ESSAYS ON LABOUR AND REGIONAL ECONOMICS

Zhexin Feng

A thesis submitted for the degree of

Doctor of Philosophy in Economics

Department of Economics

University of Essex

May 2023

Acknowledgements

I would like to first express my sincere thanks to my main supervisor, Michel Serafinelli, for his invaluable support and guidance throughout my PhD study. I'm also very grateful to Yikai Wang, my co-supervisor, and Nicholas Reynolds, for their general advice and especially for the very helpful comments on my second chapter.

I also benefited greatly from the feedback and comments from Emma Duchini, Xiaoyu Xia, Ran Gu, Daniel Friedman. And special thanks to Eike J Eser and Sabrina Di Addario, my co-authors.

I would like to also thank Catherine van der List, Ines Helm and Elena Faieta for helpful discussions, and Jayant V Ganguli for his general support and advice, including on administrative issues. I'm very lucky to have great colleagues and friends during my PhD, and I need to thank especially Aitor Irastorza Fadrique for his advice and help. Thanks also to Bartosz Korchowiec, who collaborated on the early stages of the research on Inventors' Coworker Networks and Innovation. I'm grateful for his input.

Finally, I need to express my gratitude for the continuous support and encouragement from my parents and family.

Summary

This thesis consists of three chapters in empirical labour and regional economics. They generally analyze how local labour market performance varies across different times and spaces.

The first chapter provides a comprehensive analysis of labour market evolutions in rural areas in four most populous European countries since 1970. We document large differences in employment growth and changes in the industry structure are fast. Furthermore, industry turnover is positively associated with employment growth. Finally, our evidence indicates that successful rural areas experience stronger employment growth in manufacturing of food and beverages.

In the second chapter, I investigate the employment consequences of deindustrialization between 2010 and 2020 for cities in seven Chinese provinces, which could be viewed as China's Rust Belt, and explore the role of local multipliers. Cities within this Rust Belt reacted very differently to the aggregate decreasing trend of manufacturing employment. I document a high level of spatial heterogeneity across the local labour markets. I then study the role of local multiplier effects exploiting a shift-share approach. My estimates indicate that for every job created (lost) in the tradable sector in a given city, between 1.6 and 1.9 additional jobs are created (lost) in the non-tradable sector in the same city.

The third chapter presents direct evidence on the extent to which firms' innovation is affected by access to knowledgeable labor through co-worker network connections. Displacements of inventors because of plant closures generate labor supply shocks to firms that employ their pre-

vious co-workers. We estimate (a) event-study models where the treatment is the displacement of a connected inventor and (b) IV specifications where we use such a displacement as an instrument for the hire of a connected inventor. Estimates indicate that firms take advantage of displacements to recruit connected inventors and that the improved capacity increases innovation.

Contents

List of Tables

List of Figures

Chapter 1

Labour Market Evolutions in Rural Areas

- Jointly with Eike J Eser and Michel Serafinelli

Abstract

A quarter of the population in high-income countries lives in rural areas. However, existing empirical evidence on these areas in developed countries is rather scarce. This paper provides a comprehensive analysis of labour market evolutions in rural areas. We use data for 846 rural areas in the four most populous European countries (France, Germany, Italy, United Kingdom) starting from 1970. We document large differences in employment growth across rural areas. Furthermore, changes in the industry structure are fast in rural areas, and industry turnover is positively associated with employment growth. The evidence also indicates that successful rural areas experience stronger employment growth in manufacturing of food and beverages.

1.1 Introduction

Twenty-five percent of the population in developed countries lives in rural areas (OECD, 2018). However the urban and regional economics literature on high-income countries tends to focus mostly on cities. [1] In addition to a clear interest for regional economists, a better knowledge of the economics of rural areas is important for understanding the rise of the support for anti-system parties in many developed countries (Algan et al., 2019; Bakker, 2021). [2]

Many rural areas have undergone weak labour market for several decades. For instance, during the period between 1971 and 2011, the employment in the local labour markets of Castiglione Messer Marino and Guardia Lombardi, in the Abbruzzo and Campania regions of Italy, respectively, has declined on average about 30% per decade (in deviation from Italy's mean growth). Numerous examples of rural areas with weak employment performance exist in other Italian regions, in France, Germany and UK. These developments have spurred a debate about place based policies. EU member states carry out rural development programmes (RDPs) at both national and regional level. RDPs are financed jointly by the European fund for rural development (EAFRD) and country budgets. The EAFRD budget for the 2014-20 period equalled to approximately 100 billion Euro (EU, 2017; ENRD, 2017; EU, 2021). [3] The UK is presently involved in a determined attempt to push in the same direction through its 'Levelling-up' agenda.

Nevertheless, it is unclear whether the weak rural areas are representative of the broad experience of the universe of the rural areas. And if there are rural areas which have experienced

[1] Although previous research provides some evidence on specific aspects of rural labour markets such as rural-urban migration or the rural-urban wage gap, existing empirical evidence on labour market evolutions in rural areas in high-income countries is rather scarce.

[2] See also McCann (2016), Cramer (2016), Rodríguez-Pose (2018), Wuthnow (2018), Guilluy (2019), Reckwitz (2019), McCann (2020).

[3] 'Under the Common Agricultural Policy (CAP) transitional regulation (adopted on 23 December 2020), RDPs have been conditionally extended for 2021 and 2022. During these years, RDPs will be provided with 26.9 billion Euro from the EAFRD budget for 2021-27 and an extra 8.1 billion Euro from the next generation EU recovery instrument.' (EU, 2017)

strong labour demand, it is important to understand their features.

In this paper, we study the labour market evolutions of 846 rural areas in France, Germany, Italy and the UK. These countries are broadly representative for the Western European economy, and provide comprehensive national census data for the period under study on a sufficiently granular local level. We complement decadal census data with survey data. We combine and harmonize data on employment, industry composition and other economic variables at the local labour market (LLM) level starting from 1970 (organised at decadal frequency). We make our rich database available online [4], together with a detailed description (Appendix 1.B).

Our main goal is to provide a robust descriptive account. Specifically we document several stylized facts at LLM level regarding the differences in employment growth across space, the industry turnover and the changes observed in successful areas.

We start by studying the differences in employment growth across rural areas. Here we follow the same conceptual framework and empirical approach used by Gagliardi et al. (2023) in their study of rust belt cities. We establish that there are large differences in employment growth across rural areas during the period between the early 1970s to the early 2010s. For example, the 90-10 percentile difference in decadal total employment growth of rural areas is on averages 17.4 log points – an economically large difference. It ranges from 9.8 log points in UK to 18.1 log points in Italy, indicating vast differences in labor market performance across rural communities within each country. Conclusion are similar for remote areas. For comparison's sake, and given the limited evidence in the literature on spatial heterogeneity, we report the same statistics for urban and intermediate density areas. The heterogeneity is larger within the group of rural areas than within the group of cities and intermediate density LLMs.

Next, we seek to understand the features of successful rural areas. We show that changes in industry structure are fast in rural areas. Put it differently, there is considerable industrial

[4] https://sites.google.com/site/michelserafinelli/home

turnover. Remote areas also experience a rapid changes in the composition of their economic activity. We then study whether industry turnover is positively associated with employment growth. We find that this is the case for both rural and remote areas. Furthermore, we document the specific changes in the mix of local economic activity observed in successful versus unsuccessful rural areas. Specifically, we test whether the association between total-employment growth and employment growth in a given sector/industry is stronger for rural (low-density) versus intermediate density LLMs - we make this comparison because intermediate areas are more comparable to rural than urban areas. We repeat the same exercise for rural remote versus intermediate LLMs.

The evidence indicates that successful rural areas experience stronger employment growth in manufacturing of food and beverages. In particular, we find that for each 10 log-points in total-employment growth, rural areas experience a 4.1 log points higher growth in manufacturing of food and beverages. The conclusions are similar for successful rural remote areas. In addition, successful rural remote areas experience a decline in agriculture. The evidence also indicates that successful rural areas (and remote) experience stronger employment growth in hospitality.

Our paper adds to previous research in two ways. First, it adds to the literature on industry turnover and local evolutions, which has tended to focus on cities. In particular, Duranton (2007) and Findeisen and Südekum (2008) stress fast changes in urban industry structures. [5] This literature includes Gagliardi et al. (2023) which studies the consequences of the decline of manufacturing on cities. As mentioned above, when documenting differences across rural areas in labour market performance (Section 1.3.1), we use their same conceptual framework and empirical approach. Moreover, some of the data we use overlap to those employed in their analysis.

Compared to this first body of literature, we focus more specifically on the analysis of rural areas, using a broad dataset in terms of geography. We carry out a comprehensive analy-

[5] See also Eaton and Eckstein (1997), Black and Henderson (2003). Rosenthal and Ross (2015) provides a comprehensive review.

sis of labour market evolutions in rural areas, documenting empirical regularities across the four European countries with the largest population.

Second, the present paper adds to a so far underdeveloped body of research on rural areas and rural labour markets. [6] A first strand studies causes and consequences of migration from rural to urban areas - see Michaels et al. (2012) for evidence on the United States. [7] A second strand studies policy programs that target (disadvantaged) rural areas. Recent evaluations of rural-development programs include Behaghel et al. (2015) who analyze a tax-credit program in rural France and Couture et al. (2018) who examine an e-commerce expansion in rural China. [8] Finally, some previous research outside these two main strands investigates entrepreneurship in urban and rural labour markets - Faggio and Silva (2014) on UK data - and the labour market within rural regions - e.g. Baysan et al. (2019) study the allocation of labour between farm and non-farm employment in India. [9]

Compared to this second body of literature, we concentrate on rural areas in developed countries, taking a longer run approach and documenting changes at LLM level. In essence, our study combines insights and methods from the literature on urban evolutions with a focus on rural labour markets.

The remainder of this paper is structured as follows: Section 1.2 describes the data. Section 1.3 provides the main evidence. Section 1.4 concludes.

[6] See Kilkenny (2010) for a survey.

[7] See also Kim and Margo (2004), and recent surveys by Taylor and Martin (2001), Brueckner and Lall (2015) and Desmet and Henderson (2015).

[8] See also Canzian et al. (2019) and Asher and Novosad (2020). A review of earlier work in this area is provided by De Janvry et al. (2002). See Kline and Moretti (2014) and Neumark and Simpson (2015) for general surveys of place-based policies.

[9] See also Fafchamps and Quisumbing (1999), Lanjouw and Lanjouw (2001), Reardon et al. (2007). Bollman and Bryden (2000), Terluin and Post (2000), Terluin (2003) discuss the decline of agriculture and the rise in (tourism-related) services across OECD/EU rural and the differences in employment-growth paths during the 1980s and 1990s.

1.2 Data

We combine decadal census and survey data for France, Germany, Italy and the UK between the early 1970s and the early 2010s. We approximate the start-of-decade employment using the closest available year. For instance we use the Italian census of 2011 to approximate the employment at the start of the 2010s.

Our unit of analysis are local labour markets (LLMs), defined as areas where most of the residents both live and work. For France and Italy, they are territorial groupings of municipalities characterized by a certain degree of working-day commuting by the resident population. For Germany they are groupings of districts, for UK of wards or postcode sectors.

More specifically, the analysis in this paper is based on sector-specific decadal employment data for French *Zones d'Emploi*, German *Arbeitsmarktregionen*, Italian *Sistemi Locali del Lavoro* and British *Travel-to-Work Areas*. [10] Two advantages of census data over alternative data sources are that they include all employed inhabitants of a particular country including self-employed, and that they fully record employment in all three sectors including agriculture. [11] We then complement this panel with LLM-specific decadal 2-digit industry-employment data from the Italian business census and the British Business Register and Employment Survey (BRES).

To identify rural LLMs, we build on a widely-used OECD typology (OECD, 1994) that distinguishes between rural, intermediate and urban LLMs, based on the following two-step procedure. In a first step, each municipality of a LLM is defined as rural if its population density falls

[10] For each country, we draw on the earliest available LLM-classification, namely, on 1994 *Zones d'Emploi* (INSEE, 1987; Ronsac, 1994), 1990 *Arbeitsmarktregionen* (Eckey et al., 1990), 1981 *Sistemi Locali del Lavoro* (Sforzi, 1997) and 1984 *Travel-to-Work Areas* (Department of Employment, 1984; Coombes et al., 1986). The only German population census conducted between 1970 and early 2010s was carried out in 1987, due to protests motivated by data-privacy concerns. We thus use employment statistics provided by the German Federal Statistical Office ("Erwerbstätigenrechnung") to measure employment for German LLMs in 1980, 1990, 2000 and 2010.

[11] Our census data also contains several LLM- and decade-specific sociodemographic variables such as female employment and population in three education (low, middle, high educated) and four age groups (0–24, 25–44, 45–64, 65+). Similar to Pischke and Velling (1997), sociodemographic variables for German LLMs in 1980, 1990, 2000 and 2010 are drawn from databases of the Federal and State Statistical Offices as well as from the Federal Office for Building and Regional Planning.

below 150 inhabitants per square kilometer. In a second step, LLMs are divided into rural, intermediate and urban LLMs, depending on the share of their population living in rural municipalities. In particular, a LLM is classified as rural if the share of its population living in rural municipalities exceeds 50%. Conversely, a LLM is classified as intermediate if the share of its population living in rural municipalities ranges between 15% and 50% or if it contains a city with between 200 000 and 500 000 inhabitants that represents at least 25% of the LLM population. Finally, a LLM is classified as urban if the share of its population living in rural municipalities remains below 15% or if it contains a city with more than 500 000 inhabitants that represents at least 25% of the LLM population. We apply this classification in 1970 (the base period of our data panel), and use the resulting categorization for all subsequent decades.

Apart from the population density, another important characteristic of LLMs related to their rurality is the distance to urban centers.[12] To capture this dimension, we rely on a second OECD typology that classifies geographies into remote and non-remote areas (Dijkstra and Poelman, 2008; Brezzi et al., 2011). Specifically, we categorize a LLM as remote if 50% of its inhabitants or more live in remote municipalities, that is, municipalities which exhibit driving distances to the nearest urban center (a municipality with 50 000 inhabitants or more) of more than 60 minutes. As with the degree of rurality detailed above, we apply this definition only to base periods, leaving it unchanged for all subsequent decades.

Table 1.A.1 displays the resulting number of LLMs by degree of rurality and remoteness for the four countries in the data. The data feature 846 rural areas, of which 187 are remote. Section 1.A.2 depicts country-specific maps of all LLMs listed in Table 1.A.1. Table 1.A.2 presents some descriptive statistics in 1970 and 2010, the beginning and end of our period of analysis. Appendix 1.B provides a detailed description of the dataset.

[12]The economic significance of this dimension is, for example, stressed by Redding and Sturm (2008) who use the fall of the Iron Curtain to study consequences of remoteness and lacking market access as well as by the literature on transport-network extensions surveyed in Redding and Turner (2015).

1.3 Evidence

1.3.1 Differences across rural areas in labour market performance

In this Section we provide a descriptive account of geographical heterogeneity in employment changes across rural and remote areas during the period 1970-2010. We use the same conceptual framework and empirical approach used by Gagliardi et al. (2023) to document a significant heterogeneity in employment growth across manufacturing cities after the start of the aggregate industrial decline.

Figure C.1 displays kernel density estimates for the employment-growth distribution of rural and remote areas. Visual inspection suggests that there are large differences in employment growth across rural and across remote areas. Table C.1 substantiates these claims by presenting the standard deviation of employment growth and the differences between the 90th and the 10th percentile (p90–p10). The Table reports these statistics for the whole dataset, and by country. Note that for Germany it is not possible to report these statistics for rural remote areas because of sample size - See Table 1.A.1.

For example, the 90-10 percentile difference in decadal total employment growth of rural areas is on averages 17.4 log points – an economically large difference. It ranges from 9.8 log points in UK to 18.1 log points in Italy, indicating vast differences in labor market performance across rural communities within each country. Conclusions are similar when focusing on remote areas. For comparison's sake, and given the limited evidence in the literature on spatial heterogeneity, the Table also reports the same statistics for urban and intermediate density areas. The heterogeneity is larger within the group of rural areas than within the group of cities and intermediate density LLMs.

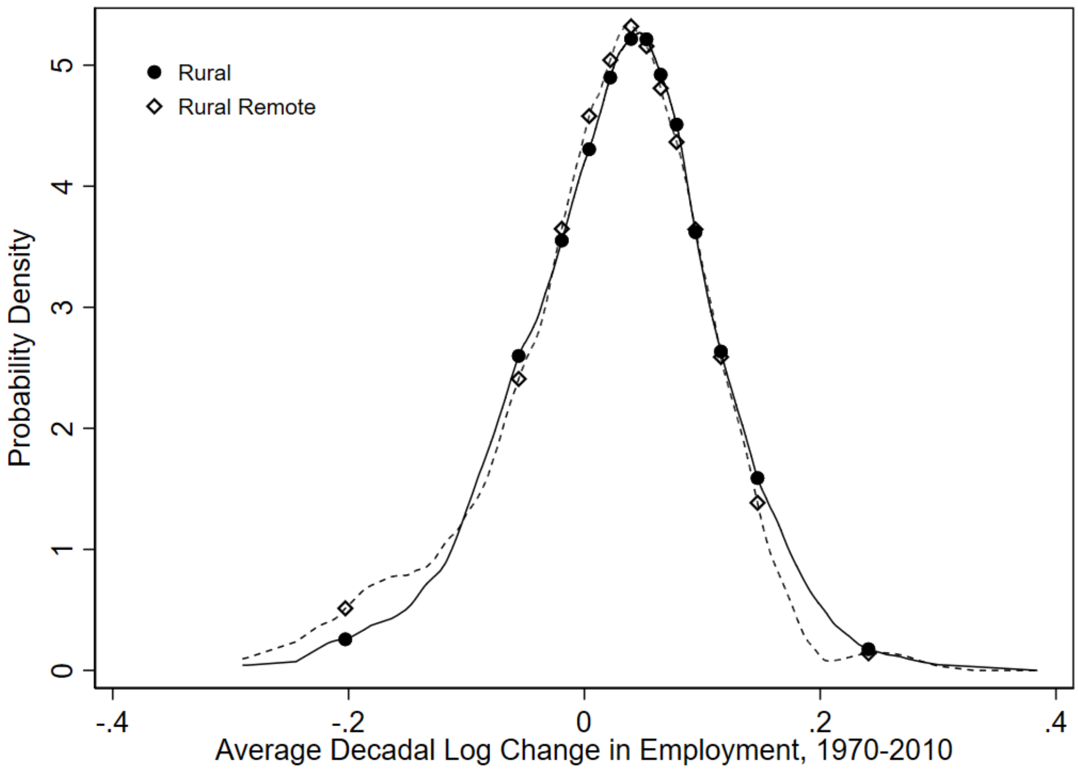


Figure C.1. *Distribution of Employment Growth by LLM Type, 1970–2010.*

Notes: The figure shows kernel density estimates of mean decadal log changes in total employment between 1970 and 2010 for rural and rural remote LLMs.

Table C.1. *Geographical Variation in Employment Growth*

	Rural	Rural Remote	Intermediate	Urban
A. Whole Sample				
Std. Deviation	0.0721	0.0682	0.0566	0.0460
p90-p10	0.1736	0.1405	0.1375	0.1287
B. France				
Std. Deviation	0.0626	0.0490	0.0617	0.0408
p90-p10	0.1603	0.1017	0.1793	0.1102
C. Germany				
Std. Deviation	0.0498	–	0.0396	0.0380
p90-p10	0.1158	–	0.1022	0.0956
D. Italy				
Std. Deviation	0.0747	0.0869	0.0528	0.0498
p90-p10	0.1814	0.2416	0.1413	0.1384
E. UK				
Std. Deviation	0.0392	0.0365	0.0397	0.0359
p90-p10	0.0986	0.1022	0.0843	0.0946

Notes: Entries are summary statistics for the distribution of average decadal log changes in total employment between 1970 and 2010 by LLM type. All statistics are weighted by population shares of LLMs in 1970. For Germany it is not possible to report these statistics for rural remote areas because of sample size - See Table 1.A.1.

1.3.2 Industry Turnover

The main message from Section 1.3.1 is that there are vast differences in labor market performance across rural communities within each country. In this Section and in Section 1.3.3, we seek to understand the features of successful rural areas. In particular this Section analyzes the following questions: (a) is there considerable industry turnover in rural areas? (b) is industry turnover positively associated with employment growth?

Table C.2 reports the industry-churning rate of LLMs, a structural-change measure based on industry-level employment. For each LLM, this measures averages decadal relative employment gains and losses over all industries and decades: [13]

$$Churn_l = \frac{1}{4 \cdot J} \sum_{t=1970}^{2000} \sum_{j=1}^{J} \frac{|e_{l,j,t+1} - e_{l,j,t}|}{e_{l,j,t}} \tag{C.1}$$

where j indexes industries (J=60), $e_{l,j,t}$ is the employment of LLM l in industry j and decade t.

The sample here consists of LLMs in Italy and UK, the two countries for which the industry break down is feasible at local level with the data at our disposal. Table C.2 also reports the aggregate total-employment change:

$$\Delta EMP_l = \frac{1}{4} \sum_{t=1970}^{2000} \frac{|e_{l,t+1} - e_{l,t}|}{e_{l,t}} \tag{C.2}$$

The Table shows that, on average across rural areas, the industry-churning rate is 6.8 times as large as the aggregate employment change. This indicates that the average rural area saw its industries changing 6.8 times the amount necessary to accommodate aggregate employment changes. Therefore, changes in the industry structure are fast in rural areas. This finding is not

[13] See Davis and Haltiwanger (1998), Duranton (2007) and Findeisen and Südekum (2008) for examples of previous applications.

driven by outliers. Results are qualitatively similar if we remove absolute employment growth rates above the 99th percentile by country. For comparison's sake, we report the same statistics for urban and intermediate density areas. The churning is faster on average for rural areas than for cities and intermediate density LLMs. [14]

Table C.2. *Churning*

	Rural	Rural Remote	Inter-mediate	Urban
Industry Churning	1.3264 (1.8401)	1.2116 (1.0129)	1.0884 (1.4713)	0.8431 (1.2732)
Aggregate Employment Change	0.1962 (0.2097)	0.2087 (0.2272)	0.1527 (0.1384)	0.1142 (0.1060)
LLMs	596	128	348	320

Notes: The Table describes industry movements across areas. Entries show industry churning indices as well as aggregate percentage changes in total employment by LLM type. Standard deviations in parentheses. All statistics are weighted by population shares of LLMs in base periods. Calculations are based on LLM-specific NACE Rev. 1 2-digit industry-employment data for Italy and the UK.

Is industry turnover associated with employment growth? In order to explore this aspect, we regress the decadal log change in employment on the decadal industry churning rate:

$$\Delta y_{l,r,c,t} = \gamma Churn_{l,t} + \lambda_t + \varphi_{r,t} + \eta_{l,r,c,t} \tag{C.3}$$

where $\Delta y_{l,r,c,t}$ is the log change in total employment for LLM i in NUTS-1 region r, country c and decade t, $Churn_{l,t}$ is the decadal industry-churning rate, [15], λ_t are decade fixed effects, $\varphi_{r,t}$ are region $\times$ decade fixed effects and $\eta_{l,r,c,t}$ is the error term. Note that this specification is similar to a four-period fixed-effects model and thus differences out any unobservable time-invariant LLM-specific confounders on the right-hand side.[16]

[14] Duranton (2007) or Findeisen and Südekum (2008) report yearly churning rate for U.S. (period: 1977-1997) and French (1985-1993) cities, and German (1977–2002) cities, respectively. Notice the following differences: first, we report decadal instead of yearly churning rates; second, we analyze Italy and UK; third, we study a different period: 1970-2010.

[15] $Churn_{l,t} = \frac{1}{J}\sum_{j=1}^{J} \frac{|e_{l,j,t} - e_{l,j,t-1}|}{e_{l,j,t-1}}$

[16] As pointed out by Autor et al. (2013a), the stacked first-differenced version poses slightly less restrictive assumptions

Table C.3. *Relation of Industry Churning and Employment Growth by LLM Type.*

	Dependent Variable: Decadal Δ Log Employment	
	(1) Rural	(2) Rural Remote
Industry-Churning Rate	0.0032**	0.0160***
	(0.0015)	(0.0028)
Decade FE	Yes	Yes
Region × Decade FE	Yes	Yes
LLMs	596	128
N	2384	512

Notes: Results are coefficients and standard errors from regressions of decadal LLM-specific log changes in total employment on decadal LLM-specific industry-churning rates. All regressions are weighted by population shares of LLMs in base periods. Standard errors are clustered by NUTS-2 regions. Industry-churning rates are calculated from LLM-specific NACE Rev. 1 2-digit industry-employment data for Italy and the UK. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.3 summarizes the association between industry churning and employment growth. The estimates are positive and significant for both rural and remote LLMs. For rural areas, a standard deviation increase in churning (1.8401) is associated to a 0.6 percent increase in employment. For remote areas, a standard deviation increase in churning (1.0129) is associated to a 1.6 percent increase in employment.

A main takeaway from this Table is that churning has, on average, been a feature of successful rural and remote LLMs in our sample period.

1.3.3 Industry Mix Changes in Successful Areas

The main messages from Section 1.3.2 are that (a) there is considerable industry turnover in rural areas; (b) industry turnover is positively associated with employment growth. In this Section we address the following question: what specific changes in the mix of local economic activity do we observe in successful versus unsuccessful rural areas? To investigate this issue we test whether the association between total-employment growth and employment growth in a given sector/industry

on the error term relative to a multiperiodic fixed-effects model.

is stronger for rural versus intermediate LLMs [17] - we make this comparison because intermediate areas are more comparable to rural than urban areas (see also Table C.1 and Table C.2). We estimate the following equation on the sample of LLMs that are classified as rural or intermediate:

$$\Delta e_{l,r,c,t} = \pi_3 \Delta y_{l,r,c,t} + \theta \ rural_l \times \Delta y_{l,r,c,t} + \pi_4 \Delta X_{l,t} + \lambda_t + \varphi_{r,t} + \nu_{l,r,c,t} \tag{C.4}$$

where $\Delta e_{l,r,c,t}$ are log changes [18] in sector or industry-level employment: in (a) agriculture, or (b) food and beverages manufacturing, or (c) hospitality, or (d) culture, or (e) retail trade. $\Delta y_{l,r,c,t}$ are log changes in *total* employment for LLM l in NUTS-1 region r, country c and decade t. As in previous specifications of this paper, λ_t are decade fixed effects, $\varphi_{r,t}$ are region $\times$ decade fixed effects and $\nu_{l,r,c,t}$ is the error term. Note that the model is estimated in stacked first differences and thus differences out any unobservable time-invariant LLM-specific confounders on the right-hand side - these include $rural_l$.

