46*(2), 515–543.

Wooldridge, J. M. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. *Economics letters*, *104*(3), 112–114.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.