We repeat the same exercise for rural remote versus intermediate LLMs.

Specifically, models in columns 1–5 of Table C.4 take as dependent variable growth rates of sector or industry-level employment: in agriculture, food and beverages manufacturing, hospitality, culture, and retail trade, respectively. Agriculture is the traditional industry in rural areas; food and beverages manufacturing and hospitality are often discussed in the policy debate on the economic development of rural areas - see EU (2017) and ENRD (2017) for examples of discussions. Culture, and retail trade are also sometimes discussed (due to their link to the hospitality industry), albeit indirectly (UNESCO, 2020; Eurostat, 2021). [19]

The estimation sample consists of LLMs in Italy and UK, the two countries for which

[17] This approach is similar in spirit to the analysis of minimum wage effects in Card (1992).

[18] The main conclusions from the below analysis are unchanged if we use the inverse hyperbolic sine transformation instead of the log transformation

[19] Quoting from UNESCO (2020): ‘Tourism can provide direct jobs to the community, such as tour guides or in the hospitality industry (hotels, bars and restaurants). Indirect employment is generated through other industries such as agriculture, food production, creative industries (art, music performance) and retail (souvenirs).’

the industry break down is feasible at local level with the data at our disposal.

Table C.4. *Industry Mix Changes in Successful Areas*

	(1) Δ Agriculture	(2) Δ Food and Beverages	(3) Δ Hospitality	(4) Δ Culture	(5) Δ Retail
A. Rural versus Intermediate LLMs					
Δ Employment $\times$ Rural	-0.3062 (0.2293)	0.4051** (0.1813)	0.1622*** (0.0591)	-0.0364 (0.1476)	-0.0010 (0.0653)
LLMs	910	944	944	934	944
B. Rural remote versus Intermediate LLMs					
Δ Employment $\times$ Rural remote	-1.0240** (0.4992)	0.5881** (0.2379)	0.3064*** (0.1084)	-0.4697 (0.3275)	-0.0354 (0.1228)
LLMs	456	476	476	471	476

Notes: Rows show coefficients and standard errors from *separate* regressions of LLM-specific decadal log changes in sector- or industry-employment on decadal log changes in total employment, and interaction with dummies indicating rural (panel A) or rural remote LLMs (panel B). All regressions are weighted by population shares of LLMs in base periods. Decade FE and Region $\times$ Decade FE always included. See Equation C.4. Note that the model is estimated in stacked first differences and thus differences out any unobservable time-invariant LLM-specific confounders on the right-hand side - these include dummies indicating rural or rural remote LLMs. Standard errors are clustered by NUTS-2 regions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In Column 1 of Table C.4, the estimated coefficient θ is negative both for rural areas and remote areas. It is significant for remote areas, implying that for remote areas growth variation in total employment is negatively and significantly associated to growth variation in agriculture. In Column 2, the estimates imply that for rural areas growth variation in total employment is positively and significantly associated to growth variation in manufacturing of food and beverages, an industry closely related to agriculture where firms add values to the agricultural products. In particular, we find that for each 10 log-points in total-employment growth, rural areas experience a 4.1 log points higher growth in manufacturing of food and beverages. The conclusions are qualitatively similar for remote areas. In Column 3, the estimates imply that for rural areas growth variation in total employment is positively and significantly associated to growth variation in hospitality. The conclusions are again qualitatively similar for remote areas. While it is beyond of the scope of the analysis in this Section, it is important to note that changes in manufacturing of food and beverages and hospitality may reinforce each other, through spillovers and local multiplier processes (Moretti, 2010; Faber and Gaubert, 2019).

In Column 4 (culture), and Column 5 (retail trade) we cannot reject the null hypothesis of no relation between total employment and industry growth, either for rural or rural remote.

1.4 Conclusions

This paper provides a comprehensive analysis of labour market evolutions in rural areas. We address the following questions. Are there large differences across rural areas in employment growth? Is there considerable industry turnover in rural areas? Is the industry turnover positively associated with employment growth? What specific changes in the mix of local economic activity do we observe in successful versus unsuccessful rural areas?

We document large differences in employment growth across rural areas. The evidence also indicates that there is considerable industry turnover in rural areas. Moreover, industry turnover is positively associated with employment growth. Finally, successful rural areas experience stronger employment growth in manufacturing of food and beverages. Overall, our evidence lends support to the hypothesis that change is common in rural areas and labour market evolutions in rural areas often result from industry-level changes. In the future we will study rural multipliers: (a) from food and beverages, and (b) more generally. Concretely, we will investigate whether an increase in local food and beverages manufacturing (or, more in general, in the tradable sector) leads to the creation of a significant number of additional jobs in the non-traded sector. More broadly, we believe that our rich cross-country and LLM-level database, which we made available online together with a detailed documentation, can allow researchers to study other questions (including comparative ones) at the intersection of Labour and Regional economics.

Appendix

Appendix 1.A Appendix

1.A.1 Main Summary Statistics

Table 1.A.1. *Total Number of LLMs by Degree of Rurality and Remoteness.*

	Urban		Intermediate		Rural	
	Non-Remote	Remote	Non-Remote	Remote	Non-Remote	Remote
France	30	0	110	7	143	58
Germany	34	0	74	1	48	1
Italy	198	4	210	13	425	105
UK	115	3	109	16	43	23
Total	377	7	503	37	659	187

1.A.2 Geographic Distribution of Rural, Intermediate, Urban and Remote Local labour Markets

Table 1.A.2. *Characteristics of Urban, Intermediate and Rural LLMs, 2010 versus 1970.*

	Urban		Intermediate		Rural		Rural Remote	
	1970	2010	1970	2010	1970	2010	1970	2010
A. Relative Size (Sample Aggregates, %)								
% of Sample Population	55.69	53.86	29.06	31.13	15.24	15.01	2.60	2.43
% of Sample Employment	59.22	56.28	27.73	30.38	13.05	13.34	2.00	1.93
B. Total Size (Average LLM, 1,000 individuals)								
Population	1346.18	1435.78	261.51	330.57	82.98	102.72	62.41	73.62
	(1501.88)	(1686.53)	(242.63)	(305.66)	(61.37)	(74.93)	(43.64)	(52.08)
Employment	588.01	670.07	97.51	140.10	27.69	39.65	16.74	23.07
	(766.54)	(841.84)	(105.66)	(148.02)	(25.22)	(34.25)	(10.65)	(15.20)
C. Sectoral Structure (Average LLM, %)								
Agriculture	4.25	1.55	12.98	3.26	27.61	6.95	28.81	7.71
	(6.75)	(2.78)	(8.48)	(3.04)	(12.09)	(5.30)	(12.34)	(5.83)
Manufact.	46.20	20.75	42.52	24.22	36.77	26.86	32.25	23.95
	(10.63)	(7.53)	(10.27)	(7.10)	(10.39)	(7.55)	(10.40)	(7.02)
Services	49.54	77.70	44.51	72.52	35.62	66.20	38.94	68.34
	(11.48)	(8.47)	(10.63)	(7.86)	(9.58)	(7.89)	(11.00)	(7.76)
D. Other Characteristics (Average LLM, %)								
Empl.-Pop. Ratio	40.84	44.04	36.65	41.13	32.90	37.47	29.63	33.44
	(8.27)	(8.05)	(9.22)	(8.50)	(8.85)	(8.13)	(8.06)	(6.81)
% Female Employment	32.16	45.42	31.44	45.59	30.89	44.42	30.01	45.79
	(5.39)	(3.53)	(5.46)	(3.46)	(6.73)	(4.21)	(5.30)	(4.26)
% High Qual. Workforce	5.92	25.17	4.95	22.87	3.31	19.00	4.13	23.23
	(3.47)	(13.18)	(3.09)	(12.78)	(2.00)	(10.34)	(2.41)	(8.54)
% Aged 65+	12.06	17.89	12.80	19.05	14.14	20.76	15.73	22.76
	(2.50)	(3.60)	(2.62)	(3.19)	(2.90)	(3.28)	(3.03)	(2.96)
LLMs	377	377	512	512	831	831	187	187

Notes: Manufacturing includes extraction and construction, services include public administration. Standard deviations in parentheses. Figures for sample aggregates do not vary within decades. All statistics in panels B–D are weighted by decadal population shares of LLMs.

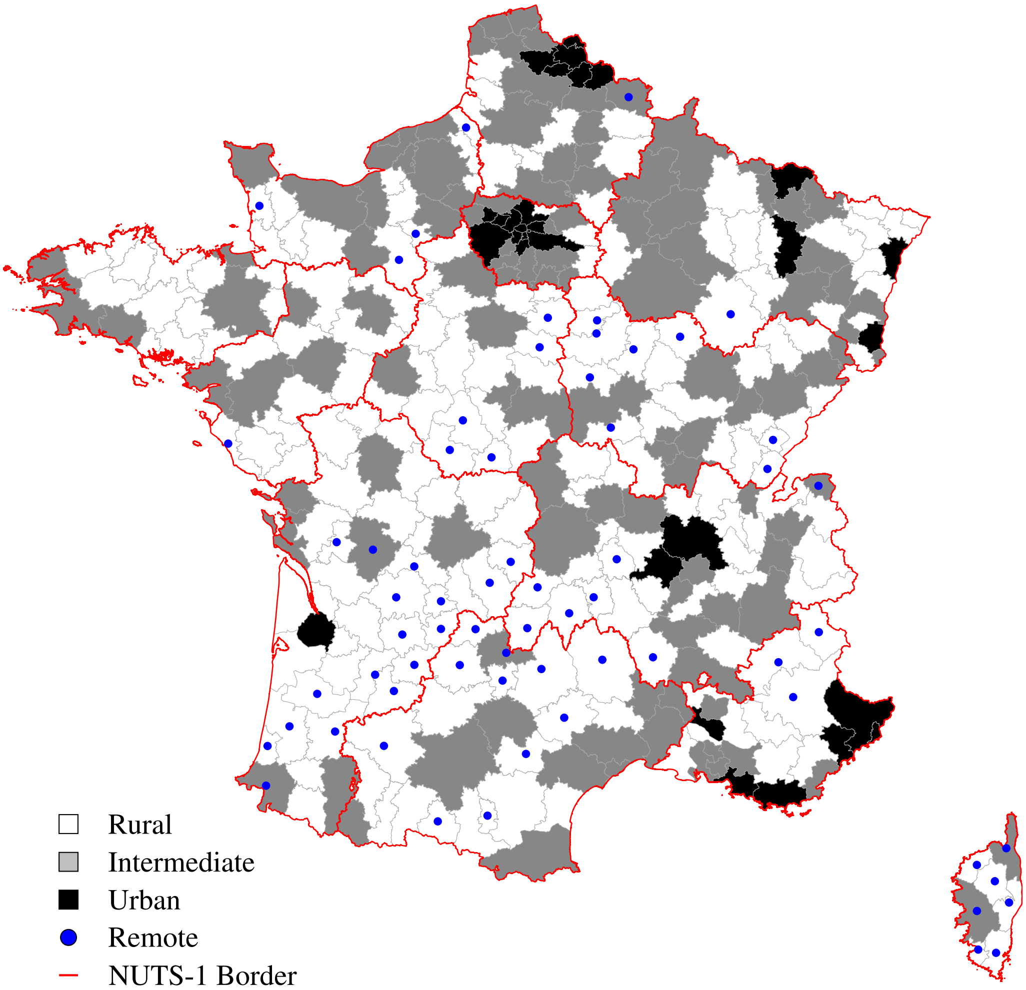


Figure 1.A.1. *Rural, Intermediate and Urban Local labour Markets in France.*

Notes: The figure shows 1994 French LLMs by degree of rurality and remoteness. Rural and remote LLMs are classified based on OECD (1994); Dijkstra and Poelman (2008); Brezzi et al. (2011). NUTS-1 borders are borders around those LLMs the centroid of which lies in the same NUTS-1 region.

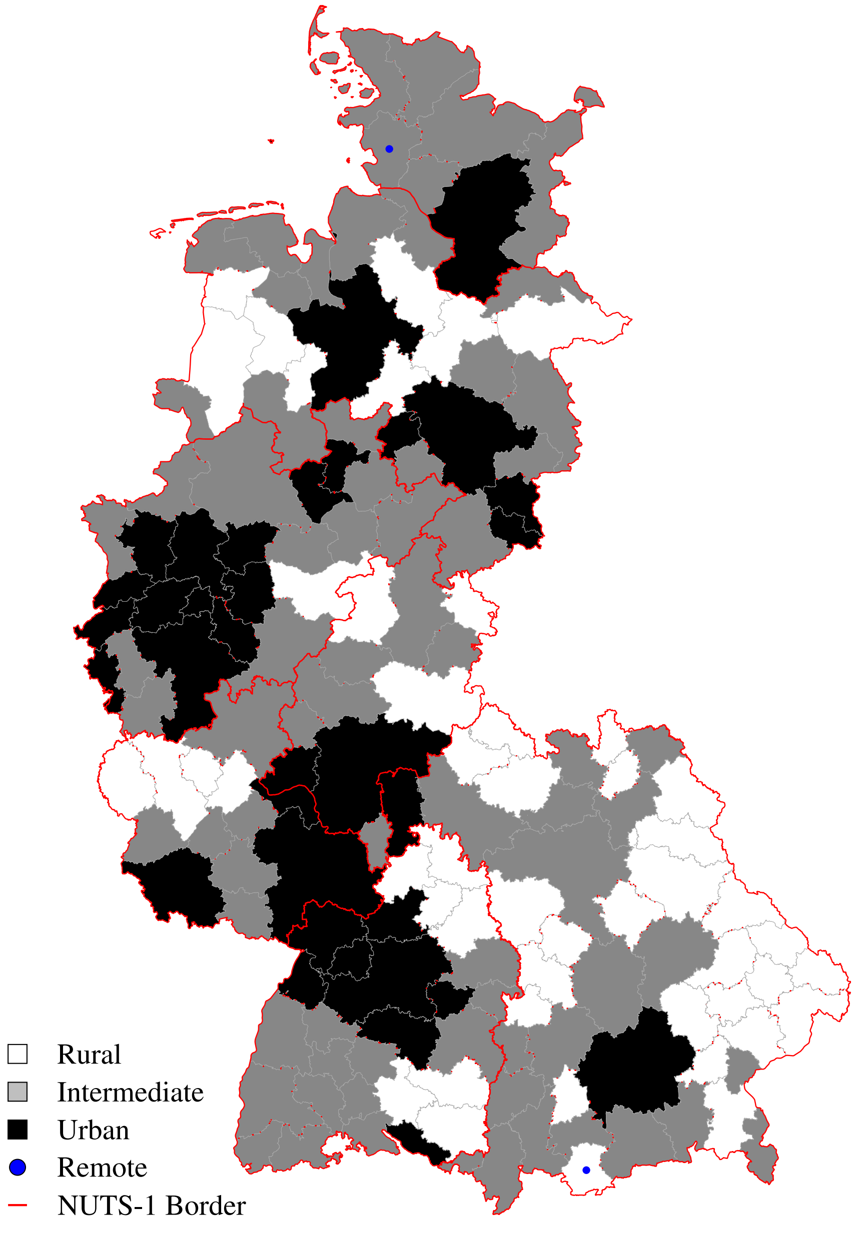


Figure 1.A.2. *Rural, Intermediate and Urban Local labour Markets in Germany.*

Notes: The figure shows 1990 German LLMs by degree of rurality and remoteness. Rural and remote LLMs are classified based on OECD (1994); Dijkstra and Poelman (2008); Brezzi et al. (2011). NUTS-1 borders are borders around those LLMs the centroid of which lies in the same NUTS-1 region. The city states of Bremen and Hamburg are (respectively) merged with the territorial states of Niedersachsen and Schleswig-Holstein. Moreover, the small territorial state of Saarland is merged with the neighboring state of Rhineland Palatinate.

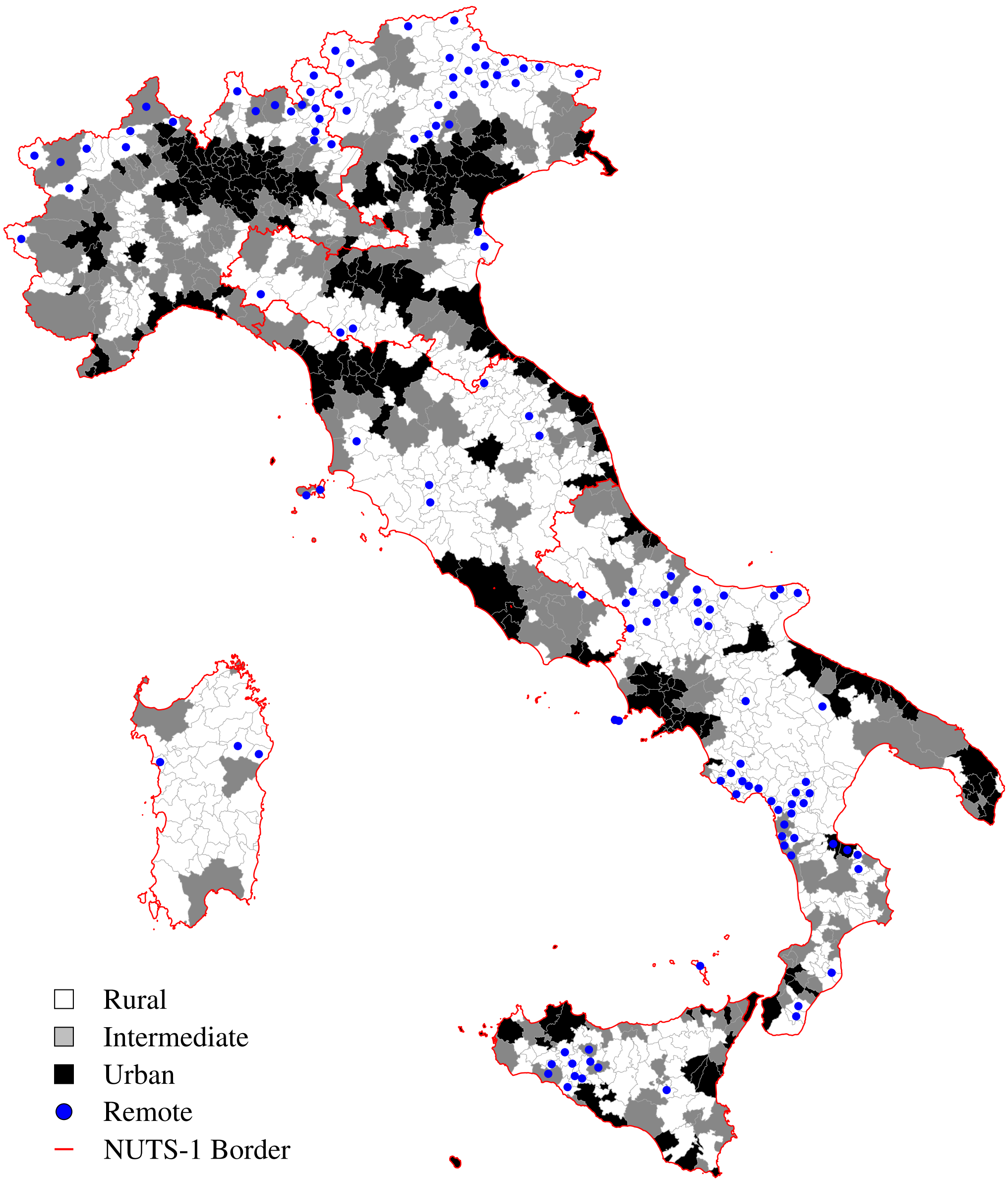


Figure 1.A.3. *Rural, Intermediate and Urban Local labour Markets in Italy.*

Notes: The figure shows 1981 Italia LLMs by degree of rurality and remoteness. Rural and remote LLMs are classified based on OECD (1994); Dijkstra and Poelman (2008); Brezzi et al. (2011). NUTS-1 borders are borders around those LLMs the centroid of which lies in the same NUTS-1 region. Sardinia and Sicily together form one NUTS-1 region.

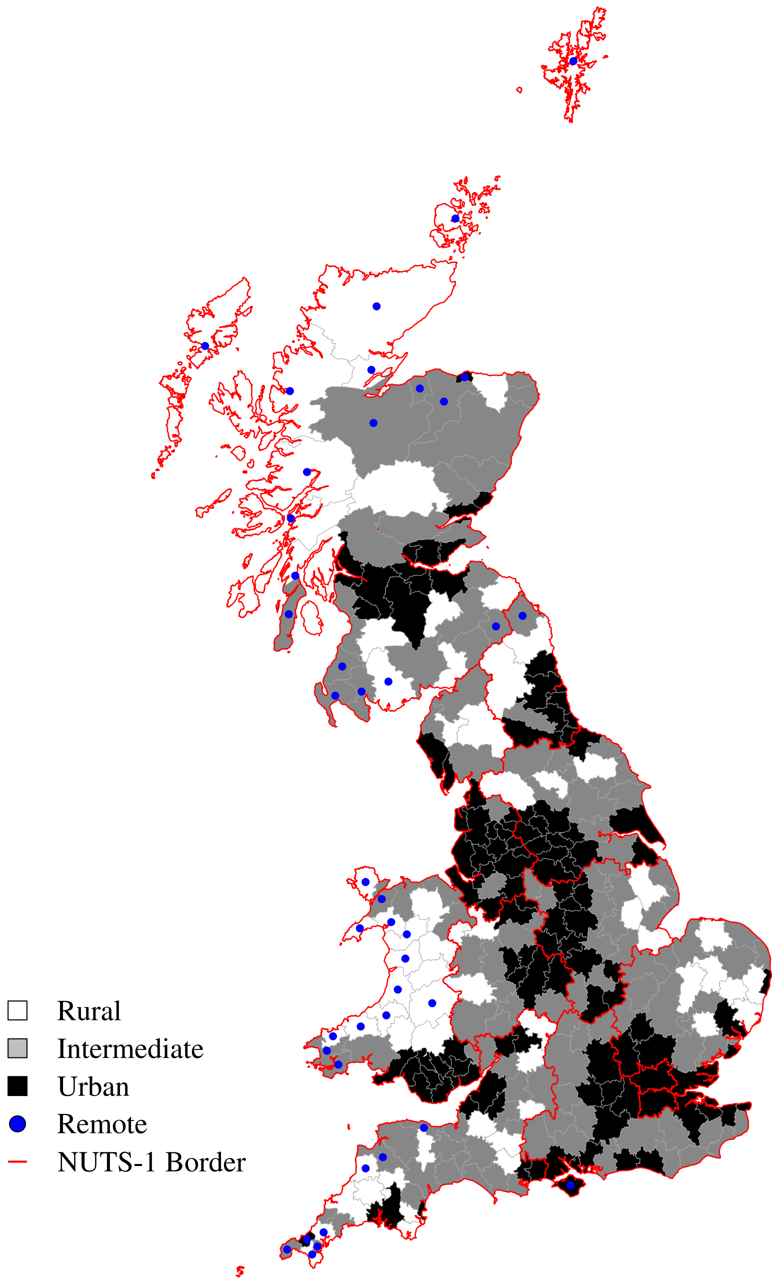


Figure 1.A.4. *Rural, Intermediate and Urban Local labour Markets in the UK.*

Notes: The figure shows 1984 British LLMs by degree of rurality and remoteness. Rural and remote LLMs are classified based on OECD (1994); Dijkstra and Poelman (2008); Brezzi et al. (2011). NUTS-1 borders are borders around those LLMs the centroid of which lies in the same NUTS-1 region.

1.A.3 Country-Specific Summary Statistics

France

Table 1.A.3. *Characteristics of French Urban, Intermediate and Rural LLMs, 2010 versus 1970.*

	Urban		Intermediate		Rural		Rural Remote	
	1970	2010	1970	2010	1970	2010	1970	2010
A. Relative Size (Sample Aggregates, %)								
% Sample Population	33.62	31.90	38.16	40.80	28.22	27.30	7.09	6.34
% Sample Employment	36.54	32.88	36.69	40.39	26.77	26.74	6.69	5.90
B. Total Size (Average LLM, 1,000 individuals)								
Popu- lation	996.22 (720.69)	1077.87 (656.01)	253.90 (165.24)	367.54 (285.73)	90.64 (39.96)	115.94 (60.30)	84.30 (38.19)	97.49 (47.07)
Employ- ment	298.91 (238.01)	366.72 (245.90)	64.44 (43.54)	118.91 (99.37)	22.63 (10.32)	36.73 (20.77)	20.95 (9.71)	29.09 (14.10)
C. Sectoral Structure (Average LLM, %)								
Agriculture	1.84 (1.92)	0.42 (0.44)	12.02 (6.05)	2.42 (1.78)	26.91 (10.73)	5.75 (3.20)	28.48 (9.71)	6.86 (3.18)
Manufact.	41.75 (9.68)	15.80 (4.72)	40.44 (9.40)	21.68 (4.59)	34.61 (10.02)	25.39 (5.79)	31.61 (9.17)	23.77 (5.42)
Services	56.40 (10.19)	83.78 (4.98)	47.54 (7.70)	75.91 (5.14)	38.49 (7.41)	68.86 (6.17)	39.91 (7.11)	69.37 (5.69)
D. Other Characteristics (Average LLM, %)								
Empl.-Pop. Ratio	28.47 (4.00)	32.94 (3.14)	25.19 (2.04)	31.64 (2.43)	24.85 (1.84)	31.29 (2.66)	24.73 (1.51)	29.77 (1.82)
% Female Employment	34.19 (6.33)	48.53 (1.34)	30.90 (4.45)	47.76 (1.22)	31.87 (4.12)	47.26 (1.14)	31.47 (3.90)	47.62 (1.41)
% High Qual. Workforce	10.42 (4.34)	44.38 (11.89)	6.94 (2.54)	35.42 (7.41)	4.44 (1.25)	27.79 (4.56)	4.58 (1.19)	26.93 (3.97)
% Aged 65+	11.82 (2.96)	15.00 (2.92)	12.31 (2.32)	17.02 (3.22)	15.37 (2.65)	20.22 (3.56)	16.80 (2.26)	23.09 (2.55)
LLMs	30	30	117	117	201	201	58	58

Notes: Manufacturing includes extraction and construction, services include public administration. Standard deviations in parentheses. Figures for sample aggregates do not vary within decades. All statistics in panels B–D are weighted by decadal population shares of LLMs.

Germany

Table 1.A.4. *Characteristics of German Urban, Intermediate and Rural LLMs, 2010 versus 1970.*

	Urban		Intermediate		Rural		Rural Remote	
	1970	2010	1970	2010	1970	2010	1970	2010
A. Relative Size (Sample Aggregates, %)								
% of Sample Population	55.09	53.88	33.94	34.90	10.97	11.22	0.13	0.13
% of Sample Employment	55.54	55.44	33.48	33.70	10.99	10.85	0.14	0.13
B. Total Size (Average LLM, 1,000 individuals)								
Population	1697.42 (879.20)	1865.28 (980.48)	423.35 (318.85)	494.98 (379.94)	155.91 (67.07)	178.14 (74.94)	75.42 (.)	86.31 (.)
Employment	749.25 (391.25)	985.33 (551.01)	182.72 (144.94)	247.54 (205.13)	67.62 (28.04)	87.13 (38.46)	35.47 (.)	41.28 (.)
C. Sectoral Structure (Average LLM, %)								
Agriculture	3.52 (2.14)	1.23 (0.52)	10.41 (3.79)	2.76 (1.09)	20.82 (6.27)	4.66 (1.41)	6.67 (.)	3.12 (.)
Manufact.	51.10 (7.26)	23.04 (6.29)	47.49 (8.56)	27.39 (6.86)	44.20 (7.45)	31.95 (6.38)	28.26 (.)	14.20 (.)
Services	45.38 (7.07)	75.73 (6.49)	42.10 (7.92)	69.84 (6.71)	34.97 (6.36)	63.38 (6.49)	65.07 (.)	82.69 (.)
D. Other Characteristics (Average LLM, %)								
Empl.-Pop. Ratio	43.98 (3.72)	51.67 (5.56)	43.03 (3.23)	48.50 (4.25)	43.69 (2.64)	48.57 (4.54)	47.03 (.)	47.83 (.)
% Female Employment	34.45 (3.37)	44.76 (1.78)	35.77 (3.79)	45.04 (3.12)	38.23 (3.45)	43.89 (3.60)	41.11 (.)	54.51 (.)
% High Qual. Workforce	3.51 (1.02)	15.41 (4.05)	3.01 (0.71)	10.43 (2.44)	2.50 (0.41)	7.08 (1.46)	4.10 (.)	7.64 (.)
% Aged 65+	12.84 (1.43)	20.19 (1.23)	12.99 (1.50)	20.21 (1.57)	12.83 (1.48)	19.95 (1.93)	14.75 (.)	23.97 (.)
LLMs	34	34	75	75	49	49	1	1

Notes: Manufacturing includes extraction and construction, services include public administration. Standard deviations in parentheses. Figures for sample aggregates do not vary within decades. All statistics in panels B–D are weighted by decadal population shares of LLMs.

Italy

Table 1.A.5. *Characteristics of Italian Urban, Intermediate and Rural LLMs, 2010 versus 1970.*

	Urban		Intermediate		Rural		Rural Remote	
	1970	2010	1970	2010	1970	2010	1970	2010
A. Relative Size (Sample Aggregates, %)								
% of Sample Population	56.39	57.11	24.74	25.59	18.88	17.30	2.61	2.22
% of Sample Employment	56.30	57.45	25.05	25.88	18.65	16.67	2.59	2.13
B. Total Size (Average LLM, 1,000 individuals)								
Population	903.85 (1004.12)	829.66 (964.74)	129.69 (114.59)	151.58 (134.34)	35.20 (30.82)	40.04 (35.92)	18.49 (13.27)	20.41 (17.88)
Employment	309.83 (350.55)	315.46 (373.49)	44.38 (37.19)	57.52 (46.09)	11.65 (9.46)	14.63 (12.78)	6.44 (5.05)	7.45 (6.31)
C. Sectoral Structure (Average LLM, %)								
Agriculture	10.05 (11.10)	4.08 (4.59)	21.65 (12.08)	6.74 (4.79)	34.02 (13.94)	11.00 (7.69)	33.12 (16.39)	11.35 (10.21)
Manufact.	45.90 (13.59)	25.25 (9.50)	43.25 (11.24)	28.14 (8.72)	36.96 (10.07)	27.33 (9.33)	37.42 (11.69)	27.70 (9.99)
Services	44.05 (13.87)	70.67 (9.89)	35.11 (9.90)	65.12 (8.13)	29.02 (9.07)	61.67 (8.62)	29.45 (10.60)	60.94 (8.71)
D. Other Characteristics (Average LLM, %)								
Empl.-Pop. Ratio	34.73 (5.07)	38.96 (6.34)	35.22 (4.32)	39.17 (5.69)	34.38 (4.69)	37.32 (5.84)	34.52 (3.97)	37.10 (6.65)
% Female Employment	26.41 (5.44)	41.76 (4.42)	26.68 (5.82)	41.34 (3.81)	25.84 (6.91)	39.45 (3.64)	27.76 (6.29)	39.02 (3.84)
% High Qual. Workforce	3.37 (1.73)	14.85 (4.17)	2.09 (0.88)	12.31 (3.01)	1.41 (0.64)	10.15 (2.84)	1.28 (0.54)	9.61 (2.77)
% Aged 65+	10.42 (2.27)	20.39 (3.29)	11.97 (2.86)	21.08 (2.88)	12.90 (3.08)	21.95 (3.37)	12.61 (2.75)	22.08 (3.97)
LLMs	202	202	223	223	530	530	105	105

Notes: Manufacturing includes extraction and construction, services include public administration. Standard deviations in parentheses. Figures for sample aggregates do not vary within decades. All statistics in panels B–D are weighted by decadal population shares of LLMs.

UK

Table 1.A.6. *Characteristics of British Urban, Intermediate and Rural LLMs, 2010 versus 1970.*

	Urban		Intermediate		Rural		Rural Remote	
	1970	2010	1970	2010	1970	2010	1970	2010
A. Relative Size (Sample Aggregates, %)								
% of Sample Population	77.19	73.27	19.21	22.55	3.60	4.18	0.96	1.06
% of Sample Employment	77.11	72.53	19.18	23.25	3.71	4.22	0.97	1.04
B. Total Size (Average LLM, 1,000 individuals)								
Population	1548.72 (2197.66)	1716.61 (2520.03)	132.41 (86.76)	187.24 (122.40)	34.89 (14.69)	49.21 (22.90)	26.21 (11.35)	33.25 (13.98)
Employment	792.24 (1168.59)	826.26 (1234.21)	64.22 (43.57)	92.96 (63.79)	17.31 (7.45)	23.57 (11.27)	12.54 (5.16)	15.40 (6.34)
C. Sectoral Structure (Average LLM, %)								
Agriculture	1.49 (1.41)	0.39 (0.35)	8.38 (4.52)	1.84 (1.33)	21.40 (8.56)	5.30 (2.26)	22.37 (10.64)	6.17 (2.88)
Manufact.	44.42 (9.33)	17.79 (4.72)	35.75 (8.66)	19.41 (3.85)	27.04 (8.43)	20.23 (3.16)	22.89 (7.70)	18.74 (3.24)
Services	54.09 (9.45)	81.82 (4.91)	55.87 (7.90)	78.75 (4.42)	51.56 (7.28)	74.46 (3.88)	54.74 (8.02)	75.09 (4.51)
D. Other Characteristics (Average LLM, %)								
Empl.-Pop. Ratio	48.21 (3.34)	46.85 (2.62)	48.18 (2.39)	48.78 (3.00)	49.75 (3.46)	47.78 (2.45)	48.53 (4.32)	46.62 (3.19)
% Female Employment	33.81 (2.29)	47.31 (0.94)	30.28 (2.43)	47.17 (0.94)	25.79 (2.84)	46.81 (0.98)	24.17 (3.52)	47.18 (0.89)
% High Qual. Workforce	7.85 (1.80)	32.01 (8.01)	8.72 (2.24)	31.66 (6.71)	7.63 (2.20)	29.53 (5.61)	8.92 (2.62)	30.22 (4.96)
% Aged 65+	12.78 (2.55)	15.49 (2.68)	14.45 (3.63)	18.66 (3.21)	16.01 (2.36)	22.00 (2.37)	16.89 (2.76)	22.01 (2.85)
LLMs	118	118	125	125	66	66	23	23

Notes: Manufacturing includes extraction and construction, services include public administration. Standard deviations in parentheses. Figures for sample aggregates do not vary within decades. All statistics in panels B–D are weighted by decadal population shares of LLMs.

Appendix 1.B Data Supplement

1.B.1 Introduction

This supplement briefly describes the sources of a decadal panel-data set containing various socioeconomic and geographic variables for local labor markets (LLMs) in France, Germany, Italy and the UK between 1970 and 2010. Specifically, the data set contains information on the the following variables:

- Total employment
- Sectoral employment
- Female employment share
- Degree of rurality
- Population-weighted population density
- Remoteness
- Population-weighted driving distance to urban centers
- Shares of three education groups (low, middle high)
- Population
- Population shares of the age groups 0–24, 25–44, 45–64, 65+
- Population shares of foreign residents
- Wages
- Unemployed inhabitants

- Industry employment
- NUTS Region IDs

Information is currently only partially provided (i.e. not for all LLMs or all decades) for wages, industry employment, unemployed inhabitants, foreign residents and education groups. In particular, the data set does currently not provide wage data for French and British LLMs, for Italian LLMs before 1990 and for German LLMs before 2000. Moreover, industry employment is not provided for French and German LLMs, information on unemployed inhabitants is not provided for German LLMs and information on foreign residents is not provided for French and Italian LLMs before 1990. Finally, education shares are only fully recorded for shares of high-educated inhabitants. Shares of middle and low educated inhabitants are missing for British LLMs before 2000 and for German LLMs in 1970.

The remainder of this supplement describes the data sources for each available variable by sample country.

1.B.2 France

LLMs

We draw on 1994 French LLMs (*zones d'emploi*) which are aggregations of French municipalities, based on 1990s commuting data. The classification and aggregation procedure is described in detail in INSEE (1987) and Ronsac (1994). All variables listed below are originally provided on the municipality level. But because municipalities are nested in LLMs, variables can be easily aggregated to LLM-level information.

Total and Sectoral Employment

To derive total and sectoral employment data by LLMs, we rely on the French population census that provides harmonized sectoral employment data for individuals aged 25–54 on the municipality level.[20]

Specifically, we draw on the number of employees in 1982 to approximate employment at the start of the 1980s, on the number of employees in 1990 to approximate employment at the start of the 1990s, on the number of employees in 1999 to approximate employment at the start of the 2000s and on the number of employees in 2011 to approximate employment at the start of the 2010s. To approximate the start-of-decade employment of the 1970s, we use the average number of employees in 1968 and 1975 because the data does not record employment information for years in between.

Apart from total employment, we also extract employment in three sectors, namely, agriculture, industry (extraction, manufacturing, construction) and services.

For consistency reasons, we exclude all data on DOM-TOMs (*départments and terretoires d'outre mer*). We then aggregate the municipality-level employment data to 1990 employment zones relying on an official crosswalk. When municipalities cannot be assigned using this crosswalk, they were often merged with other municipalities over time. To merge those formerly independent municipalities, we draw on a file by the French National Statistical Office (INSEE) that tabulates all territorial changes at the municipality level. The few remaining unmerged municipalities were assigned manually to the correct 1990 employment zones.

[20] See https://www.insee.fr/fr/statistiques/1893185.

Female Employment

Total female employment is drawn from the same census data described in Section 1.B.2. We aggregate this municipality-level information to LLMs using an identical aggregation procedure.

Degree of Rurality

To identify rural areas, we draw on population and surface data on the municipality level in 1968, available via the website of Observatoire Territorial that is operated by the French government.[21] We then assign municipalities to LLMs using the same procedure as in Section 1.B.2

Subsequently, we calculate municipality-specific population densities and apply an OECD typology (OECD, 1994) that classifies municipalities as rural if the population density falls below 150 inhabitants per square kilometer. Relying on the same OECD typology, we then divide LLMs into three types depending on their degree of rurality: First, we classify an LLM as rural if the share of its population living in rural municipalities exceeds 50%. Second, we classify an LLM as intermediate if the share of its population living in rural municipalities ranges between 15% and 50% or if it contains a city with between 200 000 and 500 000 inhabitants that represents at least 25% of the LLM population. Finally, we classify and LLM as urban if the share of its population living in rural municipalities remains below 15% or if it contains a city with more than 500 000 inhabitants that represents at least 25% of the LLM population.

Population-Weighted Population Density

Municipality-level population densities are derived from the same data sources as in Section 1.B.2. We then go on to compute the LLM-specific population-weighted average of these densities.

[21] See https://www.observatoire-des-territoires.gouv.fr/outils/cartographie-interactive/#c=home.

Remoteness

Based on a second OECD typology (Dijkstra and Poelman, 2008; Brezzi et al., 2011), we classify an LLM as remote if 50% of its inhabitants or more live in remote municipalities. Remote municipalities are municipalities which exhibit driving distances to the nearest urban center (a municipality with 50 000 inhabitants or more) of more than 60 minutes. To calculate the driving distance from each of the municipalities to every urban center, we draw on Open Street Map data and Stata's OSRM package.

Population-Weighted Driving Distance to Urban Centers

Municipality-level driving distances to urban centers (i.e. municipalities with 50 000 inhabitants or more) are derived from the same data sources as in Section 1.B.2. We then go on to compute the LLM-specific population-weighted average of these driving distances.

Education Groups

Like sectoral and total employment data, education data come from the French population census that provides education data for individuals aged 25–54 on the municipality level.[22] For consistency reasons, we exclude all data on DOM-TOMs (*départments and terretoires d'outre mer*). We then assign municipalities to LLMs using the same procedure as in Section 1.B.2. Subsequently, we aggregate total employment and numbers of people, (1), with a higher education degree (*diplôme de niveau supérieur à bac+2*)[23], (2), with a medium level of education (*baccalaureat* or vocational degree, e.g. CAP, BEP) and, (3), with a low level of education (no vocational education degree or *baccalaureat*) at the LLM level and calculate workforce shares of low-, medium- and high-educated people, dividing LLM-specific education groups by the sum of these education

[22] See https://www.insee.fr/fr/statistiques/1893185.

[23] This includes *licence, maîtrise, master, dea, dess, doctorat, diplôme de grande école*. See as well https://www.insee.fr/fr/metadonnees/definition/c1076.

groups (i.e. the total workforce).[24]

Population

Population data for 1968, 1975, 1982, 1990, 1999 and 2011 on the municipality level is extracted from the Observatoire Territorial. We then assign municipalities to LLMs using the same procedure as in Section 1.B.2. For consistency reasons, we exclude all data on DOM-TOMs (*départments and terretoires d'outre mer*).

Age Groups

Like sectoral employment data, age-group data come from the French population census that records municipality populations in age groups. Corresponding data is provided on by the French National Statistical Office.[25] For consistency reasons, we exclude all data on DOM-TOMs (*départments and terretoires d'outre mer*). We then assign municipalities to LLMs using the same procedure as in Section 1.B.2. Subsequently, we aggregate numbers of people aged 0–24, 25–44, 45–64 and 65+ at the LLM level and calculate age-group shares, dividing by the sum of individuals in all age groups.

Unemployment

Like sectoral employment data, unemployment data come from the French population census that records the employment status of individuals aged 25–54 on the municipality level. Corresponding data is provided on the homepage of the French National Statistical Office.[26] For consistency reasons, we exclude all data on DOM-TOMs (*départments and terretoires d'outre mer*). We then assign municipalities to LLMs using the same procedure as in Section 1.B.2. Subsequently, we

[24] See `https://www.insee.fr/fr/metadonnees/definition/c1076`.
[25] See `https://www.insee.fr/fr/statistiques/1893204`.
[26] `https://www.insee.fr/fr/statistiques/1893185`.

aggregate numbers of unemployed individuals at the LLM level.

NUTS-Region IDs

We assign each LLM to a NUTS-1 and a NUTS-2 region, depending on the location of the LLM centroid.

1.B.3 Germany

LLMs

We draw on 1990 West-German LLMs (*Arbeitsmarktregionen*) which are aggregations of German districts, based on 1980s commuting data. The classification and aggregation procedure is described in detail in Eckey et al. (1990). All variables listed below are originally provided at the district or municipality level. But because districts are nested in LLMs, variables can be easily aggregated to LLM-level information.

Total and Sectoral Employment

To derive total and sectoral employment data by LLMs, we draw on 1970 census data and employment statistics by the Federal Statistical Office ("Erwerbstätigenrechnung") for 1980, 1990, 2000 and 2009. This data reports employment at the district level.

Due to (state-specific) territorial reorganizations in the 1970s, districts recorded in the 1970 census do not correspond to the districts that form the basis of the 1990 German LLMs. We thus use a version of the 1970 census data that has been adjusted to territorial changes and records contemporary districts (Schmitt et al., 1994). In particular, we extract data on total employment by LLM as well as data on employment in three sectors, namely, agriculture, industry (extraction, manufacturing, construction, energy and water) and services (including trade and public administration).

Analogous employment data from the *Erwerbstätigenrechnung* for the other years cited above can be accessed via the homepage of the Federal Statistical Office[27] or the German Regional Accounts[28]. We use data from the 2005 revision for 1980 and 1990 and data from the 2010 revision for 2000 and 2009.

Female Employment

Like sectoral and total employment data, 1970 total female employment is drawn from the adjusted version of the 1970 census data cited above. Moreover, we compute district-specific female employment for 1980, 1990 and 2000 from reports of the Federal Office for Building and Regional Planning that have, for example, been used previously by Pischke and Velling (1997). Specifically, we extract female employment in 1980 from Böltken et al. (1995), in 1989 from Böltken et al. (1992) and in 2000 from Böltken et al. (2002). Analogous data for 2010 come from the Regional Database of the Federal Statistical Office.[29]

Degree of Rurality

To identify rural areas, we draw on population and surface data on the municipality level from municipal records ("Gemeindeverzeichnis").[30] Specifically, we draw on 1980 data, owing to the territorial changes mentioned in Section 1.B.3. We then map municipalities to LLMs via districts, omitting "statistical municipalities" without inhabitants that are not part of a district.

Subsequently, we calculate municipality-specific population densities and apply an OECD typology (OECD, 1994) that classifies municipalities as rural if the population density falls below 150 inhabitants per square kilometer. Relying on the same OECD typology, we then divide LLMs

[27] See http://www.statistikportal.de/de/etr.
[28] See https://www.statistik-bw.de/VGRdL/?lang=en-GB.
[29] See https://www.regionalstatistik.de/.
[30] See https://www.destatis.de/DE/Themen/Laender-Regionen/Regionales/Gemeindeverzeichnis/.

into three types depending on their degree of rurality: First, we classify an LLM as rural if the share of its population living in rural municipalities exceeds 50%. Second, we classify an LLM is as intermediate if the share of its population living in rural municipalities ranges between 15% and 50% or if it contains a city with between 200 000 and 500 000 inhabitants that represents at least 25% of the LLM population. Finally, we classify and LLM as urban if the share of its population living in rural municipalities remains below 15% or if it contains a city with more than 500 000 inhabitants that represents at least 25% of the LLM population.

Population-Weighted Population Density

Municipality-level population densities are derived from the same data sources as in Section 1.B.3. We then go on to compute the LLM-specific population-weighted average of these densities.

Remoteness

Based on a second OECD typology (Dijkstra and Poelman, 2008; Brezzi et al., 2011), we classify an LLM as remote if 50% of its inhabitants or more live in remote municipalities. Remote municipalities are municipalities which exhibit driving distances to the nearest urban center (a municipality with 50 000 inhabitants or more) of more than 60 minutes. To calculate the driving distance from each of the municipalities to every urban center, we draw on Open Street Map data and Stata's OSRM package.

Population-Weighted Driving Distance to Urban Centers

Municipality-level driving distances to urban centers (i.e. municipalities with 50 000 inhabitants or more) are derived from the same data sources as in Section 1.B.3. We then go on to compute the LLM-specific population-weighted average of these driving distances.

Education Groups

Like (sectoral) employment data, 1970 education data is drawn from the adjusted version of the 1970 census data cited above. In particular, we approximate the workforce share of high-educated individuals dividing the number of respondents with a university degree by the number of inhabitants aged 25 and over.

District-specific education data for 1980, 1990 and 2000 is taken from reports by the Federal Office for Building and Regional Planning. Specifically, we draw on Gatzweiler and Runge (1984) for 1983 education data, on Böltken et al. (1992) for 1989 education data and on Böltken et al. (2002) for 2000 education data. Analogous data for 2010 are extracted from the Regional Database of the Federal Statistical Office.

In each case, we calculate the workforce share of high-educated individuals as the number of employees with a university degree over the total number of employees. Moreover, we calculate the district- and decade-specific workforce share of low-educated individuals as the number of employees without vocational or university degree over the total number of employees.

Population

District-level population data for 1970 is drawn from the adjusted version of the 1970 census data cited above. Population data for 1980 and 1990 come from municipal records (“Gemeindeverzeichnis”). Population data for 2000 and 2010 is extracted from the Regional Database of the Federal Statistical Office.

Age Groups

District-level data on inhabitants in the four age groups 0–24, 25–44, 45–64 and 65+ for 1970 is drawn from the adjusted version of the 1970 census data cited above. Because this data records only inhabitants in the age group 0–20 instead of 0–24, we rescale the district-specific age group by a state-specific factor, computed from state-specific age-group shares in 1970.[31] Specifically, we apply the following two-step rescaling procedure: In a first step, we multiply the number of inhabitants in the district-specific age group 0–20 by the state-specific factor $\left({}^{Age_{0-24}}/{}_{Age_{0-20}}\right)$ where Age_{0-20} are inhabitants aged 0–20 and Age_{0-24} are inhabitants aged 0–24. In a second step, we adjust the original age group 21–44 by subtracting the number of inhabitants in the rescaled age group as well as those in the age groups 45–64 and 65+ from the total number of inhabitants of a district.

Analogous age-group data for 1980 and 1990 comes from reports and databases of the State Statistical Offices. In particular, data for the states of Bremen, Lower Saxony, North-Rhine Westphalia, Rhineland Palatinate, Baden-Wurttemberg[32] in 1980 and 1990 and data for Bavaria in 1990 are provided online or directly by the respective State Statistical Office. Moreover, we extract data for the states of Hamburg and Saarland from the state-level information provided by the Federal Statistical office mentioned above.[33] Data for the states of Schleswig-Holstein in 1980 and 1990 and for Hesse and Bavaria in 1980 are taken from respective State Statistical Yearbooks and reports.[34][35] Finally, we extract data for Hesse in 1990 from Böltken et al. (2001).[36]

Age-group data for 2000 and 2010 is again drawn from the Regional Database of the Federal Statistical Office.

[31] The data comes from table 12411-0012 of the Federal Statistical Office's Genesis Database https://www-genesis.destatis.de/genesis/online.

[32] Data for Baden Wurttemberg in 1980 record only information about the age group 25–49 instead of 25-44. We thus rescale this data using a procedure analogous to the approach described above.

[33] See table 12411-0012 of the Federal Statistical Office's Genesis Database. Using state-level information is possible because Hamburg encompasses only one district and the 1990 LLM of Saarbrücken comprises all districts of the state of Saarland.

[34] See State Stat. Office of Bavaria (1981); State Stat. Office of Hesse (1981); State Stat. Office of Schleswig-Holstein (1981, 1990).

[35] Data for Hesse and Bavaria in 1980 record only information about the age group 0–14 instead of 0–24 (Hesse) or 25–39 instead of 25–44 (Bavaria). We thus rescale this data using a procedure analogous to the approach described above.

[36] This data records only information about the age group 25–49 instead of 25–44. We again rescale this data using a procedure analogous to the approach described above.

Foreign Residents

Like (sectoral) employment data, district-specific numbers of foreign residents in 1970 are drawn from the adjusted version of the 1970 census data cited above.

District-specific data for 1980 and 1990 is taken from reports of the Federal Office for Building and Regional Planning. Specifically, we draw on Böltken et al. (1995) for 1980 data and on Böltken et al. (1992) for 1989 data. Analogous data for 2000 and 2010 is extracted from the Regional Database of the Federal Statistical Office.

Wages

District-specific average hourly wages per employee for 2000 and 2010 are contained in German Regional Accounts.[37] We use this data to compute LLM-specific weighted averages, weighting hourly wages per employee by the share of employees and hours of an LLM. Subsequently, we compute LLM-specific hourly real wages, deflating nominal wages by the applicable consumer price index of the central bank.[38]

NUTS-Region IDs

We assign each LLM to a NUTS-1 and a NUTS-2 region, depending on the location of the LLM centroid. For NUTS-1 regions, we merge the city states Bremen and Hamburg (respectively) with the territorial states of Niedersachsen and Schleswig-Holstein and the small territorial state of Saarland with the neighboring state of Rhineland Palatinate, resulting in 7 instead of 10 German NUTS-1 regions.

[37] See https://www.statistik-bw.de/VGRdL/?lang=en-GB.
[38] See https://www.bundesbank.de/dynamic/action/de/statistiken/zeitreihen-datenbanken/zeitreihen-datenbank/759778/759778?listId=www_s311_lr_vpi.

1.B.4 Italy

LLMs

We draw on 1981 Italian LLMs (*Sistemi Locali del Lavoro*) which are aggregations of Italian municipalities, based on 1980s commuting data. The classification and aggregation procedure is described in detail in Sforzi (1997). All variables listed below are originally derived from municipality-level information. But because municipalities are nested in LLMs, variables can be easily aggregated to LLM-level information.

Total and Sectoral Employment

To derive total and sectoral employment data by LLMs, we rely on the Italian population census that records sectoral employment on the 1981 LLM level for 1971, 1981, 1991 and 2001 and on the municipality level for 2011.[39]

Specifically, we use the number of employees in 1971 to approximate employment at the start of the 1970s, the number of employees in 1981 to approximate employment at the start of the 1980s, the number of employees in 1991 to approximate employment at the start of the 1980s, the number of employees in 2001 to approximate employment at the start of the 1980s and the number of employees in 2011 to approximate employment at the start of the 2010s. We then aggregate the 2011 municipality-level employment data to 1981 LLMs drawing on an official crosswalk.

Apart from total employment, we also extract employment in three sectors, namely, agriculture, industry (extraction, manufacturing, construction) and services.

[39] Corresponding data is provided on the homepage of the Italian National Statistical Office (ISTAT): Data for 1971–2001 can be accessed via the interface on https://www.istat.it/it/archivio/113712, data for 2011 can be accessed via http://asc.istat.it/asc_BL/ or http://dati-censimentopopolazione.istat.it/Index.aspx?lang=en#.

Female Employment

Total female employment is drawn from the same census data described in Section 1.B.4. We aggregate this municipality-level information to LLMs using an equivalent aggregation procedure.

Degree of Rurality

To identify rural areas, we draw on population and surface data on the municipality level in 1971, available via the above mentioned interface-data by the Italian National Statistical Office.[40] We then assign municipalities to LLMs using the same procedure as in Section 1.B.4

Subsequently, we calculate municipality-specific population densities and apply an OECD typology (OECD, 1994) that classifies municipalities as rural if the population density falls below 150 inhabitants per square kilometer. Relying on the same OECD typology, we then divide LLMs into three types depending on their degree of rurality: First, we classify an LLM as rural if the share of its population living in rural municipalities exceeds 50%. Second, we classify an LLM as intermediate if the share of its population living in rural municipalities ranges between 15% and 50% or if it contains a city with between 200 000 and 500 000 inhabitants that represents at least 25% of the LLM population. Finally, we classify and LLM as urban if the share of its population living in rural municipalities remains below 15% or if it contains a city with more than 500 000 inhabitants that represents at least 25% of the LLM population.

Population-Weighted Population Density

Municipality-level population densities are derived from the same data sources as in Section 1.B.4. We then go on to compute the LLM-specific population-weighted average of these densities.

[40] See https://www.istat.it/it/archivio/113712.

Remoteness

Based on a second OECD typology (Dijkstra and Poelman, 2008; Brezzi et al., 2011), we classify an LLM as remote if 50% of its inhabitants or more live in remote municipalities. Remote municipalities are municipalities which exhibit driving distances to the nearest urban center (a municipality with 50 000 inhabitants or more) of more than 60 minutes. To calculate the driving distance from each of the municipalities to every urban center, we draw on Open Street Map data and Stata's OSRM package.

Population-Weighted Driving Distance to Urban Centers

Municipality-level driving distances to urban centers (i.e. municipalities with 50 000 inhabitants or more) are derived from the same data sources as in Section 1.B.4. We then go on to compute the LLM-specific population-weighted average of these driving distances.

Education Groups

Like total and sectoral employment data, education data comes from the Italian population census that records residents with a *diploma* (medium educated) as well as people with a *laurea* degree or above (high educated) on the LLM level between 1971 and 2001 and on the municipality level in 2011. More precisely, data is drawn from the same census data described in Section 1.B.4. We then assign 2011 municipalities to LLMs using the same procedure as in Section 1.B.4. Subsequently, we aggregate numbers of medium- and high-qualified residents at the LLM level and calculate education-group shares, dividing LLM-specific numbers of people with a medium or high education by the LLM-specific population aged 25 and over.[41] The share of low-educated people is calculated as a residual.

[41] See Section 1.B.4 for information on data sources for age groups.

Population

Population data is available on the LLM level for 1971, 1981, 1991 and 2001 and on the municipality level for 2011. More precisely, data is drawn from the same census data described in Section 1.B.4. We again assign 2011 municipalities to LLMs relying on an equivalent procedure as in Section 1.B.4 and aggregate data for all years at the LLM level.

Age Groups

Like total and sectoral employment data, age-group data comes from the Italian population census that records age groups on the LLM level between 1971 and 2001 and on the municipality level in 2011. More precisely, data is drawn from the same census data described in Section 1.B.4. We then assign 2011 municipalities to LLMs relying on an equivalent procedure as in Section 1.B.4. Subsequently, we aggregate numbers of people aged 0–24, 25–44, 45–64 and 65+ calculate age-group shares, dividing by the sum of all age groups which is equivalent to the LLM-specific population.

Foreign Residents

Information on foreign residents at the LLM level is available for 2001 and 2010 via the above-mentioned interface-data by the Italian National Statistical Office.[42] Municipality-level data for 1990 is provided directly by the Italian National Statistical Office. We assign 1990 municipalities to LLMs using the same procedure as in Section 1.B.4. Subsequently, we aggregate numbers of foreign residents at the LLM level.

Wages

Monthly gross wages for 1991, 2001 and 2011 at the LLM level are provided by the National Social Insurance Institute (INPS). Note that this data is only available for 941 out of 955 LLMs

[42] See https://www.istat.it/it/archivio/113712.

(for the remaining LLMs, data would come from less than 10 enterprises). We deflate the wages for each decade by the (January) consumer price index of the respective year that is reported on the homepage of the Federal Reserve Bank of St. Louis.[43]

Unemployment

Unemployment data is available on the LLM level for 1971, 1981, 1991 and 2001 and on the municipality level for 2011. More precisely, data is drawn from the same census data described in Section 1.B.4. For consistency reasons we use data on economically active people looking for employment (*"in cerca di occupazzione"*). We then assign 2011 municipalities to LLMs using the same procedure as in section 3.1 above and aggregate data for all years at the LLM level.

Industry Employment

We extract business-census data on 2-digit 1991 ATECO industries by 1981 LLM from the above-mentioned interface by the Italian National Statistical Office for 1971, 1981, 1991 and 2001.[44] For 2011, data on 3-digit ATECO 2007 industries at the municipality level is provided by the Italian National Statistical Office.

We then, (1), merge municipalities to 1981 LLMs using an official crosswalk and, (2), map 3-digit ATECO 2007 to 2-digit ATECO 1991 industries based official conversion tables to obtain a panel-data set on 2-digit ATECO 1991 industries at the 1981 LLM level. Note that 2-digit ATECO 1991 industries correspond one-to-one to NACE Rev. 1 2-digit industries.

NUTS-Region IDs

We assign each LLM to a NUTS-1 and a NUTS-2 region, depending on the location of the LLM centroid.

[43] See `https://fred.stlouisfed.org/series/ITACPIALLMINMEI`.
[44] See `https://www.istat.it/it/archivio/113712`.

1.B.5 UK

LLMs

We draw on 1984 British LLMs (*Travel-to-Work Areas*) which are aggregations of British wards (England, Wales) or postcode sectors (Scotland), based on 1980s commuting data. The classification and aggregation procedure is described in detail in Department of Employment (1984) and Coombes et al. (1986).

Note that we do not extract data for LLMs in Northern Ireland. Moreover, we merge several LLMs for consistency reasons. In particular, we merge the TTWAs Aberdeen and Huntley, Barnstaple & Ilfracombe and South Molton, Bideford and Torrington, Dumfries and Lockerbie, Dunoon & Bute and Islay Mid Argyll, Elgin and Keith, Inverness and Badenoch, Kendal and Windermere, Perth and Crief, Skipton and Settle, Thurso, Sutherland and Wick, as well as Llanelli and Carmarthen.

Total and Sectoral Employment

To derive total and sectoral employment data by LLMs, we rely on the UK population census that records employment data on the travel-to-work-area or enumeration-district level, at least since 1961. Corresponding data is provided by the Office for National Statistics via Nomis[45] or by the UK Data service via Casweb[46] and Infuse[47].

Specifically, we use the number of employees in 1971 to approximate employment at the start of the 1970s, the number of employees in 1981 to approximate employment at the start of the 1980s, the number of employees in 1991 to approximate employment at the start of the 1990s, the number of employees in 2001 to approximate employment at the start of the 2000s and

[45] See https://www.nomisweb.co.uk/.
[46] See http://casweb.ukdataservice.ac.uk/.
[47] See http://infuse.ukdataservice.ac.uk/.

the number of employees in 2011 to approximate employment at the start of the 2010s. Because censuses before 2001 provide employment data mostly in the form of 10% samples, we multiply relevant statistics by a factor of 10.

To obtain travel-to-work-area statistics, we map the centroids of enumeration districts to 1984 travel-to-work areas using GIS boundary data provided by the UK data service.[48]

Apart from total employment, we also extract employment in three sectors, namely, agriculture, industry (extraction, manufacturing, construction, energy) and services.

Female Employment

Total female employment is drawn from the same census data described in Section 1.B.5. We aggregate this data to LLMs relying on an equivalent aggregation procedure.

Degree of Rurality

To identify rural areas, we primarily draw on population data at the ward level[49] from the 1971 Census as well as on surface data from 1971 boundary data.[50] We then assign wards to LLMs using the same procedure as in Section 1.B.5.

Subsequently, we calculate ward-specific population densities and apply an OECD typology (OECD, 1994) that classifies wards as rural if the population density falls below 150 inhabitants per square kilometer. Relying on the same OECD typology, we then divide LLMs into three types depending on their degree of rurality: First, we classify an LLM as rural if the share of its population living in rural wards exceeds 50%. Second, we classify an LLM is as intermediate if the share of its population living in rural wards ranges between 15% and 50% or if it contains a city

[48] See https://census.ukdataservice.ac.uk/get-data/boundary-data.aspx.

[49] We use population figures at the ward instead of the enumeration-district level when defining the degree of rurality since this is common practice in similar calculations by the OECD (see https://www.oecd.org/cfe/regional-policy/OECD_regional_typology_Nov2012.pdf) or EU (see https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/population-distribution-demography/geostat#geostat11).

[50] See https://census.ukdataservice.ac.uk/get-data/boundary-data.aspx.

with between 200 000 and 500 000 inhabitants that represents at least 25% of the LLM population. Finally, we classify and LLM as urban if the share of its population living in rural wards remains below 15% or if it contains a city with more than 500 000 inhabitants that represents at least 25% of the LLM population.

Population-Weighted Population Density

Ward-level population densities are derived from the same data sources as in Section 1.B.5. We then go on to compute the LLM-specific population-weighted average of these densities.

Remoteness

Based on a second OECD typology (Dijkstra and Poelman, 2008; Brezzi et al., 2011), we classify an LLM as remote if 50% of its inhabitants or more live in remote wards. Remote wards are wards which exhibit driving distances to the nearest urban center (a municipality with 50 000 inhabitants or more) of more than 60 minutes.

To identify urban centers, we draw on 1971 population data at the district level ("UK municipalities") excluding all rural districts (these district do not contain cities, but are composed of multiple smaller entities) as well as some other districts that do not contain a city with 50,000 inhabitants or more.

To calculate the driving distance from each of the wards to every urban center, we draw on Open Street Map data and Stata's OSRM package.

Population-Weighted Driving Distance to Urban Centers

Ward-level driving distances to urban centers (i.e. municipalities with 50 000 inhabitants or more) are derived from the same data sources as in Section 1.B.5. We then go on to compute the LLM-specific population-weighted average of these driving distances.

Education Groups

Education data comes from the same census data described in Section 1.B.5.

We classify employees as high qualified if they have a degree. This includes individuals with degree or above in 1971, individuals with degrees or professional vocational qualification in 1981, individuals with diploma, degree or higher degree (level a,b,c) in 1991, individuals aged 16-74 with a level-4 qualification in 2001 as well as individuals aged 16 or more with a level-4 qualification in 2011.

To derive an indicator for the workforce share of high qualified inhabitants, we divide the number of high qualified inhabitants by the population in an LLM aged 25 and over for all years except for 2001.[51] In 2001 we use the number of inhabitants aged 25–74 because the education data are recorded for inhabitants aged 16-74 only.

For 2001 and 2010 we also derive the workforce share of medium qualified individuals, dividing inhabitants with level-3 qualification by the number of inhabitants aged 25–74 (2001) or 25 and over (2010) and calculate the workforce share of low qualified individuals as a residual.

Subsequently, we aggregate data at the LLM level, relying on an equivalent procedure as in Section 1.B.5.

Population

Population data comes from the same census data described in Section 1.B.5. We then aggregate data at the LLM level, relying on an equivalent procedure as in Section 1.B.5.

Age Groups

Age-group data (0–24, 25–44, 45–64, 65+) comes from the same census data described in Section 1.B.5. We then aggregate data at the LLM level, relying on an equivalent procedure as in

[51] See Section 1.B.5 for information on age-group data sources.

Section 1.B.5.

Foreign Residents

To approximate the number of foreign residents, we use data on individuals by country of birth, based on the same census data described in Section 1.B.5. We then aggregate data at the LLM level, relying on an equivalent procedure as in Section 1.B.5.

Unemployment

Unemployment data comes from the same census data described in Section 1.B.5. We then aggregate data at the LLM level, relying on an equivalent procedure as in Section 1.B.5.

Industry Employment

We extract data from the Business Register and Employment Survey (BRES) that is available via Nomis.[52]

For 1992 and 2001, the used UK standard industry classification (SIC) 1992 is identical to NACE Rev. 1 up to at least the 2nd digit. For 1971, BRES records data on the 2-digit SIC 1968, for 1981 on the 2-digit SIC 1980 and for 2011 on the 4-digit SIC 2007 level. We use proportional crosswalks by Jennifer Smith[53] to map these classifications to SIC 1992/NACE Rev. 1. For years before 2011, data is available at the travel-to-work-area 1984 level. Since the 2011 data is only available at the enumeration-district level, we map again centroids of enumeration districts to travel-to-work areas.

[52] See https://www.nomisweb.co.uk/.

[53] See https://warwick.ac.uk/fac/soc/economics/staff/jcsmith/sicmapping/resources/proportional.

NUTS-Region IDs

We assign each LLM to a NUTS-1 and a NUTS-2 region, depending on the location of the LLM centroid.

Chapter 2

China's Rust Belt: Spatial Heterogeneity and Local Multipliers

Abstract

In this paper, I investigate the employment consequences of deindustrialization for cities in seven Chinese provinces, and explore the role of local multipliers. During the last decade, China's manufacturing employment has passed its peak after continuous expansion since the 1980s, and some former manufacturing centers have started to decline. The Northeast region experienced a particularly large drop in manufacturing employment; more broadly, seven provinces can be seen as China's Rust Belt. Cities within this Rust Belt faced a decreasing regional trend of manufacturing employment, and reacted very differently to the negative aggregate shock. Using the Population Census, I document a high level of spatial heterogeneity across the local labor markets in those Rust Belt regions between 2010 and 2020. I then study the role of local multiplier effects exploiting a shift-share approach. My estimates indicate that for every job created (lost) in the tradable sector in a given city, between 1.6 and 1.9 additional jobs are created (lost) in the non-tradable sector in the same city.

2.1 Introduction

China's manufacturing employment has expanded dramatically since its economic reform in 1980s. Secondary industry employment (including manufacturing, mining and utility) in China increased from 77 million in 1980 to 232 million in 2012. The rapid expansion and productivity increase of the manufacturing sector became a major driving force behind its economic miracle (Song et al., 2011; Zhu, 2012). However, this growing trend has changed during the last decade with manufacturing employment already starting to stagnate and decline. Data on urban manufacturing shows a drop from 52 million in 2013 to 38 million in 2020. A similar trend can be found in secondary industry employment. According to the National Bureau of Statistics, China's secondary industry employment peaked in 2012 at 232 million, then gradually decreased to 215 million in 2020.

In this paper, I investigate the employment consequences of deindustrialization for cities in seven Chinese provinces, documenting a high level of spatial heterogeneity in terms of their local labor market performance. And I explore the role of local multipliers using a shift-share research design to answer the question: when one job is created (lost) in the tradable sector, how many additional jobs are created (lost) in the non-tradable sector?

Economic and employment trends are highly heterogeneous across regions of China. Some former manufacturing centers have experienced a sharp decline in secondary industry employment since the 1990s. The Northeast region experienced a particularly large drop, with its secondary industry employment peaking at 17 million in 1993 and then declining to only 9 million in 2020, together with a drop in total employment and population. Its share of secondary employment also decreased from 36.2% in 1993 to 18.5% in 2020. The Northeast region is sometimes also called China's Rust Belt, showing its difficult economic prospects (compared with the fast-growing south coastal provinces), shrinking population and employment level. [1]

[1]See Weston (2004); Man et al. (2021); Attrill (2021); Li and Liang (2022) for examples referring to the Northeast

However, the Northeast region is not the only region that experienced shrinking manufacturing employment. To provide a thorough overview, I further define the provinces with a decline in both manufacturing and total employment between 2010 and 2020 as the broader Rust Belt in China, which also includes all three provinces in the Northeast region. This broader Rust Belt consists of seven provinces in China. Between 2010 and 2020, the mean growth rate of manufacturing employment is -0.17 for cities in this broader Rust Belt; and -0.22 for the mean growth rate of total employment. To summarize, all these Rust Belt provinces experienced significant manufacturing decline, with the Northeast region experiencing the most significant one.

Many place-based policies aiming at restoring local economies and overcoming imbalanced development have been proposed and implemented by the central or local government, with a large amount of investment as well as preferential policy. One of the largest programs is the "Northeast Revitalization Plan" which started in 2003 and targeted the Northeast region. In 2016, a new round of investment was announced with 1.6 trillion RMB (around 0.24 trillion USD) aiming to rejuvenate the local economy. After the sharp decline in the 1990s, many cities started to recover around 2000. However, during the last decade, particularly between 2015 and 2020, they experienced another dramatic drop and reached around the lowest level of manufacturing employment. This paper will focus on the time period between 2010 and 2020.

Using the Population Census data, the first part of this paper provides an overview of the local labor market performance for cities in the Northeast region and broader Rust Belt between 2010 and 2020. Here I follow the same conceptual framework and empirical approach used by Gagliardi et al. (2023) in their study of Rust Belt cities in France, Germany, Italy, Japan, UK and US. Chinese cities within this Rust Belt faced a decreasing regional trend of manufacturing employment, and reacted very differently at the local level to the negative aggregate shock.

Since the manufacturing industry is generally spatially concentrated, the demise of man-

region as China's Rust Belt.

ufacturing employment should have profound effects on cities that used to have a large share of employment in manufacturing. Gagliardi et al. (2023) find that cities where manufacturing initially accounted for a larger share of employment experienced lower subsequent total employment growth. However, in this paper, I show no evidence of a negative relation on average between a city's manufacturing employment share in 2010 before the decline and its following changes in manufacturing or total employment. More notably, the data indicate very heterogeneous responses to the overall negative manufacturing shock at local level. A high level of spatial heterogeneity is found in the effect of shrinking manufacturing employment across cities in those Rust Belt regions in China: 24% (8%) of cities in those Rust Belt regions still got positive growth in manufacturing (total) employment despite the declining trend. And the differences between the 90th/10th percentile and 75th/25th percentile of manufacturing employment growth distribution are 0.61 and 0.31, respectively. For total employment, the numbers are 0.31 and 0.19. To summarize, the differences in their local labor market performance are large both in terms of manufacturing and total employment growth. This paper also finds a clear positive relationship between a city's total employment growth and growth in the service sector. This suggests that the service sector might play an important role for cities to reinvent themselves and recover from the loss in manufacturing employment in those Rust Belt regions.

The second part of this paper explores the effect of local multipliers, a crucial channel for job creation in the service sector. When a job is created in the tradable (manufacturing) sector, the increased demand and wage level in this city will also lead to additional jobs being created in the non-tradable (service) sector. Combining data from the Annual Survey of Industrial Firms (ASIF), I estimate this local multiplier effect using a shift-share instrument following Moretti (2010) and Hornbeck and Moretti (2022)'s approach. My results show that for each job created in the tradable sector in a given city in the broader Rust Belt, 1.93 additional jobs are created in the non-tradable sector in the same city. This magnitude is higher than the Northeast region's and average national level, where increasing employment in the tradable sector by 1 unit will result in an increase of 1.59 and 1.25 additional units of non-tradable employment, respectively. Considering the overall declining trend in manufacturing, this estimate also implies that one tradable job loss will lead to 1.59/1.93 further non-tradable job losses in the Northeast/broader Rust Belt region, a channel that will worsen the local labor markets and might also help to explain why cities in those Rust Belt regions where the manufacturing employment dropped generally experienced a larger decline in their total employment during the same period.

This paper contributes to two important strands of literature. The first strand is research on the relationship between manufacturing and local economies. The closest related one is Gagliardi et al. (2023), who study the heterogeneous effect of deindustrialization in six industrialized countries, and find that a significant number of former manufacturing hubs were able to fully recover from the loss of manufacturing jobs. They also find one important factor that raised the probability of recovery was the share of workers with a college degree, through the channel of job creation in human capital intensive services. Some other examples are Bound and Holzer (2000); Findeisen and Südekum (2008); Glaeser (2009); Greenstone et al. (2010); Dauth et al. (2014); Fort et al. (2018); Charles et al. (2019); Dauth et al. (2021); Hornbeck and Moretti (2022). This paper extends the analysis to Rust Bult regions in China and documents large spatial heterogeneity in local labor market performance. My study is also related to Heblich et al. (2022), who find a rise-and-fall pattern in counties hosting a factory during the construction of 156 "Million-Rouble plants" in the 1950s and show that over-specialization explains the long-run decline in those industrial clusters.

Another strand of literature this paper relates to is the estimation of the local multipliers across time and space. Moretti (2010) first explore the local multipliers in the US labor market and find that one job created in the manufacturing sector led to 1.59 additional jobs in the non-tradable sector during 1980–2000, with a larger magnitude of skilled manufacturing jobs compared with unskilled. Moretti and Thulin (2013) further explore the local multipliers in Sweden. Faggio and Overman (2014) find that public sector employment has no identifiable multiplier effect and strong crowding out effect. Some other related literature includes Van Dijk (2017, 2018); Gathmann et al. (2020); Osman and Kemeny (2022). This paper closely relates to Wang and Chanda (2018), who studies the impact of employment growth in manufacturing on job creation in the non-tradable sector for prefecture-level cities in China between 2000 and 2010. This paper examines the same local multiplier effect in China but between 2010 and 2020 when the aggregate manufacturing employment started to fall, with a particular focus on China's Rust Belt regions and using a different shift-share setting following Moretti (2010) to isolate exogenous shifts in labor demand for the manufacturing sector.

The remainder of this paper is structured as follows: Section 2.2 describes the data and background. Section 2.3 discusses the evidence of spatial heterogeneity. Section 2.4 introduces the empirical strategy of estimating local multipliers and reports the baseline results. Section 2.5 concludes.

2.2 Data and Background

2.2.1 Data

The main data sources are the 2010 and 2020 Chinese Population Censuses. China's Population Census is a national census conducted by the National Bureau of Statistics with November 1st in the corresponding year as the reference time. It covers all persons residing in the territory of the People's Republic of China and the Chinese citizens residing outside but not permanently settled down in locations beyond the territory of the People's Republic of China at the census reference time. The census includes population tables broken down by age, sex, region, nationality, educational attainment, employment, domestic migration, and household size and composition. This paper uses employment data at city level as the main variable, and data on population/education attainment as controls.

Two types of questionnaires were used for Population Census, the short form and the long form. Employment information is included in the long form, and 10 percent of households are selected by a random sampling program to complete. The 2010 and 2020 Population Census provides the employment data at cities' level for 20 1-digit industry categories: one sector for the Primary industry (agriculture), three for the Secondary industry [2], and sixteen for the Tertiary industry (services). The 2-digit employment data is only available at the province and national levels.

This paper also uses 1995, 2005, and 2015's 1% National Population Sample Survey, which provides the same employment data. In order to make them comparable with the 10% long form survey in Population Census, I further multiply the employment level in those 1% surveys by 10.

Since the city-level 2-digit employment data is not available in the Population Census, I further use data from the China's Annual Survey of Industrial Firms (ASIF) in 2010 to obtain the 2-digit employment data in manufacturing industry at city level. [3] The ASIF contains rich firm-level demographic, operational and financial information in mainly the manufacturing industry, including data on the number of employees that this paper uses.[4] The ASIF includes all firms that are either state-owned or non-state firms with current-year sales above CNY 5 million in the manufacturing sector.[5] Since the unit of observation in ASIF is at the firm's level, I then aggregate

[2] Secondary employment includes employment in manufacturing, mining, and utility industries. In this paper, secondary employment is sometimes used to reflect manufacturing employment when manufacturing employment data is not available.

[3] ASIF is sometimes also referred to as Annual Survey of Industrial Enterprises, Annual Industrial Survey Database, or China Industry Census.

[4] ASIF also includes firms in several industries outside the manufacturing sector, including mining and utility.

[5] Although the ASIF only includes manufacturing firms above a certain scale, they roughly account for 89.9 percent of manufacturing employment in the Northeast region and 63.4 percent for the whole country. This result is obtained

manufacturing employment data for each industry classification at city level.

2.2.2 Background

This paper chooses the Northeast region as the most representative example of China's Rust Belt, which consists of three provinces: Liaoning, Jilin and Heilongjiang with 36 prefecture-level cities. The Northeast region was one of the most industrialized regions until around the 1980s. It was the center of heavy industries after the establishment of P.R.C. During the massive investment and technology transfer from the U.S.S.R. to China (also called the First Five-Year Plan), the Northeast region had 30 industry programs in the first wave compared with only 42 in total at the national level.[6] In 1978, the Northeast region accounted for 13.98% of the total GDP in China. However, due to a combination of factors, the region started to decline since the 1990s. The Northeast region's share of GDP relative to the whole country fell from 11.7 percent in 1990 to 5.05 percent in 2020. Its secondary industry employment peaked at 17 million in 1993, then declined to only 9 million in 2020. The total employment in the Northeast region also decreased in the last decade from 52 million in 2010 to 49.7 million in 2020, and the total population dropped from 109 million in 2010 to 98 million in 2020. The Northeast region also faces severe problems like population outflow and aging.

To provide a thorough overview about the effect of declining manufacturing employment, I further define the provinces with a decline in both manufacturing and total employment between 2010 and 2020 as the broader Rust Belt, which consists of seven provinces (including three provinces in the Northeast region): Liaoning, Jilin, Heilongjiang, Shandong, Shanxi, Tianjin, Jiangsu.[7] There're 78 prefecture-level cities in this broader Rust Belt region, accounting for 25%

by comparing employment data from the ASIF and Population Census in 2010.

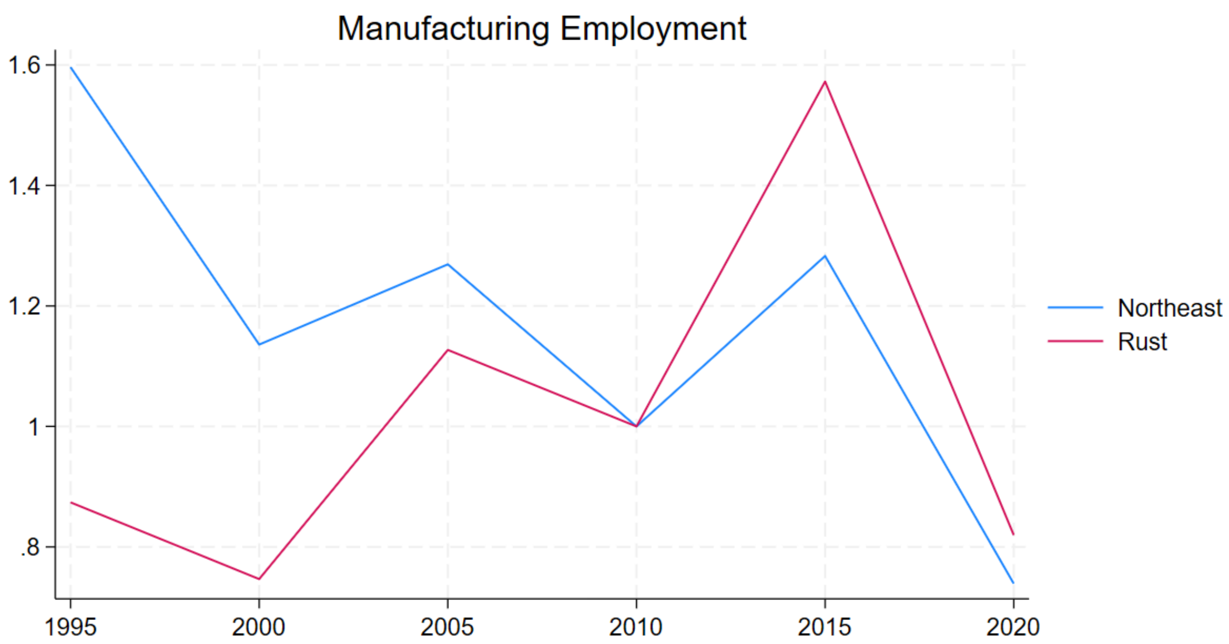
[6]See Heblich et al. (2022) for a review and its long term impact.

[7]The employment growth in Jiangsu strongly varies between the south and the middle/north. Three cities in the south together province capital experienced a mean growth rate of 5.3 percent in total employment between 2010 and 2020, while the other nine cities decreased by 18.6 percent on average.

of China's total population in 2010.[8] The decline of those Rust Belt regions has been driven by a combination of factors, including industrial transformation/reallocation, low productivity from state-owned enterprises, large entry barriers due to the size of the state sector, and the environment less conducive to entrepreneurship (Faber, 2014; Brandt et al., 2020; Banerjee et al., 2020; Heblich et al., 2022).

2.3 Spatial Heterogeneity in Employment Changes

Figure 2.3.1. *Manufacturing Employment for the Northeast and Broader Rust Belt Region*



Note: Manufacturing employment is normalized to 1 in the year of 2010. Data on 1995/2005/2015 from 1% population sample survey are multiplied by 10 to be comparable with the 10% sample survey in 2000/2010/2020.

Figure 2.3.1 shows the changes in manufacturing industry employment since 1995 in the Northeast region and broader Rust Belt in China. The figure shows a different pattern compared with the cases of developed economies like Europe and the US, where the decline in manufacturing employment tends to be monotonic after its peak time (Gagliardi et al., 2023). For both the

[8]Shannxi is not included since ASIF 2010 doesn't contain data on firms in Shannxi.

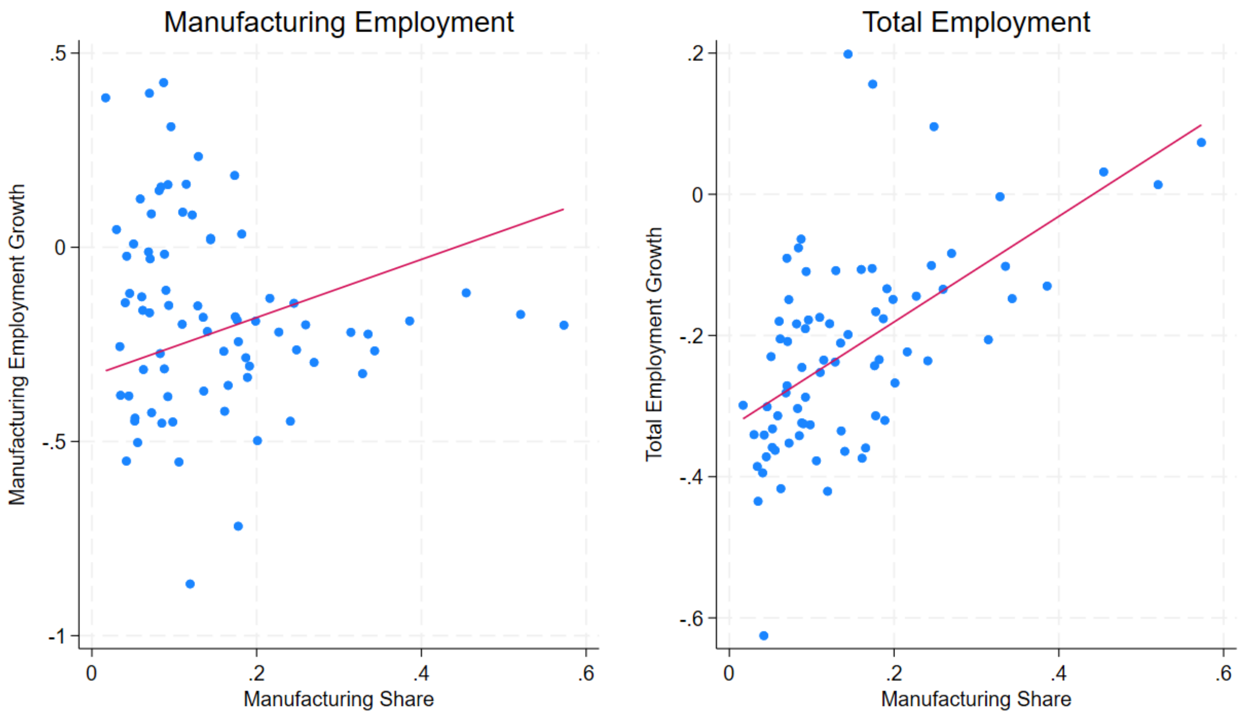
Northeast and broader Rust Belt region, their manufacturing employment recovered to some extent after the decline between 1995-2000 and 2005-2010. The broader Rust Belt region even recovered to a higher level than before in 2015. However, the largest drop happened after 2015 which led their employment in manufacturing being close to or below their lowest level. The Northeast and broader Rust Belt region generally share a very similar pattern. But for the Northeast region, the highest point was 0.87 million in 1995, and despite the recovery that happened, they were never able to get back again. In 2020, manufacturing employment in the Northeast region was only 0.4 million, less than half compared with 1995's level. The peak point for the broader Rust Belt region was in 2015, with 5.18 million for manufacturing employment. It then became 2.7 million in 2020, which is close to its lowest level in 2000.[9] In the rest of this paper, I focus on the time between 2010 and 2020 when both the Northeast and broader Rust Belt in China faced a sharp decline in manufacturing employment.

While manufacturing employment has declined dramatically in those regions, the specific shocks to cities differed because of the different local industry mix. Manufacturing jobs were not evenly distributed across the local labor markets. Therefore, cities with a larger share of manufacturing employment are expected to experience a larger negative shock in labor demand during the decline than cities with only a small share. Thus, it's reasonable to believe that there should be a negative relation between the share of manufacturing employment in a given city before decline and its change in manufacturing or total employment afterward, a pattern Gagliardi et al. (2023) found for developed economies during their deindustrialization time period.

However, this negative relation is not found in China's Rust Belt regions. Figure 2.3.2 presents two scatter plots for cities in the broader Rust Belt in China. The left one shows the city-

[9] In appendix, Figure 2.A.1 uses data from China Statistical Yearbook to show the yearly changes in the secondary industry and urban manufacturing employment, which also confirms the patterns in Figure 2.3.1. Figure 2.A.2 shows how manufacturing employment changed for each province in the broader Rust Belt region.

Figure 2.3.2. *Manufacturing Employment Share in 2010 and Growth Rate of Manufacturing and Total Employment between 2010 and 2020 for Cities in the Broader Rust Belt*

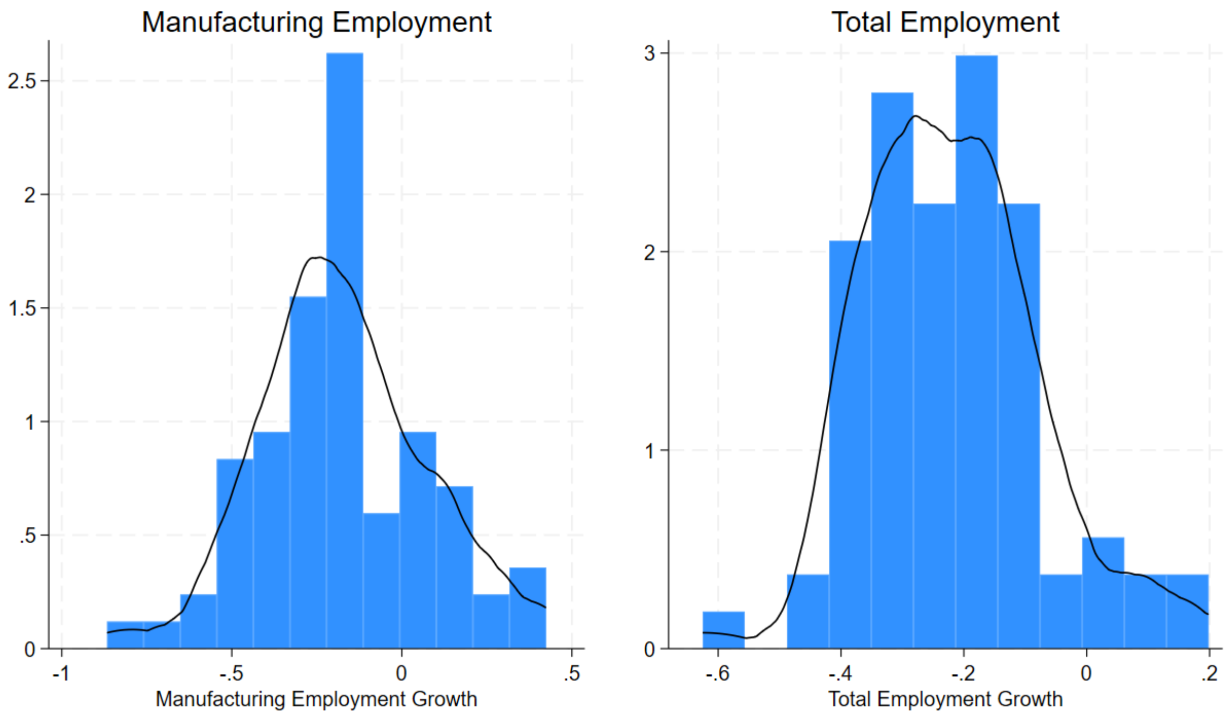


Note: Data includes 78 prefecture-level cities in broader Rust Belt in China.

level growth rate of manufacturing employment between 2010-2020 and its manufacturing share in 2010, while the right one shows the growth of total employment and its manufacturing share. Despite the fact that the whole region experienced a sharp decline in manufacturing employment, there is no evidence of negative relation between a city's manufacturing share before the decline and its following change in manufacturing/total employment. The figure even shows a slightly positive relation, indicating a very heterogeneous response to shocks in the manufacturing industry. This finding shows a different pattern compared with the cases of developed economies Glaeser (2009); Autor et al. (2013b); Hornbeck and Moretti (2022); Gagliardi et al. (2023).[10] The spreading points around the average trend in Figure 2.3.2 also indicate a high level of heterogeneity exists in the effect of shrinking manufacturing employment across cities in those Rust Belt regions.

[10]However, it should be interpreted cautiously since this paper only examines time period between 2010 and 2020, which may not necessarily reflect its average long-term trend in the future.

Figure 2.3.3. *Distribution of Manufacturing and Total Employment Growth Rate between 2010 and 2020 for Cities in the Broader Rust Belt*



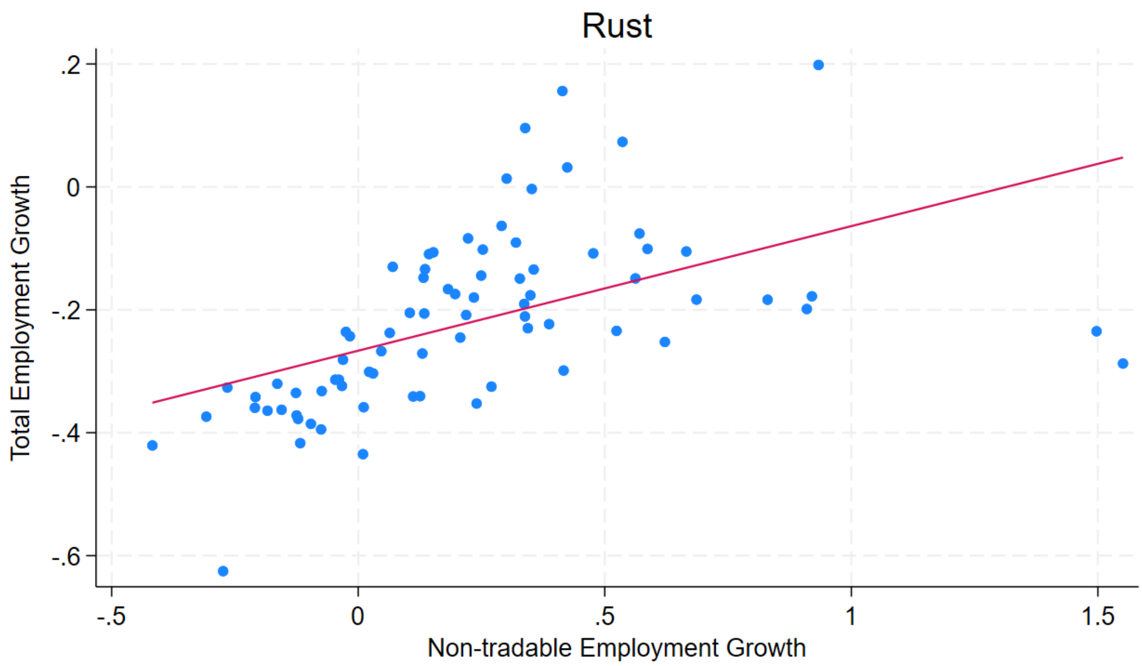
Note: Data includes 78 prefecture-level cities in broader Rust Belt in China.

I further show this heterogeneity in Figure 2.3.3. Figure 2.3.3 presents the distribution of total and manufacturing employment growth rates between 2010 and 2020 for cities in China's broader Rust Belt. It clearly shows that the local labor market reacted very differently to the overall declining trend in manufacturing. Although most cities experienced a drop in manufacturing and total employment, 24% (8%) cities still got positive growth in manufacturing (total) employment. The differences in their local labor market performance are also pretty large. When looking into the distribution of manufacturing employment growth, the differences between the 90th/10th percentile and 75th/25th percentile are 0.61 and 0.31, respectively. For total employment, the numbers are 0.31 and 0.19.[11] It's also worth noting that the mean and median levels of total employment growth are -0.22 and -0.23, which is slightly lower than the growth rate of manufacturing em-

[11]Table 2.A.1 in appendix shows top 3 and bottom 3 cities regarding the growth rate of total employment between 2010 and 2020 in broader Rust Belt together with their manufacturing share in 2010 and manufacturing employment growth between 2010 and 2020.

ployment with -0.17 and -0.19, showing a larger drop in total employment after the manufacturing decline.

Figure 2.3.4. *Growth Rate of Service Sector and Total Employment between 2010 and 2020 for Cities in the Broader Rust Belt*



Note: Data includes 78 prefecture-level cities in broader Rust Belt in China.

What drives this spatial heterogeneity worth further investigation in further research. Finally, this paper also finds a clear positive correlation between a city's total employment growth and growth in the service sector as suggested by Figure 2.3.4, indicating that the service sector plays an important role for cities in those China's Rust Belt regions to reinvent and recover the loss from their manufacturing employment. In the next section, I'll explore the effect of local multipliers, a crucial channel for job creation in the service sector.

2.4 Local multipliers

In this section, I explore the effect of local multipliers in local labor markets in China following Moretti (2010)'s research about the impact of employment in the tradable sector on the non-tradable sector in the US, with a particular focus on China's Rust Belt regions. Here I use cities to proxy the local labor markets. Regarding the definition of the tradable/non-tradable industries, in principle, the conceptual classification is founded on the spatial scope of their markets. In practice, I include manufacturing in the tradable sector and services in the non-tradable sector, which is the same as Moretti (2010) and Moretti and Thulin (2013). The definition I employ for the latter about non-tradable is grounded on the observation that many services are produced for the local economy as they require in-person meetings.

The idea behind this local multiplier effect is that when a local economy successfully attracts new manufacturing firms or undergoes large expansions in manufacturing employment, the increased local wage level could also lead to an increase in the local demand for services like recreation, hospitality, and retail. The expansion in the manufacturing sector itself may also demand more producer-related services, like banking and legal services. As a result, the local labor demand in services (non-tradable) industries might also increase because of the increase in manufacturing (tradable) employment, leading to a multiplier effect in the local labor market. Since a main driving force behind China's economic boom during the past decades is the rapid expansion of manufacturing sector (Song et al., 2011; Zhu, 2012), therefore this multiplier effect is expected to play an important role in the services job creation in China. The local multipliers effect is also particularly important in China's Rust Belt context. Because the service sector plays an important role for cities in those declining regions to reinvent themselves and recover from manufacturing job loss, as discussed in Section 2.3. And when those regions lose their attraction to manufacturing jobs, it will further prevent the local economies from transforming into a more service-oriented structure and getting employment growth.

It's also worth noting that, in theory, this local multiplier may be offset by the increased wage level and cost of housing because of the general equilibrium effect. Furthermore, its magnitude will be affected by the local labor elasticity, which is also particularly relevant in China. Because the "Hukou" system and land policy restrict China's internal migration, thus creating a barrier to labor mobility and preventing the local labor market from being more elastic.[12] Therefore, it's not clear whether, in theory, the local multipliers will be positive or negative. A clear empirical estimation of this local multiplier will help us have a better understanding of the labor market condition and provide an important tool to analyze the potential benefits of many place-based policies in China.

2.4.1 Empirical strategy

The relationship between changes in tradable sector employment and non-tradable sector employment can be estimated using the following baseline regression:

$$\Delta E_{ct}^{NT} = \alpha + \beta \Delta E_{ct}^{T} + \gamma X_{ct} + \varepsilon_{ct} \tag{D.1}$$

Where ΔE_{ct}^{NT} is the growth rate of the non-tradable sector employment for city c between two census years starting with time t, and ΔE_{ct}^{T} is the growth rate of the tradable sector employment.X_{ct} is a set of city-specific characteristics that could affect the non-tradable sector employment growth, measured in time t. In this regression, β measures the effect of tradable employment on non-tradable employment, which reflects the corresponding elasticity since both

[12]See Brandt and Zhu (2010); Ngai et al. (2019); Adamopoulos et al. (2022) for examples of discussion

ΔE_{ct}^{NT} and ΔE_{ct}^{T} are growth rates. It could be further converted into the local multiplier by multiplying β by the relative size of the non-tradable to the tradable employment, which means how many new jobs are created in the non-tradable sector for each additional job in the tradable sector.

$$\beta \times \frac{\sum_c E_{ct}^{NT}}{\sum_c E_{ct}^{T}} \tag{D.2}$$

However, this OLS estimator might be inconsistent if there are unobservable time-varying shocks that affect both tradable and non-tradable employment in the local labor market. To address this endogeneity problem, I use a similar research design as Moretti (2010), Moretti and Thulin (2013) and Hornbeck and Moretti (2022) by implementing a shift-share instrumental variable, first introduced by Bartik (1991). More specifically, I use the weighted average of provincial employment growth by 30 narrowly defined 2-digit industries within the manufacturing sector, with weights reflecting the city-specific employment share in those industries relative to the whole manufacturing employment at the beginning of the period in 2010.[13] Cities with different industry structures will suffer differently from specific industry employment shocks, therefore this instrumental variable will be able to isolate exogenous shifts in the labor demand in the tradable sector since those provincial changes do not reflect local labor market conditions at the city level.[14] Equation (D.3) describes the shift-share IV this paper uses:

$$\sum_j \omega_{jc} \Delta N_{jt}^{T} \tag{D.3}$$

[13] Since the national average trend does not well predict the local trend at city level, therefore I don't use the national employment growth in this paper.

[14] Due to data availability, I couldn't implement the leave-one-out adjustment to this shift-share IV. However, recent literature like Adao et al. (2019); Goldsmith-Pinkham et al. (2020); Borusyak et al. (2022) shows that this adjustment is unimportant.

Where ω_{jc} is the share of employment in 2-digit industry j relative to the whole manufacturing industry in city c in 2010, and ΔN_{jt}^{T} is the provincial change in employment level between 2010 and 2020 in industry j.

In this paper, I classify the manufacturing sector as tradable and the service sectors (excluding government-related sectors as well as intermediate sectors including finance and software) as non-tradable. The results remain quantitatively similar if I define them according to different criteria, including adding mining to tradable or dropping relevant service sectors from non-tradable that might be influenced by central government policies like education/scientific research.

2.4.2 Baseline results

Figure 2.4.1. *Tradable and Non-tradable Sector Employment Growth for Cities in the Broader Rust Belt between 2010 and 2020*

Figure 2.4.1 presents the relation between tradable and non-tradable employment growth. It plots the growth rate of the tradable sector for cities in the broader Rust Belt with declining manu-

facturing and total employment between 2010 and 2020 on the x-axis, and the non-tradable sector employment growth rate on the y-axis. The figure visually shows a clear positive relationship. Cities with higher tradable employment growth also generally have higher growth in non-tradable employment, confirming the local multipliers effect. Similar patterns could also be found if focusing only on the Northeast or all cities in China. This positive correlation could be further tested by regressions as discussed in Section 2.4.1.

Table 2.4.1 reports the OLS and IV estimations of Equation (D.1) corresponding to Figure 2.4.1 for cities in the broader Rust Belt. The second row shows estimates of β in Equation (D.1). And the first row presents the result of the local multiplier as Equation (D.2) by multiplying the second row by the relative size of the total non-tradable employment to tradable employment. Column 1 and Column 4 show the OLS and IV estimates are 1.57 and 2.09, respectively. In Columns 2 and 5, I add a control for the total urban population in a given city. The coefficients on population are also highly significant and show that the magnitude of this local multipliers effect is higher for cities with larger populations. In Columns 3 and 6, I further control the share of the population with a bachelor's degree as a measure of the local human capital level. The coefficients on college share, although not significant, are negative which indicates that cities with lower bachelor's degree share tend to have a higher local multipliers effect.[15] Since the OLS estimation suffers from endogeneity as discussed in Section 2.4.1, I then focus on the results in Column 6 with the Bartik shift-share IV and controls including population and college share. The entry in the second row of Column 6 indicates that a ten percent increase in the number of tradable (manufacturing) jobs in a city is associated with a 11.6 percent increase in employment in the local non-tradable sector. And the corresponding multiplier in the first row is 1.93, which means for each job created in the tradable sector in a given city, 1.93 additional jobs are created in the non-tradable sector in

[15] This negative result on college share is consistent with Van Dijk (2018) about the US, but contrasts with Wang and Chanda (2018) which also studies the local employment multipliers in China between 2000 and 2010 and obtains a positive relation.

the same city.[16] Considering the overall declining trend in manufacturing, this estimate could also mean that one job loss in the tradable sector leads to 1.93 further job losses in the non-tradable sector, a channel that will clearly worsen the local labor markets where manufacturing employment dropped dramatically. It also helps to explain why cities in those Rust Belt regions generally experienced an even larger decline in their total employment during the same period.

Table 2.4.1. *Estimate of the Local Multipliers of Tradable Sector Employment in Non-tradable Sector Employment for Cities in the Broader Rust Belt between 2010 and 2020*

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Multiplier	1.57^{***}	1.58^{***}	1.56^{***}	2.09^{***}	1.87^{***}	1.93^{***}
	(0.26)	(0.24)	(0.23)	(0.42)	(0.36)	(0.38)
Tradable	0.94^{***}	0.95^{***}	0.94^{***}	1.26^{***}	1.12^{***}	1.16^{***}
	(0.16)	(0.14)	(0.14)	(0.25)	(0.22)	(0.23)
Population		0.07^{***}	0.09^{***}		0.07^{***}	0.09^{***}
		(0.02)	(0.03)		(0.02)	(0.02)
College Share			-2.03			-1.88
			(1.44)			(1.36)
Constant	0.39^{***}	0.23^{***}	0.26^{***}	0.45^{***}	0.26^{***}	0.29^{***}
	(0.05)	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)
First-stage F-stat				31.05	33.97	48.43
N	78	78	78	78	78	78

Dependent variable: change of employment in the non-tradable sector between 2010 and 2020. Robust standard errors are reported in parentheses. *Multiplier* is obtained by multiplying the coefficient on *Tradable* and the relative size of the total non-tradable employment to tradable employment. *Population*: Total urban population in millions. *CollegeShare*: Share of the population aged above 6 with a bachelor's degree. Data include 78 cities in the broader Rust Belt of China. First-stage F-stat: Angrist-Pischke multivariate test of excluded instruments F-statistic. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In Table 2.4.2, I further explore how this multiplier effect varies across different regions

[16] The result is similar in magnitude with Moretti (2010) and Moretti and Thulin (2013), slightly higher than 1.59 for the US.

Table 2.4.2. *Estimate of the Local Multipliers of Tradable Sector Employment in Non-tradable Sector Employment between 2010 and 2020 - by regions*

	OLS			IV		
	NE	Rust	All	NE	Rust	All
Multiplier	1.87***	1.56***	0.92***	1.59***	1.93***	1.25***
	(0.25)	(0.23)	(0.10)	(0.41)	(0.38)	(0.30)
Tradable	0.60 ***	0.94***	0.56 ***	0.51***	1.16***	0.76***
	(0.08)	(0.14)	(0.06)	(0.13)	(0.23)	(0.18)
Population	0.12***	0.09***	0.04***	0.12***	0.09***	0.05***
	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)	(0.01)
College Share	-3.45*	-2.03	-3.42***	-3.04*	-1.88	-2.89***
	(1.70)	(1.44)	(0.83)	(1.69)	(1.36)	(0.88)
Constant	0.10**	0.26***	0.64***	0.07	0.29***	0.55***
	(0.05)	(0.07)	(0.04)	(0.05)	(0.07)	(0.07)
First-stage F-stat				20.84	48.43	65.27
N	36	78	325	36	78	325

Dependent variable: change of employment in the non-tradable sector between 2010 and 2020. Robust standard errors are reported in parentheses. *Multiplier* is obtained by multiplying the coefficient on *Tradable* and the relative size of the total non-tradable employment to tradable employment. *Population*: Total urban population in millions. *CollegeShare*: Share of the population aged above 6 with a bachelor's degree. First-stage F-stat: Angrist-Pischke multivariate test of excluded instruments F-statistic. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

in China. Table 2.4.2 shows the result of Equation (D.1) for 1) Northeast region (NE), 2) broader Rust Belt (Rust), 3) the whole country (All). Population and college share are included as controls. Results from IV show that the local multiplier effect in the Northeast region is lower compared with the average level in the broader Rust Belt region. Increasing employment in the tradable sector by 1 unit in the Northeast region only results in an increase of 1.59 additional units of non-tradable employment. However, the broader Rust Belt region's average magnitude is 1.93. This pattern remains if looking at the coefficient on tradable. A ten percent increase in tradable jobs is associated with a 5.1 percent increase in non-tradable jobs in the Northeast regions, compared with 11.6 percent for the broader Rust Belt. When comparing the results between the Northeast region and the broader Rust Belt, it's also worth noting that since the average manufacturing employment declined, a lower local multiplier magnitude in the Northeast region could also mean that cities in the Northeast region are more resilient to the negative manufacturing shock. This implies when a manufacturing (tradable) job is lost, Northeast cities will experience a lower level of further job loss in the non-tradable sector compared with the average level in the broader Rust Belt region. Regarding the controls, results are consistent with findings from Table 2.4.1, that is cities with higher population and lower college share generally have a larger local multiplier effect. The strong relation between a city's population and the local multiplier effect throughout different regions could also mean that for large cities, their potential in this multiplier effect has not been reached due to the labor mobility barriers in China, which limits the internal migration to those mega cities especially.

2.5 Conclusions

Some former manufacturing centers in China experienced a sharp decline in manufacturing employment during the recent decade. This paper investigates the employment consequences of deindustrialization for cities in seven Chinese provinces, and explores the role of local multipliers. I use the Northeast region as the most representative example of China's Rust Belt, and further define seven provinces with a decline in both manufacturing and total employment as the broader Rust Belt in China. Although manufacturing employment declined dramatically in those regions and accounted for a significant share, the specific shocks to local economies at city level differed due to different local industry mixes. I document a large spatial heterogeneity across the local labor markets in those Rust Belt regions. This paper shows no evidence of a negative relation between a city's manufacturing employment share in 2010 before the decline and its subsequent change in manufacturing or total employment, a pattern indicating very heterogeneous responses to the overall negative manufacturing shock at local level and contrasts with findings from Gagliardi et al. (2023) about six industrialized countries. 24% (8%) cities in those Rust Belt regions still got positive growth in manufacturing (total) employment despite the overall declining trend. The differences between the 90th/10th percentile and 75th/25th percentile of manufacturing employment growth are 0.61 and 0.31, respectively. And the numbers are 0.31 and 0.19 for total employment. This paper also finds a clear positive relationship between a city's total employment growth and growth in the service sector, highlighting the importance of the service sector for cities to reinvent and recover from the loss in manufacturing employment.

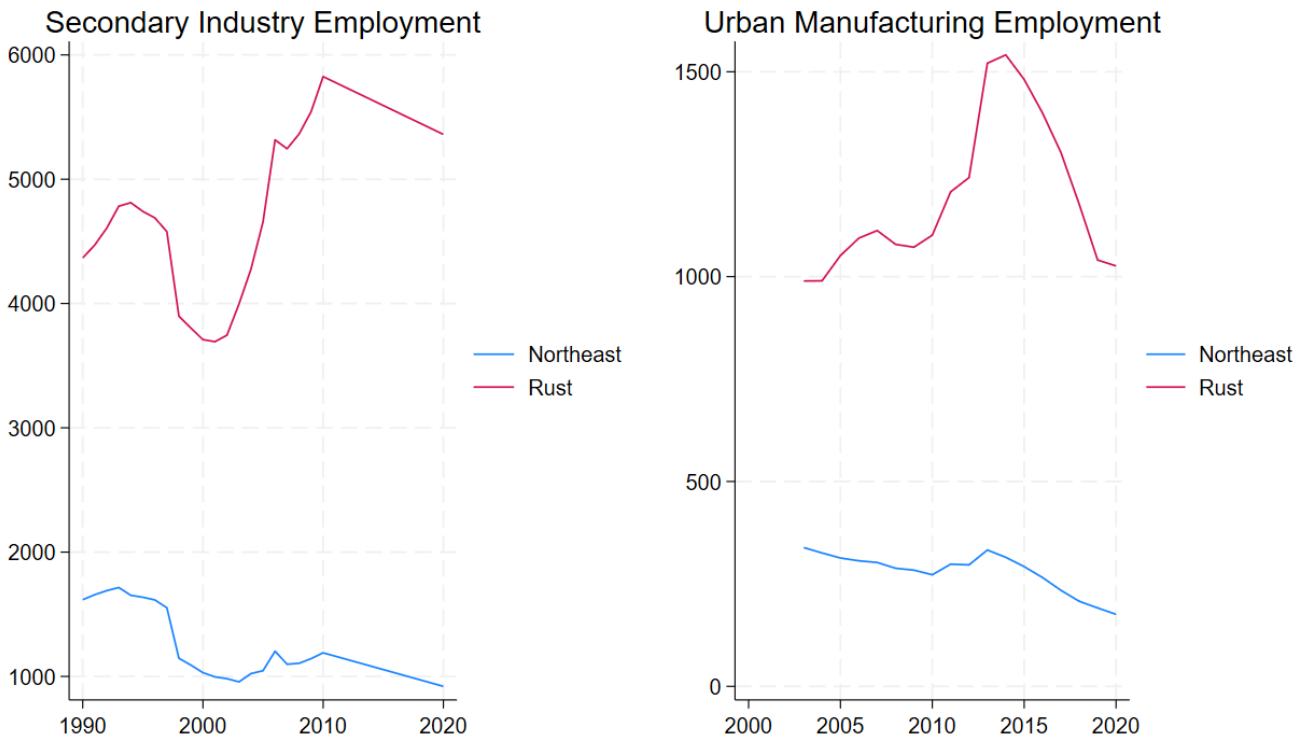
This paper then further explores the effect of local multipliers, a crucial channel for job creation in the service sector. Combining the Population Census and Annual Survey of Industrial Firms (ASIF), I estimate this local multiplier effect using a shift-share IV design following Moretti (2010) and Hornbeck and Moretti (2022) to isolate exogenous shifts in labor demand for the manufacturing sector. For every job created (lost) in the tradable sector in a given city in the Northeast and broader Rust Belt region, the results indicate 1.59 and 1.93 additional jobs are created (lost) in the non-tradable sector in the same city, respectively. Considering the declining manufacturing trend, this channel means the local labor market will face a further loss in non-tradable employment and it might also explain why cities in those Rust Belt regions where manufacturing employment dropped generally experienced a larger decline in their total employment. The local multiplier effect is also robust to adding controls like population and college share.

In further research, I plan to explore several directions: 1) repeat the main analysis at the county level for robustness and check if conclusions are similar; 2) distinguish between high-tech and low-tech manufacturing industries and compare the magnitude of their local multiplier effect; 3) explore spatial heterogeneity in environmental outcomes and its implication for health and overall welfare.

Appendix

Appendix 2.A Appendix

Figure 2.A.1. *The Secondary Industry and Urban Manufacturing Employment for the Northeast and Broader Rust Belt Region*



Note: Data on secondary industry employment between 2011 and 2019 is not available.

Source: China Statistical Yearbook.

Figure 2.A.2. *Manufacturing Employment for the Broader Rust Belt Region - By Province*

Note: Data on 1995/2005/2015 from 1% population sample survey are multiplied by 10 to be comparable with the 10% sample survey in 2000/2010/2020 for employment information.

Table 2.A.1. *Top 3 and Bottom 3 Cities in Broader Rust Belt Regarding Decadal Growth Rate of Total Employment between 2010 and 2020*

		(1)	(2)	(3)
		Tot Empl Growth between 2010-2020	Manuf. Share in 2010	Manuf. Empl Growth between 2010-2020
Top 3	Jinan	0.20	0.14	0.02
	Taiyuan	0.16	0.17	-0.18
	Nanjing	0.10	0.25	-0.26
Bottom 3	Siping	-0.63	0.04	-0.55
	Suihua	-0.43	0.03	-0.38
	Daxing'anling	-0.42	0.12	-0.87

Table 2.A.2. *Estimate of the Local Multipliers of Tradable Sector Employment in Non-tradable Sector Employment for Cities in the Northeast region between 2010 and 2020 Using Regional Trend*

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Multiplier	1.72***	1.69***	1.79***	2.78***	2.12***	2.00***
	(0.30)	(0.24)	(0.24)	(0.69)	(0.48)	(0.45)
Tradable	0.58***	0.57***	0.60***	0.94***	0.72***	0.67***
	(0.10)	(0.08)	(0.08)	(0.23)	(0.16)	(0.15)
Population		0.07***	0.12***		0.07***	0.13***
		(0.01)	(0.02)		(0.01)	(0.03)
College Share			-3.59**			-3.91**
			(1.71)			(1.63)
Constant	0.17***	0.04	0.09*	0.27***	0.08*	0.12**
	(0.04)	(0.04)	(0.05)	(0.06)	(0.04)	(0.05)
First-stage F-stat				15.25	13.82	14.84
N	36	36	36	36	36	36

The figure shows estimates of the local multipliers in the Northeast region using regional trend consisting of all three provinces. Dependent variable: change of employment in the non-tradable sector between 2010 and 2020. Robust standard errors are reported in parentheses. *Multiplier* is obtained by multiplying the coefficient on *Tradable* and the relative size of the total non-tradable employment to tradable employment. *Population*: Total urban population in millions. *CollegeShare*: Share of the population aged above 6 with a bachelor's degree. Data include 78 cities in the broader Rust Belt of China. First-stage F-stat: Angrist-Pischke multivariate test of excluded instruments F-statistic. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 3

Inventors' Coworker Networks and Innovation

- Jointly with Sabrina Di Addario and Michel Serafinelli

Abstract

This paper presents direct evidence on the extent to which firms' innovation is affected by access to knowledgeable labor through co-worker network connections. We use a unique dataset that matches patent data for the period 1987-2008 to administrative employer-employee records from 'Third Italy' – a region with many successful industrial clusters. Displacements of inventors because of establishment closures generate labor supply shocks to firms that employ their previous co-workers. We estimate (a) event-study models where the treatment is the displacement of a connected inventor and (b) IV specifications where we use such a displacement as an instrument for the hire of a connected inventor. Estimates indicate that firms take advantage of displacements to recruit connected inventors and that the improved capacity to employ knowledgeable labor within the network increases innovation.

3.1 Introduction

A prominent feature of the labor market is the tendency for firms to recruit through informal networks: surveys across OECD countries indicate that 15 - 50 percent of jobs are found through social connections, and around 70 percent of firms in the United States encourage referral-based hiring.[1]

Researchers have speculated that firms may benefit from using informal networks, for instance because of reduced hiring costs and lower turnover. Nevertheless, the knowledge on the extent to which available connections have an impact on firms' innovation is rather limited. This is the first paper that presents direct evidence on the extent to that firms' innovation is affected by access to knowledgeable labor through co-worker network connections. Specifically, we estimate the effect of hiring connected inventors on firms' innovative activity, proxied by patent applications.

In confronting the non-trivial measurement challenges involved, we take advantage of a unique dataset that matches patent data for the period 1987-2008 to administrative employer-employee records from the so called 'Third Italy', a macro-area in the North-East of the country characterised by a high concentration of successful industrial clusters.

Our empirical strategy exploits establishment closures in which displaced inventors are connected to other firms because of former co-workers. We take essentially the same conceptual framework of the functioning of the labour market as in Eliason et al. (2017) and apply it to our context. [2] The co-worker connections generate a firm-specific shock to the supply of knowledgeable labor, by directing the displaced inventors towards the connected firms. As a result, these firms experience an improvement in the chances to recruit connected inventors. Specifically, the underlying idea is that a given firm has access to a very limited supply of connected inventors who

[1] Pellizzari (2010), Topa (2011), Saygin et al. (2019), Friebel et al. (2019).
[2] See Section 3.2 for details.

can be recruited with reduced frictions - see Dustmann et al. (2016). Establishment closures within the network decrease the value of the alternative options for the connected inventors affected by the displacement shocks, thus expanding the connected supply of knowledgeable labor. In other words, the possibility to draw from pools of inventors, displaced because of establishment closures, and connected to firm's employees may help the recruitment of such knowledgeable workers.[3]

We adopt two main estimation strategies. First, we estimate event-study models in which the displacement of a connected inventor is the event. Second, we estimate the effect of hiring a connected inventor on firms' innovative activity by instrumental variables (IV), using the displacement of a connected inventor as an instrument for the hire of a connected inventor. This approach assumes that the impact of a connected inventor displacement on the firm's capability to innovate occurs entirely through hiring. The underlying intuition is that knowledge, which is mostly embedded in inventors, spreads when these workers move across firms (Dasgupta, 2012).

A potential identification concern may arise in case shocks to the supply of knowledgeable labor also capture market-level shocks.[4] We do not expect this to be a major issue in our context, since the closing establishments in our sample are mostly small to medium-sized (the median is around 100 employees), and thus the market effects originated from their closure are likely to be rather limited. Nevertheless, to allay concerns of market effects, we also control for the number of displaced workers in the Local Labor Market (LLM) and industry. Furthermore, we perform a "placebo"-type analysis, showing no effect from the displacement of inventors with connections to other firms in the same LLM and industry (i.e. firms different from the focal firm). Specifically, we investigate the extent to which innovation at firm j reacts to the displacement of inventors who are connected to other firms in the same LLM and industry but not to the focal firm j. The estimates indicate that the estimated average change over the five years starting with the

[3] Eliason et al. (2017, p.14-19)

[4] See Gathmann et al. (2020); Cestone et al. (2016).

year of the placebo event is very small (an order of magnitude smaller than that in the main estimates) and non-significant. While we can't completely rule out the possibility of market effects, the placebo result does not appear consistent with this possibility.

Our empirical evidence can be summarised as follows. We document that the displacement of a connected inventor significantly increases hiring of connected inventors, while not affecting the hiring of non-connected inventors. Moreover, the improved capability to employ knowledgeable workers raises firms' innovative activity. Specifically, in the event-study the estimated average increase in patent applications over the five years starting with the year of a connected inventor's displacement is between 0.14 and 0.18 standard-deviations. Non-connected inventor hires are not affected by events of displacement of a connected inventor.

The IV estimates indicate that hiring a connected inventor raises innovation; an increase of approximately 0.6 patent applications, equivalent to an increase of 1.875 standard-deviations. [5] The additional output is not restricted to the patents authored or co-authored by the newly hired connected inventor; the evidence also suggests an increase in patents exclusively authored by the other workers of the destination firm. Thus, the addition of a new inventor appears to 'fertilize' the firm, spurring the birth of new ideas in their coworkers.

Overall, the estimates indicate that firms take advantage of displacements to recruit connected inventors. Moreover, the improved capacity to employ connected inventors increases firms' patenting activity. More generally, our estimates suggest that informal connections involving knowledgeable workers reduce hiring frictions and channel valuable information to firms. This process benefits firms' innovation by expanding the availability of knowledgeable labor. [6]

The remainder of this paper is organized as follows. Section 3.2 discusses the relation to previous research section 3.3 provides some background information for 'Third Italy' and presents

[5] As discussed in Section 3.5.3, when interpreting these estimates it is important to highlight that the hire of a connected inventor is a major change in terms of workforce for the average firm in our data.

[6] Eliason et al. (2017, p.46)

the data. Section 3.4 discusses our econometric strategy. The main results, in addition to various robustness checks, are presented in Section 3.5. Section 3.6 concludes.

3.2 Relation to Previous Research

Our work is mainly related to two strands of the literature. First, it is linked to research on the transmission of information through networks, and in particular on co-worker connections in the context of displacement. Several studies find a significant and positive relation between network employment rate and the probability of finding a new job (Cingano and Rosolia, 2012).[7] A related set of studies uses matched employer-employee data to explore network effects in the labor market. For instance, Dustmann et al. (2016) and Glitz and Vejlin (2019) document a larger initial wage premium and a longer job tenure for referred workers. Using the armed-force test, Hensvik and Skans (2016) report that firms hire workers with higher cognitive skills when recruiting previous colleagues of current employees. Kramarz and Skans (2014) show that family ties are an important determinant for where young workers find their first job, while Korchowiec (2019) shows that hires from a firm's own network increase its productivity.[8]. Our work is also linked to some recent papers that have studied how firm's hiring decisions are affected by increased access to labor with desirable skills (e.g. Horton (2017) and Cahuc et al. (2019)). Additional related studies are Burks et al. (2015), who find that referred workers in call centers and trucking yield substantially higher profits per worker than non-referred ones, and Friebel et al. (2019), who find that having an employee referral program reduces attrition and decreases firm labor costs.

Closest to our study is the analysis of Eliason et al. (2017) who, using Swedish register

[7] See also Colussi (2015), Glitz (2017), Saygin et al. (2019), Dalla-Zuanna (2020) and Gyetvai and Zhu (2020). More in general, on information transmission through networks see Pellizzari (2010); Zinovyeva and Bagues (2015); Schmutte (2015); Battisti et al. (2016); Caldwell and Harmon (2019); De Giorgi et al. (2020); San (2020); Gualdani (2020); Willis (2022).

[8] On the contrary, Kramarz and Thesmar (2013) find that social networks are detrimental to corporate governance. Cingano and Pinotti (2013) and Akcigit et al. (2023) study the effect of political connections on firm level outcomes (including innovation in the latter paper).

data, assess the causal effect of social connections on total hires, job separations, and value-added. We build on the empirical strategy of these authors, using essentially the same type of supply shocks and, more generally, conceptual framework of how the labour market operates. [9]

We contribute to this strand of the literature by focusing on inventors and innovation, while using a research design that also allows us to test for the presence of pre-trends in the outcomes and enables us to recover the dynamics of the effects of interest. Even though the mechanisms we document may also apply to other worker-types and outcomes, we focus on inventors and patenting because innovation is deemed to foster sizable positive social spillovers and is generally regarded as a key driver of economic growth (Bloom et al., 2013; Bell et al., 2019). Moreover, while the issues analyzed in this paper are of general interest, the specific case of 'Third Italy' is also important. This is a macro-region rich of networks of specialized producers frequently organized in industrial districts (IDs). IDs have been effective in promoting and adapting to technological change during the period of analysis (1987-2008), and this large economic area has received a good deal of attention by researchers, both in Europe and in the United States.[10]

The second strand of the literature our work is mainly related to is on R&D spillovers, the mobility of *R&D* personnel and more broadly on the implications of firm-to-firm labor mobility for firm-level outcomes. For instance, Fons-Rosen (2013) finds that foreign direct investment has a greater impact on the host economy in terms of knowledge diffusion when firms relocate inventors from the already established *R&D* labs in their home country to the newly developed ones in the host country. Maliranta et al. (2009) find that firms involved in non-R&D activities hiring workers from R&D-intensive firms tend to perform better.[11] Balsvik (2011) offers a detailed account of

[9]See also their companion paper Eliason et al. (2023) that focuses on the question whether social connections increase inequality by reinforcing the sorting of high-wage workers to high-wage firms.

[10]Brusco (1983); Piore and Sabel (1984); Trigilia (1990); Whitford (2001); Becattini et al. (2014); Trigilia (2020)

[11]Bloom et al. (2013) are able to identify the impact of technology spillovers from that of the product market rivalry effects of R&D. They analyze a 20-year panel of U.S. firms and show that knowledge spillovers quantitatively dominate product market spillovers. Kaiser et al. (2015) show that the mobility of R&D personnel enhanced the patenting output of Danish firms during the period 1999-2004. Other papers combine register data with patents data and study features of the work history of inventors. See, for instance, Depalo and Di Addario (2014) and Kline et al.

productivity gains linked to worker flows from foreign multinationals to domestic firms in Norway.[12] Parrotta and Pozzoli (2012) provide evidence from Denmark regarding the positive impact of the recruitment of knowledge carriers – technicians and highly educated workers recruited from a donor firm – on a firm's value added; and Stoyanov and Zubanov (2012) show that Danish firms that hire workers from more productive firms increase their productivity. Fons-Rosen et al. (2017) study the impact of FDI on the productivity of host-country firms and show that inventor mobility across sectors is a key channel of technology transfer.

Our findings are consistent with these empirical contributions. Unlike the above authors, who focus on the relationship between labor mobility and productivity or related firm-level outcomes, we also seek to shed light on a broader question: the extent to that firms' innovation is affected by access to knowledgeable labor through co-worker network connections, focusing on inventors. Even though inventors are not the only workers who may transfer relevant information from one firm to another, they undoubtedly have large potential to do so.

More broadly, this paper adds to the literature on knowledge diffusion and innovation. (Kantor and Whalley, 2014; Fons-Rosen et al., 2016; Moretti, 2021; Ganguli et al., 2020; Huang et al., 2020). [13] In particular, our study is related to research investigating network effects in science. For instance, Mohnen (2018) shows that network position is crucial in determining scientific production by facilitating access to other scientists' non-redundant knowledge through coauthorship links.[14] Another related body of work analyzes peer effects in the workplace induced by knowledge spillovers and finds mixed evidence. On one hand, for instance Waldinger (2010) finds that faculty quality is a very important determinant of PhD student outcomes. On the other hand,

(2019).

[12]Likewise, Poole (2013) finds a positive effect of the share of new workers previously employed by foreign-owned firms on wages paid in domestic firms in Brazil.

[13]A related body of work focuses on the consequences of innovation on productivity and employment growth (Hall et al., 2008; Marin and Lotti, 2016).

[14]More generally, a number of studies explore co-author relationships and social ties in research (Jaravel et al., 2018; Colussi, 2018; Azoulay et al., 2019; Zacchia, 2019).

Cornelissen et al. (2016) find only small peer effects in wages in high skilled occupations, and Waldinger (2012) shows that even very high-quality scientists do not affect the productivity of their local peers. Guryan et al. (2009) study team mates in golf and find no evidence of knowledge spillovers. Other papers within this body of work, focusing on social pressure, report productivity spillovers (Mas and Moretti, 2009; Bandiera et al., 2010). A final set of related studies focus on the mobility of immigrant scientists. For instance, Moser et al. (2014) focus on chemical inventions and compare the changes in US patenting by US inventors in research fields of German Jewish émigrés with changes in US patenting by US inventors in fields of other German chemists. They provide evidence that the U.S. patenting activity has increased in the research fields of German-Jewish refugees after 1933.

3.3 Background and Data

3.3.1 'Third Italy'

The data used in this paper covers the period 1987-2008 and a large economic area: 'Third Italy'. This includes the following administrative regions located in the Center-North-East of the country: Emilia-Romagna, Friuli-Venezia Giulia, Marche, Toscana, Trentino-Alto Adige/Südtirol, and Veneto. The combined population of these regions includes around 16.9 million people (28 percent of the total population in Italy).

In the 21 years analysed in this paper the labor market of this macro-area has been characterized overall by a good performance in terms of total employment, job creation in manufacturing, migration flows, and business creation (de Blasio and Di Addario, 2005), especially in Emilia-Romagna and Veneto. A distinctive feature of 'Third Italy' is the large presence, since the early 1970s, of networks of flexible producers frequently organized in IDs, with a level of industrial value added often greatly exceeding the national average, particularly in the areas around Bologna, Padua, and Verona.[15] Germany's Baden-Wuerttemberg and the British Motor Valley (centred in Oxfordshire and stretching into East Anglia and into Surrey) are other examples of similar regional network-based industrial systems; additional ones have been identified in recent decades in Japan, Scandinavia, Spain, and the United States (Saxenian, 1994; Henry and Pinch, 2000; Becattini et al., 2014).

Manufacturing firms in the dynamic districts of Third Italy specialize in metal, mechanical and electrical engineering, automotive, biomedical industries, construction materials and technologies, goldsmithing, plastics, ceramics, glass, agri-food, furniture, printing and publishing, musical instruments, toys, and fashion-wear. Several of these clusters feature some leader firms, especially in Veneto.[16]

As pointed out by Piore (2009, p.259):

> The Italian industrial district first captured the attention of scholars in the 1970's. Since that time it has become a seductive model, attracting public policymakers and industrial development consultants across a wide spectrum. It has drawn the interests of developing countries seeking the survival and prosperity of their traditional industries in an increasingly open and global economy. But it has also become a model for local areas within advanced developed economies seeking to create high tech clusters.

3.3.2 Data

Administrative Records and Patent Data

Our dataset pools two main sources of information: the employer-employee matched data from the

[15] Tattara and Valentini (2010), Trigilia (2020).

[16] An example is the eyewear district in the province of Belluno, where Luxottica, the world's largest manufacturer of eyeglasses, has production establishments. Benetton, Sisley, Geox, Diesel, and Replay are examples of brands of fashion-wear Veneto leading firms.

Italian Social Security Institute (Istituto Nazionale di Previdenza Sociale, INPS) and patent data from the European Patent Office (EPO) Worldwide Patent Statistical Database (Patstat, henceforth). Both are described in detail below. The INPS dataset has information on all private sector employees in the period 1987-2008. Specifically, it contains register-based information for any job lasting at least one day. We could reconstruct the employment history of each worker in the analyzed period. The available information at the individual level includes: age, gender, municipality of residence and municipality of birth, work status (blue collar; white collar; manager; other), type of contract (full-time versus part-time), and gross yearly earnings. The information on firms includes: average gross yearly earnings, yearly number of employees, industry, location (at the municipality level), date of firm opening and closure.

Patstat provides the universe of patent applications and grants presented at the EPO by any Italian "applicant" (i.e. the firm submitting a patent application and retaining the relative property rights). The database provides a detailed description of each patent submission, including its title, abstract and technological field, the name and address of all its inventors and applicants, the dates of application filing, publication and grant obtainment and the citations received. Inventor status is defined on the basis of the date of the first patent application. More precisely, we define a worker as being an inventor in year m if she is observed submitting a patent application in year $t \leq m$.

Patstat does not have a reliable firm identifier. Therefore a matching procedure was needed in order to merge the information to the INPS dataset (on the basis of the applicant name and location). An in-depth description of the matching procedure, with descriptive statistics, is provided in Depalo and Di Addario (2014), that used these two sources, combined for the period 1987-2006, to study inventors' returns to patents. In summary, the datasets were merged in several steps. First, VAT codes were attributed to Patstat applicants on the basis of the name and location. The code was verified using four alternative datasets (Cebi, Infocamere, INPS, Orbis). Then

INPS staff linked Patstat applicants to all possible INPS establishments that had the same VAT identifier/same name and location (at the municipality level). Finally, INPS verified in its records that the inventors appearing in each patent submission were indeed employed in the corresponding applicant (from Patstat). The resulting dataset includes the full work history of the inventors, i.e. Social Security information for all the firms at which an inventor has worked during her career, covering also establishment-year observations before an inventor's first patent application. For all these establishment-year observations we also observe the co-workers of the inventors. Notice that the dataset includes both firms that have one or more patent applications during the sample period and firms that have zero patent applications.

Co-worker Network

We construct the firm's network using co-worker links, detected from the employment history of each worker. More precisely, the employee's network comprises all former co-workers. The firm's network is a collection of co-worker networks of each incumbent employee.

The co-worker network is constructed for each establishment and year in the sample. We build a network that comprises all the former co-workers of each individual in their employment history of the previous 5 years. We include in the sample only the establishments with less than 500 employees to reduce the incidence of imprecise connections, since the chances of having a real contact among the workers is low in the very large establishments.

Establishment closures, Displaced Inventors and Summary Statistics

Our empirical strategy employs establishment closures to identify the supply shock of knowledgeable workers within a firm's own network. The INPS dataset includes the information on the date of establishment closure. Considering the five year interval necessary to form the firm's network, we are interested in closures between 1992 and 2008.

In order to identify "true" establishment closures, i.e. the ones that are not a result of a merger, a change of tax identifier, or a spin-off, we analyse worker flows from exiting establishments and denote a closure as "true" whenever the maximum cluster of outflow from the closing establishment to any other establishment is below 50 percent of the workforce at the exiting one - estimates are qualitatively similar if a 30 percent threshold is used.

Using the information on establishment closures, we are able to detect all the employees (independently on whether they are inventors) who are subject to displacement. We denote workers as displaced at time t if they terminate their job in the same year their establishment closes (at t). In our data inventors account for approximately 0.5 percent of all the workers displaced because of a establishment closure.

Our main estimation sample consists of the firms employing at least one inventor between 1992 and 2007. The outcome of interest is firms' innovative activity: we take a patent application as a signal of the presence of some innovative output. The panel includes $80,310$ firm-year observations (for $7,301$ firms), and its main characteristics are summarized in Table 3.6.1. [17] The first row shows that hiring a connected inventor is a major change in terms of workforce for the average firm in our data, since the mean of the number of connected inventor hires is 0.008. The second row shows that the mean number of patent applications is 0.035. The third row indicates the average non-connected inventor hires is 0.004, lower than the connected inventor hires. The table also reports in the fourth and fifth row that the average firm in our sample employs 106 workers, with a mean co-worker network of 849. And the last two rows show the mean connected inventors and non-inventors who are displaced in a given year are 0.008 and 3.317, respectively.

[17] The Table reports unweighted means.

3.4 Econometric Framework

Our econometric analysis exploits establishment closures for identification. The underlying idea is that firm j's ability to hire through the network is affected by the displacement (from some other establishment q) of inventors connected to j's current workers. Specifically, the co-worker connections generate a firm-specific shock to the supply of knowledgeable labor, by directing the displaced inventors towards the connected firms. As a result, these firms experience an improvement in the chances to recruit connected inventors. Our empirical strategy builds on the one of Eliason et al. (2017). In contrast to these authors, we estimate event-study models where the event is the displacement of an inventor connected to firm j's current workers. Our research design allows us to test for the presence of firm-specific pre-trends in the outcomes and to recover the dynamics of the effect of interest. Similarly to Eliason et al. (2017), we estimate IV specifications instrumenting the hire of a connected inventor with the displacement of a connected inventor.

3.4.1 Event-Study

We use an "event-study" research design - see Autor (2003) and Kline (2012) - in order to investigate how displacement events affect both a connected inventor hiring and also the patenting activity of the destination firm. Specifically, the regression equation is:

$$Y_{jslt} = \beta_0 + \sum_{\tau} \beta_\tau D^{\tau}_{jt} + \beta_n N_{jt} + \beta_d Displaced_{slt} + Trend_{st} + Trend_{lt} + \lambda_j + \alpha_t + u_{jslt}, \qquad \text{(D.1)}$$

where the dependent variable is: (a) a dummy equal to one if firm j of industry s and local labor market (LLM)[18] l hires a connected inventor at time t (from any industry or LLM) or (b) the

[18]Information on local labor markets (LLMs) is obtained from the National Institute of Statistics (ISTAT). The LLMs are territorial groupings of municipalities characterized by a certain degree of working-day commuting flows by the resident population. In 1991, the 1898 municipalities (*comuni*) in our 6 administrative regions were grouped into 236 LLMs.

number of firm j's patent applications. The D_{jt}^{τ} are a sequence of "event-time" dummies equal to one when the displacement of a connected inventor is τ years away. Thus, the β_{τ} coefficients characterize the time path of innovation relative to the date of the event. We include year dummies (α_t), and allow for permanent differences across firms (λ_j), industry-specific and LLM-specific trends ($Trend_{st}$ and $Trend_{lt}$). We also control for network size (N_{jt}), and the number of displaced workers in the LLM and industry ($Displaced_{slt}$).

The results are obtained by estimating Equation (D.1) by OLS, while adding a set of event-time dummies prior to and after the event to the other control variables. The event time indicator "-4" is set to 1 both for the fourth year preceding the event and for all the years before and 0 otherwise; the event time indicator "+5" is set to 1 for all the period successive the fifth year after the event and 0 otherwise. Since the sample of treated firms is unbalanced in event time, these endpoint coefficients give different weights to firms experiencing the treatment early or late in the sample period. Therefore, in discussing the treatment effects, we concentrate on the event-time coefficients falling within $\tau = 0$ and $\tau = 4$ that are identified from a nearly balanced panel of firms. We normalize β_{-1} to zero, so that all post-treatment coefficients can be thought of as treatment effects. We cluster standard errors at the LLM level.

A potential identification concern arises if the directed shocks to the supply of knowledgeable labor also pick up market-level supply or demand shocks. We do not expect this to be a major factor in our context. The sample comprises mostly closures of small to medium-size firms for which the market effects are likely to be limited - the median closing establishment has around 100 employees. To explore this possibility further, we control for the number of displaced workers in the LLM and industry ($Displaced_{slt}$). Estimates are nearly identical if we split this variable into displaced inventors and displaced non-inventors. In Section 3.5.4, we also perform a ”placebo”-type analysis, exploiting the displacement of inventors with connections to firms in same LLM and industry.

3.4.2 IV Estimation

We estimate 2SLS specifications where the displacement of a connected inventor (in any LLM or industry) is used to instrument the hire of a connected inventor. This analysis assumes that the whole impact of a connected inventor displacement occurs through the connected inventor hire. The underlying idea is the following: it is possible that knowledge is partly embedded in inventors; firms can then gain access to this knowledge by hiring them. The possibility of knowledge transfer through firm-to-firm labor mobility idea is explored, for instance, by Dasgupta (2012) who studies a dynamic general equilibrium model with mobility of workers among countries, in which the long-term dynamic learning process plays a crucial role. Workers in the model learn from their managers and knowledge diffusion takes place through labor flows.[19] In a case study of the British Motor Valley, Henry and Pinch (2000, p.198–99) conclude that

> as personnel move, they bring with them knowledge and ideas about how things are done in other firms helping to raise the knowledge throughout the industry...The crucial point is that whilst this process may not change the pecking order within the industry, this 'churning' of personnel raises the knowledge base of the industry as a whole within the region. The knowledge community is continually reinvigorated and, synonymous with this, so is production within Motor Sport Valley.

The implementation of our IV strategy is as follows. Denote with $Inventor\ Hire^{conn.}$ a dummy equal to one in each of the five years following a connected inventor hire, and zero

[19] Similar theoretical contributions include the studies by Cooper (2001), Markusen (2001), Glass and Saggi (2002) and Fosfuri et al. (2001). In the theoretical analysis by Combes and Duranton (2006), firms selecting their production site foresee that they can enhance their productivity by poaching workers from other firms.

otherwise. The econometric equation is:

$$Y_{jslt} = \beta_h Inventor\ Hire^{conn.}{}_{jt} + \beta_n N_{jt} + \beta_d Displaced_{slt} + Trend_{st} + Trend_{lt} + \lambda_j + \alpha_t + u_{jslt}. \tag{D.2}$$

where the dependent variable is the number of firm j's patent applications. We instrument *Inventor Hire*$^{conn.}$ with *Displ. Inventor*$^{conn.}$, i.e. a dummy equal to one in each of the five years following a connected inventor displacement, and zero otherwise.

3.5 Evidence

3.5.1 Recruitment of Connected Inventors

How is the hiring of connected inventors affected by displacement events? To investigate this aspect we estimate Equation (D.1) whereby the dependent variable is a dummy equal to one if firm j hires a connected inventor at time t. [20] The period 1992-2008 [21] includes 555 events of displacement of connected inventors. The estimates, displayed in Figure 3.6.1, show that the frequency of connected inventor hires has a distinct peak at the time of a connected inventor displacement; the probability of hiring a connected inventors increases by 4 percentage points. This is consistent with the hypothesis that firms take advantage of the displacement of a connected inventor to recruit connected knowledgeable labor. Figure 3.6.2 shows that non-connected inventor hires are not affected by events of displacement of a connected inventor.

[20] This analysis is similar in spirit to Figure 5 in Eliason et al. (2017).

[21] Recall that, considering the five year interval necessary to form the firm's network, we are interested in closures between 1992 and 2008.

3.5.2 Connected Inventor Displacements and Innovation: Event-Study Estimates

The main goal of this paper is to measure the extent to which access to connected knowledgeable workers has an impact on firms' innovation. In this Section we present the first of the two main sets of results using patent applications as dependent variable. Figure 3.6.3 plots the baseline β_τ coefficients from estimating Equation (D.1), comparing changes in patent applications of firms that experience the displacement of a connected inventor both to firms that have yet to experience such an event and to firms that will never do so during our sample period.

The Figure has two important features. First, there is no pretreatment trend in the coefficients, lending support to the validity of the research design. This support is reinforced by the lack of pre-trend in the hiring of connected inventors documented in Figure 3.6.1, and in the hiring of unconnected inventors (Figure 3.6.2). The second important feature of Figure 3.6.3 is that there is a upward shift in innovation after the displacement of a connected inventor. In Figure 3.6.4 we drop the never treated firms, and therefore identification comes from the differential timing of treatment onset among the treated firms. The general pattern is broadly similar.

While the patterns in Figure 3.6.3 and 3.6.4 are quite clear, the individual β_τ coefficients are not estimated very precisely. It is helpful to offer more formal tests of the null hypothesis that the displacement of a connected inventor has no impact on firms' innovation. To increase statistical power we test hypotheses about the average of the β_τ coefficients over various time intervals as in Kline (2012).

The results are shown in Table 3.6.2. The first row corresponds to Figure 3.6.3: the estimated average increase over the five years starting with the year of a connected inventor's displacement (i.e. the average of the coefficients on $\tau = 0$, $\tau = 1$, $\tau = 2$, $\tau = 3$, $\tau = 4$) is of 0.045 patent application and is statistically distinguishable from zero at conventional levels. An increase in the number of patent applications of 0.045 is equivalent to a 0.14-standard-deviation increase (the standard deviation of the number of patent applications in the estimation sample is 0.32; see Table 3.6.1). The second row of Table 3.6.2 corresponds to Figure 3.6.4: the average increase is equivalent to 0.18 standard deviations. As discussed above, we control for displacement in LLM and industry and for industry-specific and LLM-specific trends but all the results reported in this Section are virtually unchanged if we do not include these control variables.

3.5.3 Connected Inventor Hires and Innovation: 2SLS Estimates

In this Section we use the displacement of a connected inventor as an instrument for the hire of a connected inventor. Columns (1) - (3) of Table 3.6.3 display the main 2SLS estimates for three specifications: the first one controls for network size, firm and time fixed effects (Col 1), the second one includes displacement in LLM and industry (Col 2), and the last one adds industry-specific and LLM-specific trends (Col 3). The first-stage F-statistics range from 12 to 14. The coefficient of our variable of interest is significant at the 1 percent level: the estimated average increase in the number of firm patents applications submitted to the EPO over the five years starting with the year of a connected inventor's hire is 0.6. To put the magnitude of the estimated effect in perspective, we calculate the fraction of overall variation in innovation explained by the hire of a connected inventor. A change of 0.6 patent applications is equivalent to an increase of 1.875-standard-deviations (recall that the standard deviation of the number of patent applications in the estimation sample is 0.32). In interpreting these estimates, it is important to keep in mind that, ad discussed above, hiring a connected inventor is a major change in terms of workforce for the average firm in our data. We therefore think that this implied shift in the number of patent application following the hire is large but not unrealistic.

In column (4) we restrict the dependent variable to the yearly number of patent submissions that are not authored or co-authored by the newly hired connected inventor. The estimates indicate a 0.325 increase in the patents submissions authored by the other workers of the focal firm, excluding those with the hired connected inventor in the team (significant at 5 percent).

3.5.4 Validity and Robustness

Interaction weighted estimator

Connected inventor displacements happening later may be different from those happening earlier, generating cohort-specific treatment effects. We therefore implement the interaction weighted estimator for an event study. Sun and Abraham (2021) prove that this estimator is consistent for the average dynamic effect at a given relative time even under heterogeneous treatment effects. [22] The estimates, shown in Fig. 3.6.5, are qualitatively similar to the baseline ones.

A Placebo exercise

As discussed above, a potential identification concern arises if the shocks to the supply of knowledgeable labor deriving from establishment closure also pick up market-level supply shocks or demand shocks. To further explore this possibility, we perform a "placebo"-type analysis. Specifically we investigate the extent to which innovation at firm j reacts to the displacement of inventors who are connected to other firms in the same LLM and industry but not to the focal firm j.

Panel A of Table 3.6.4 indicates that the estimated average change over the five years starting with the year of the placebo event is very small (an order of magnitude smaller than that in the main estimates) and non-significant. These results suggest that the effect identified in the previous Section genuinely captures the improved capacity to employ connected inventors, and does not reflect market-level supply shocks or demand shocks.

[22] We use the eventstudyinteract Stata routine available at https://economics.mit.edu/grad/lsun20/stata.

Citation-weighted Patent Counts

The baseline analysis uses simple patent counts. We now explore the sensitivity of our results when we use citation-weighted patent counts (Griliches et al., 1991; Hall et al., 2005; Dechezleprêtre et al., 2018). In constructing this dependent variable, we employ the truncation correction weights devised by Hall et al. (2001) to correct for systematic citation differences across different technology classes and for the fact that earlier patents will have more years during which they can receive citations. The estimates, shown in Panel B of Table 3.6.4 are consistent with the main findings. Specifically the estimated average increase over the five years, starting with the year of the event, is statistically distinguishable from zero at 10 percent level and equivalent to a 0.13-standard-deviation increase.

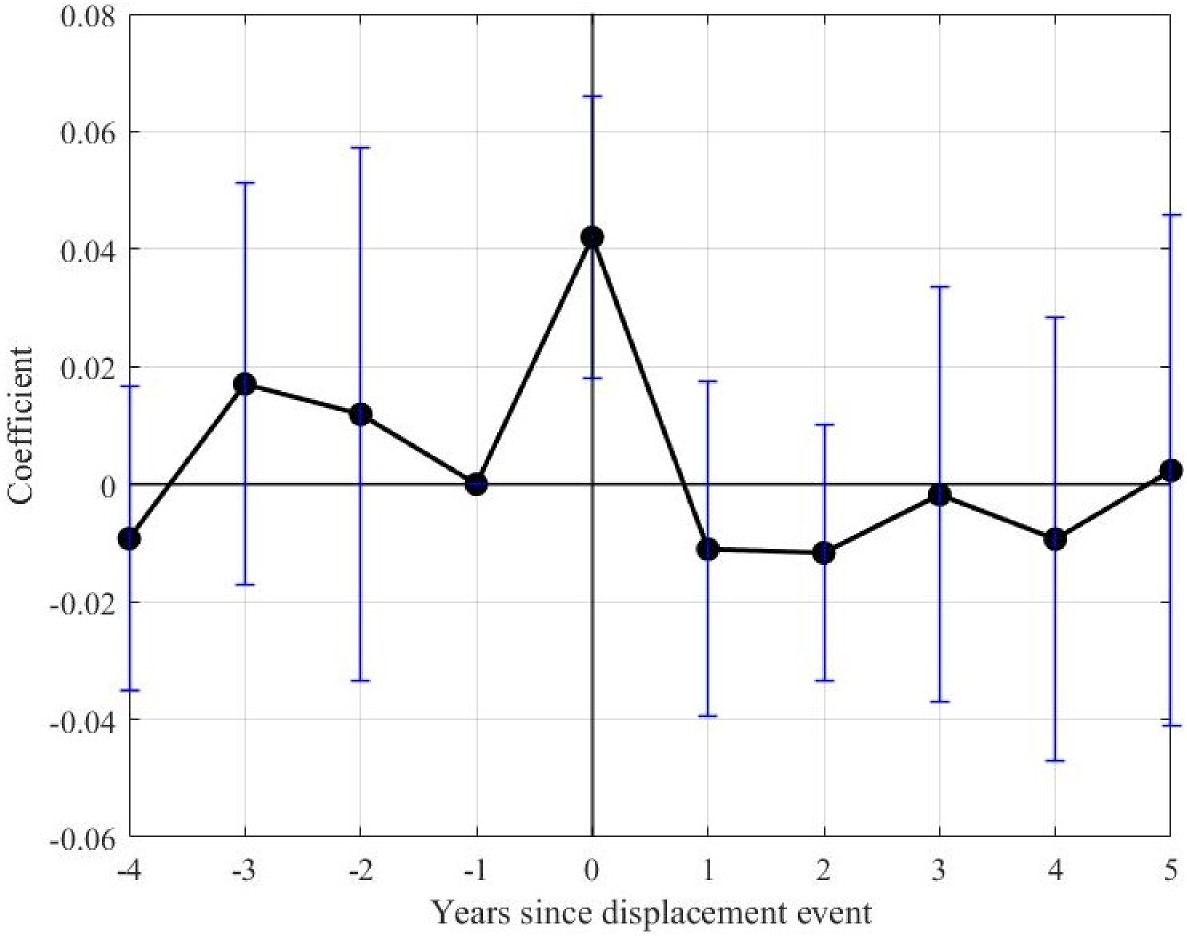
Poisson Estimates

The main estimation framework introduced in Section 3.4.1 has several advantages. OLS is the best linear unbiased estimator and its consistency properties are transparent. Nevertheless, we explore the robustness of our conclusion when using quasi-maximum likelihood fixed-effects Poisson estimates (QMLE Poisson), which allow for the count data features of patents (Hausman et al., 1984). The estimates, reported in Panel C of Table 3.6.4, are consistent with the main findings. Specifically, the average increase starting with the year of a connected inventor's displacement is equal to 41.2 percent - the percentage change is calculated as (exp(0.345)-1)*100=41.2.

3.6 Concluding Remarks

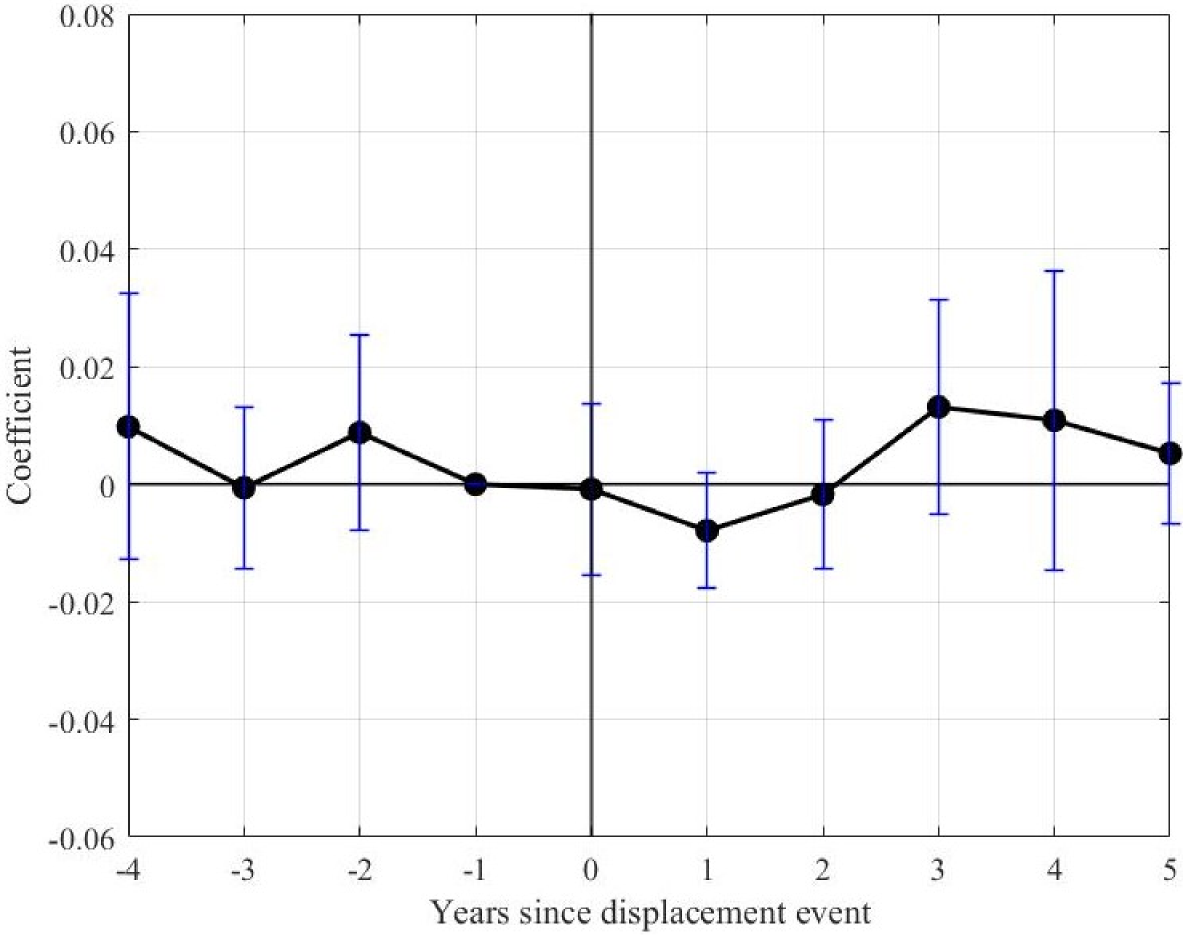
A prominent feature of the labor market in many developed countries is the tendency for firms to hire through social connections. Nevertheless, we have very limited knowledge regarding the extent to which available connections have an impact on firms' innovation. The central empirical goal of the paper is to measure the extent to which access to connected knowledgeable workers raises firms' hiring knowledgeable labor and thus fosters innovation. Displacements of inventors because of establishment closures generate labor supply shocks to firms that employ their previous co-workers. Estimates indicate that firms take advantage of such displacements to recruit connected inventors. Moreover, the improved capacity to employ connected inventors increases firms' patenting activity. Therefore our estimates also lend support to the hypothesis of knowledge transfer through firm-to-firm labor mobility.

Figure 3.6.1. *Connected Inventor Hiring, Relative to the Year of a Connected Inventor Displacement.*



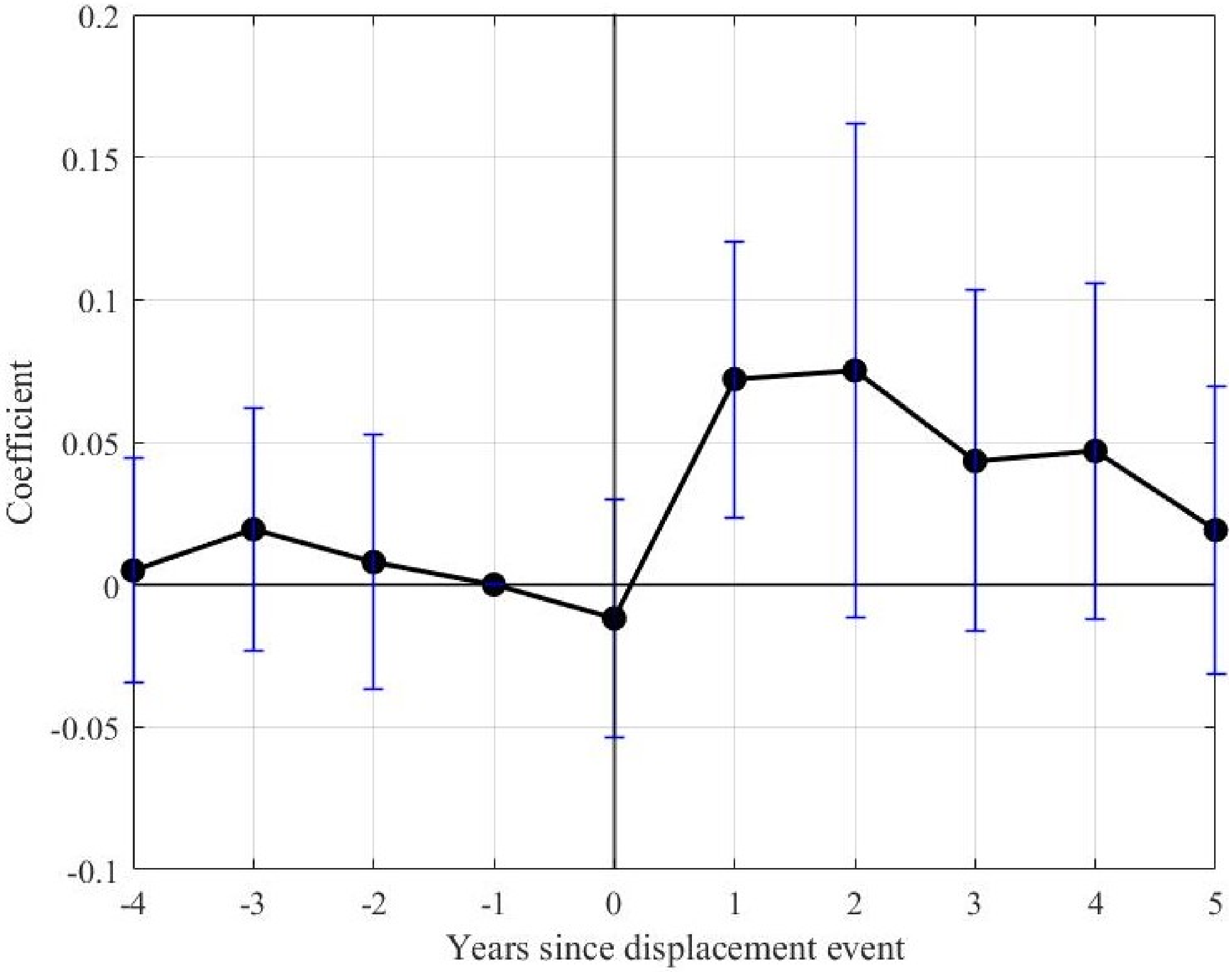
Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. The dependent variable is a dummy equal to one if firm j of industry s and local labor market (LLM) l hires a connected inventor at time t (from any industry or LLM). Event time indicator "-4" set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" set to 1 for all periods 5 periods after the event and 0 otherwise. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent cluster-robust confidence intervals (the clustering level is LLM).

Figure 3.6.2. *Non-Connected Inventor Hiring, Relative to the Year of a Connected Inventor Displacement.*



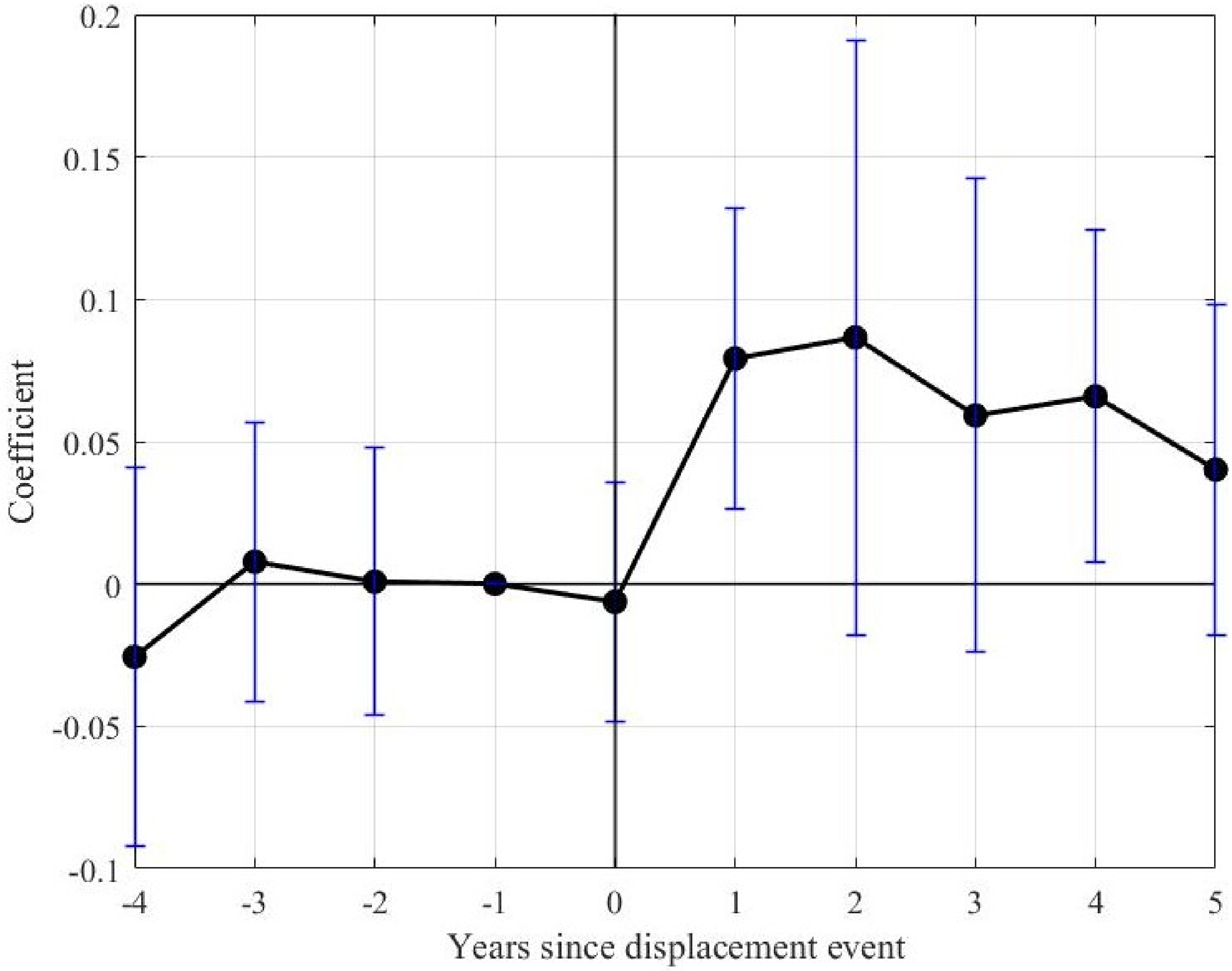
Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. The dependent variable is a dummy equal to one if firm j of industry s and local labor market (LLM) l hires a non-connected inventor at time t (from any industry or LLM). Event time indicator "-4" set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" set to 1 for all periods 5 periods after the event and 0 otherwise. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent cluster-robust confidence intervals (the clustering level is LLM).

Figure 3.6.3. *Patent Applications, Relative to the Year of a Connected Inventor Displacement.*



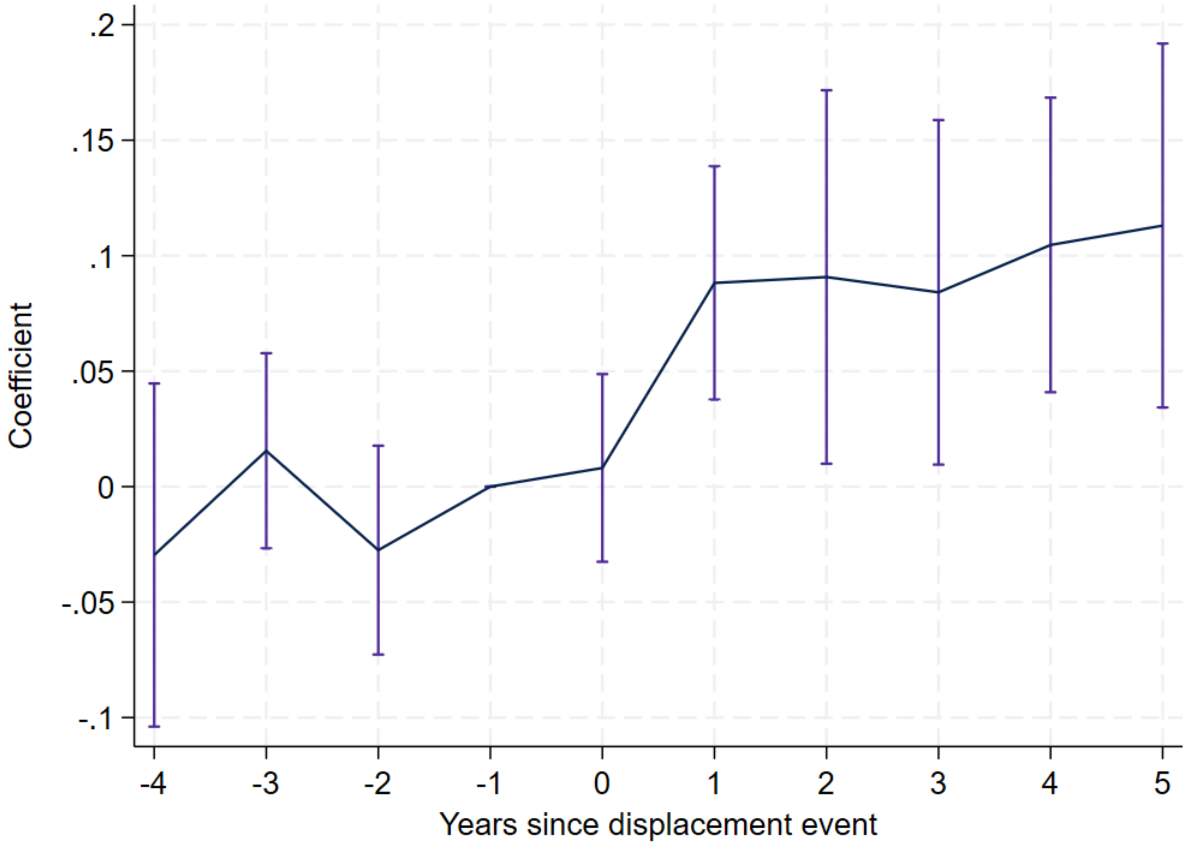
Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. Event time indicator "-4" set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" set to 1 for all periods 5 periods after the event and 0 otherwise. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent cluster-robust confidence intervals (the clustering level is LLM).

Figure 3.6.4. *Patent Applications, Relative to the Year of a Connected Inventor Displacement. Treated firms Only.*



Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. Event time indicator "-4" set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" set to 1 for all periods 5 periods after the event and 0 otherwise. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent cluster-robust confidence intervals (the clustering level is LLM).

Figure 3.6.5. *Patent Applications, Relative to the Year of a Connected Inventor Displacement; Interaction weighted estimator.*



Note: The figure implements the interaction weighted estimator for an event study (Sun and Abraham, 2021). It plots point estimates for leading and lagging indicators for the displacement of a connected inventor. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent confidence intervals.

Table 3.6.1. *Summary statistics for estimation sample (1992-2008).*

	Mean	SD	Min	Max
Inventor Hire $^{conn.}$	0.008	0.100	0	7
No. of Patent Applications	0.035	0.322	0	20
Inventor Hire $^{non-conn.}$	0.004	0.083	0	11
Employees	106.102	111.916	5	496
Firm Network	849.039	1180.871	1	22197
Displaced Inventors $^{conn.}$	0.008	0.170	0	35
Displaced Non-Inventors $^{conn.}$	3.317	15.280	0	670

Note: Sample size contains 80,310 observations for 7,301 firms. *Inventor Hire* $^{conn.}$ is the number of connected inventor hires. *No. of Patent Applications* is the average number of patent applications submitted by the firms in the sample. *Inventor Hire* $^{non-conn.}$ is the number of non-connected inventor hires. *Employees* is the average number of employees employed by the firms in the sample. *Firm Network* is the number of former co-workers of current employees. *Displaced Inventors* $^{conn.}$ is the number of connected inventors who are displaced in a given year. *Displaced Non-Inventors* $^{conn.}$ is the number of connected non-inventors who are displaced in a given year.

Table 3.6.2. *Connected Inventor Displacements and Patent Applications - Event Study.*

	$\tau = 0$	$\tau \in [1,2]$	$\tau \in [3,4]$	$\tau \in [0,4]$
Baseline Sample	-0.012	0.074***	0.045**	0.045**
	(0.021)	(0.029)	(0.020)	(0.019)
Treated Only	-0.006	0.083**	0.063**	0.057**
	(0.021)	(0.035)	(0.029)	(0.026)

Note: Estimates refer to Equation (D.1) whereby the dependent variable is the number of patents applications. The first row corresponds to Figure 3.6.3. The first row corresponds to Figure 3.6.3. The *Baseline Sample* size is 80,310 (7,301 firms), lowering to 6,954 (551 firms) for the *Treated only* sub-sample. Samples includes only firms with more than 5 observations in the period of interest. The model includes year and firm fixed effects, industry trends and LLM trends, network size, number of displaced workers in the LLM×industry×year. Numbers in parentheses are standard errors clustered at the LLM level. $\tau \in [a,b]$ refers to the average of the coefficients between period $\tau = a$ and period $\tau = b$. $*p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$.

Table 3.6.3. *Connected Inventor Hires and Patent Applications: 2SLS Estimates*

Dependent Variable	**All Patent Applications**			**W/o conn. hires**
	(1)	(2)	(3)	(4)
	Panel A: **2SLS Estimates**			
Inventor Hire$^{conn.}$	0.623***	0.623***	0.681***	0.325**
	(0.226)	(0.226)	(0.252)	(0.165)
F-stat, 1st *stage*	13.93	13.93	12.05	12.05
No.obs.	80,121	80,121	80,121	80,121
$Displaced_{slt}$	-	+	+	+
Industry and LLM Trends	-	-	+	+
	Panel B: **First stage estimates**			
Displ. Inventor$^{conn.}$	0.051***	0.051***	0.049***	0.049***
	(0.014)	(0.014)	(0.014)	(0.014)
	Panel C: **Reduced form estimates**			
Displ. Inventor$^{conn.}$	0.032***	0.032***	0.033***	0.016*
	(0.009)	(0.009)	(0.009)	(0.009)

Note: Estimates refer to Equation (D.2). In columns (1)-(3) the dependent variable is the number of patents applications, while in column (4) it is the number of patents submissions excluding those authored or co-authored by the newly hired connected inventor(s). Estimation sample includes only firms with more than 5 observations in the period of interest. Numbers in parentheses are standard errors clustered at the LLM level. Network size, firm and time fixed effects are always included. $Displaced_{slt}$: number of displaced workers in the same LLM×industry×year. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

Table 3.6.4. *Citation-weighted Patent Counts, Poisson and Placebo Estimates*

Panel A: **Placebo**				
Dep. Var.: *No. Patent Applications*	$\tau = 0$	$\tau \in [1,2]$	$\tau \in [3,4]$	$\tau \in [0,4]$
	0.006	0.009	-0.002	0.004
	(0.009)	(0.011)	(0.013)	(0.010)
Panel B: **Citation-Weighted Patent Counts**				
Dep. Var.: *No. citation-weighted Patent Applications*	$\tau = 0$	$\tau \in [1,2]$	$\tau \in [3,4]$	$\tau \in [0,4]$
	-0.054	0.154**	0.059	0.074**
	(0.047)	(0.073)	(0.084)	(0.035)
Panel C: **Poisson**				
Dep. Var.: *No. Patent Applications*	$\tau = 0$	$\tau \in [1,2]$	$\tau \in [3,4]$	$\tau \in [0,4]$
	-0.085	0.517**	0.389*	0.345*
	(0.201)	(0.233)	(0.202)	(0.188)

Note: Estimates refer to Equation (D.1). Panels A and C: the dependent variable is number of patent applications. Panel B: the dependent variable is the citation-weighted Patent Count. Sample size is $49,176$ ($4,709$ firms) in Panel A, $80,310$ ($7,301$ firms) in Panel B and $9,486$ (707 firms) in Panel C. The reduced sample size in Panel A stems from the fact that we discard firms experiencing multiple placebo events. Sample in Panel C is smaller because firms with all outcomes equal to zero are dropped in the estimation routine (Stata xtpoisson). Estimation samples include only firms with more than 5 observations. The model includes year and firm fixed effects, industry trends and LLM trends, network size, number of displaced workers in the LLM$\times$industry$\times$year. Numbers in parentheses are standard errors clustered at the LLM level. $\tau \in [a,b]$ refers to the average of the coefficients between period $\tau = a$ and period $\tau = b$. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

Bibliography

Adamopoulos, T., Brandt, L., Leight, J., and Restuccia, D. (2022). Misallocation, selection, and productivity: A quantitative analysis with panel data from china. *Econometrica*, 90(3):1261–1282.

Adao, R., Kolesár, M., and Morales, E. (2019). Shift-share designs: Theory and inference. *The Quarterly Journal of Economics*, 134(4):1949–2010.

Akcigit, U., Baslandze, S., and Lotti, F. (2023). Connecting to power: political connections, innovation, and firm dynamics. *Econometrica*, 91(2):529–564.

Algan, Y., Malgouyres, C., and Senik, C. (2019). Territoires, bien-être et politiques publiques. *Notes du conseil danalyse economique*, (7):1–12.

Asher, S. and Novosad, P. (2020). Rural Roads and Local Economic Development. *American Economic Review*, 110(3):797–823.

Attrill, N. (2021). *Revitalising Northeast China: Rust Belt Politics and Policy Failures*. PhD thesis, The Australian National University (Australia).

Autor, D. H. (2003). Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of labor economics*, 21(1):1–42.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013a). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, 103(6):2121–2168.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013b). The China Syndrome: Local Labor Market

Effects of Import Competition in the United States. *American Economic Review*, 103(6):2121–2168.

Azoulay, P., Fons-Rosen, C., and Graff Zivin, J. S. (2019). Does science advance one funeral at a time? *American Economic Review*, 109(8):2889–2920.

Bakker, J. D. (2021). Trade and Agglomeration: Theory and Evidence from France. SSRN Working Paper No. 3757053.

Balsvik, R. (2011). Is labor mobility a channel for spillovers from multinationals? evidence from norwegian manufacturing. *Review of Economics and Statistics*, 93(1):285–297.

Bandiera, O., Barankay, I., and Rasul, I. (2010). Social incentives in the workplace. *The Review of Economic Studies*, 77(2):417–458.

Banerjee, A., Duflo, E., and Qian, N. (2020). On the road: Access to transportation infrastructure and economic growth in China. *Journal of Development Economics*, 145(6):2121–2168.

Bartik, T. J. (1991). *Who benefits from state and local economic development policies? Kalamazoo, MI: WE Upjohn Institute for Employment Research*.

Battisti, M., Peri, G., and Romiti, A. (2016). Dynamic effects of co-ethnic networks on immigrants' economic success. Technical report, National Bureau of Economic Research.

Baysan, C., Dar, M. H., Emerick, K., and Sadoulet, E. (2019). The Agricultural Wage Gap Within Rural Villages. CEGA Working Paper No. 086, CEGA (Center for Effective Global Action).

Becattini, G., Bellandi, M., and De Propris, L. (2014). *A handbook of industrial districts*. Edward Elgar Publishing.

Behaghel, L., Lorenceau, A., and Quantin, S. (2015). Replacing Churches and Mason Lodges? Tax Exemptions and Rural Development. *Journal of Public Economics*, 125:1–15.

Bell, A., Chetty, R., Jaravel, X., Petkova, N., and Van Reenen, J. (2019). Who becomes an inventor in america? the importance of exposure to innovation. *The Quarterly Journal of Economics*, 134(2):647–713.

Black, D. and Henderson, V. (2003). Urban Evolution in the USA. *Journal of Economic Geography*, 3(4):343–372.

Bloom, N., Schankerman, M., and Van Reenen, J. (2013). Identifying technology spillovers and product market rivalry. *Econometrica*, 81(4):1347–1393.

Bollman, R. and Bryden, J. (2000). Rural Employment in Industrialised Countries. *Agricultural Economics*, 22(2):185–197.

Böltken, F., Bublys, J., Janich, H., Kuhlmann, P., Runge, L., and Schmidt-Seiwert, V. (2002). *Aktuelle Daten zur Entwicklung der Städte, Kreise und Gemeinden 2002*, volume 14 of *Berichte des Bundesamtes für Bauwesen und Raumordnung*. Bundesamt für Bauwesen und Raumordnung, Bonn.

Böltken, F., Hartenstein, S., Irmen, S., Janich, H., Runge, L., and Wittmann, F.-T. (1992). *Aktuelle Daten zur Entwicklung der Städte, Kreise und Gemeinden 1989/90*, volume 47 of *Materialien zur Raumentwicklung*. Bundesforschungsanstalt für Landeskunde und Raumordnung, Bonn.

Böltken, F., Hartenstein, S., Janich, H., Runge, L., and Wittmann, F.-T. (1995). *Aktuelle Daten zur Entwicklung der Städte, Kreise und Gemeinden 1992/93*, volume 67 of *Materialien zur Raumentwicklung*. Bundesforschungsanstalt für Landeskunde und Raumordnung, Bonn.

Böltken, F., Janich, H., Kuhlmann, P., Meyer, K., Runge, L., and Schmidt-Seiwert, V. (2001). *Aktuelle Daten zur Entwicklung der Städte, Kreise und Gemeinden, Ausgabe 2000*, volume 8 of *Berichte des Bundesamtes für Bauwesen und Raumordnung*. Bundesforschungsanstalt für Landeskunde und Raumordnung, Bonn.

Borusyak, K., Hull, P., and Jaravel, X. (2022). Quasi-experimental shift-share research designs. *The Review of Economic Studies*, 89(1):181–213.

Bound, J. and Holzer, H. J. (2000). Demand shifts, population adjustments, and labor market outcomes during the 1980s. *Journal of labor Economics*, 18(1):20–54.

Brandt, L., Kambourov, G., and Storesletten, K. (2020). Barriers to entry and regional economic growth in china.

Brandt, L. and Zhu, X. (2010). Accounting for china's growth.

Brezzi, M., Dijkstra, L., and Ruiz, V. (2011). OECD Extended Regional Typology. OECD Regional Development Working Papers 2011/06, Organisation for Economic Co-operation and Development (OECD).

Brueckner, J. K. and Lall, S. V. (2015). Cities in Developing Countries: Fueled by Rural–Urban Migration, Lacking in Tenure Security, and Short of Affordable Housing. In Duranton, G., Henderson, V. J., and Strange, W., editors, *Handbook of Agricultural Economics*, volume 5B, chapter 21, pages 1399–1455. Elsevier.

Brusco, S. (1983). The emilian model: Productive decentralisation and social integration. *Cambridge Journal of Economics*, 6(2):167–184.

Burks, S. V., Cowgill, B., Hoffman, M., and Housman, M. (2015). The value of hiring through employee referrals. *The Quarterly Journal of Economics*, 130(2):805–839.

Cahuc, P., Carcillo, S., and Le Barbanchon, T. (2019). The effectiveness of hiring credits. *The Review of Economic Studies*, 86(2):593–626.

Caldwell, S. and Harmon, N. (2019). Outside options, bargaining, and wages: Evidence from coworker networks. *Unpublished manuscript, Univ. Copenhagen*.

Canzian, G., Poy, S., and Schüller, S. (2019). Broadband Upgrade and Firm Performance in Rural Areas: Quasi-Experimental Evidence. *Regional Science and Urban Economics*, 77:87–103.

Card, D. (1992). Using Regional Variation in Wages to Measure the Effects of the Federal Minimum Wage. *Industrial and Labor Relations Review*, 46(1):22–37.

Cestone, G., Fumagalli, C., Kramarz, F., and Pica, G. (2016). Insurance between firms: The role of internal labor markets. *Centre for Economic Policy Research DP*, (11336).

Charles, K. K., Hurst, E., and Schwartz, M. (2019). The transformation of manufacturing and the decline in us employment. *NBER Macroeconomics Annual*, 33(1):307–372.

Cingano, F. and Pinotti, P. (2013). Politicians at work: The private returns and social costs of political connections. *Journal of the European Economic Association*, 11(2):433–465.

Cingano, F. and Rosolia, A. (2012). People I Know: Job Search and Social Networks. *Journal of Labor Economics*, 30(2):291–332.

Colussi, T. (2015). Migrant networks and job search outcomes: Evidence from displaced workers.

Colussi, T. (2018). Social ties in academia: A friend is a treasure. *Review of Economics and Statistics*, 100(1):45–50.

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

Coombes, M. G., Green, A. E., and Openshaw, S. (1986). An Efficient Algorithm to Generate Official Statistical Reporting Areas: The Case of the 1984 Travel-to-Work Areas Revision in Britain. *The Journal of the Operational Research Society*, 37(10):943–953.

Cooper, D. P. (2001). Innovation and reciprocal externalities: Information transmission via job mobility. *Journal of Economic Behavior and Organization*, 45(4):403–425.

Cornelissen, T., Dustmann, C., and Schönberg, U. (2016). Peer effects in the workplace. *American Economic Review, forthcoming*.

Couture, V., Faber, B., Gu, Y., and Liu, L. (2018). Connecting the Countryside via E-Commerce: Evidence from China. NBER Working Paper No. 24384.

Cramer, K. J. J. (2016). *The Politics of Resentment: Rural Consciousness in Wisconsin and the Rise of Scott Walker*. University of Chicago Press, Chicago; London.

Dalla-Zuanna, A. (2020). The long-term effects of work-related networks on earnings. *Unpublished manuscript, Norwegian School of Economics*.

Dasgupta, K. (2012). Learning and knowledge diffusion in a global economy. *Journal of International Economics*, 87(2):323–336.

Dauth, W., Findeisen, S., and Suedekum, J. (2014). The rise of the east and the far east: German labor markets and trade integration. *Journal of the European Economic Association*, 12(6):1643–1675.

Dauth, W., Findeisen, S., and Suedekum, J. (2021). Adjusting to globalization in germany. *Journal of Labor Economics*, 39(1):263–302.

Davis, S. J. and Haltiwanger, J. (1998). Measuring Gross Worker and Job Flows. In Haltiwanger, J., Manser, M. E., and Topel, R., editors, *Measuring Gross Worker and Job Flows*, chapter 3, pages 77–122. University of Chicago Press, Chicago.

de Blasio, G. and Di Addario, S. (2005). Do workers benefit from industrial agglomeration? evidence from displaced workers. *Journal of Regional Science*, 45(4):797—-827.

De Giorgi, G., Frederiksen, A., and Pistaferri, L. (2020). Consumption network effects. *The Review of Economic Studies*, 87(1):130–163.

De Janvry, A., Sadoulet, E., and Murgai, R. (2002). Rural Development and Rural Policy. In Gardner, B. L. and Rausser, G. C., editors, *Handbook of Agricultural Economics*, volume 2A, chapter 31, pages 1593–1658. Elsevier.

Dechezleprêtre, A., Martin, R., and Mohnen, M. (2018). Knowledge spillovers from clean and dirty technologies.

Depalo, D. and Di Addario, S. L. (2014). Shedding light on inventors' returns to patents. *Development Studies Working Papers , Centro Studi Luca d'Agliano*, (375).

Department of Employment (1984). *Revised Travel-to-Work Areas*. Occasional Supplement No. 3 Issued With Employment Gazette Vol. 92, No. 9, September 1984.

Desmet, K. and Henderson, V. J. (2015). The Geography of Development Within Countries. In Duranton, G., Henderson, V. J., and Strange, W., editors, *Handbook of Regional and Urban Economics*, volume 5B, chapter 22, pages 1457–1517. Elsevier, Amsterdam.

Dijkstra, L. and Poelman, H. (2008). Remote Rural Regions: How Proximity to a City Influences the Performance of Rural Regions. Regional Focus 01/2008, EU Direcorate General for Regional Policy.

Duranton, G. (2007). Urban Evolutions: The Fast, the Slow, and the Still. *American Economic Review*, 97(1):197–221.

Dustmann, C., Glitz, A., Schönberg, U., and Brücker, H. (2016). Referral-based job search networks. *The Review of Economic Studies*, 83(2):514–546.

Eaton, J. and Eckstein, Z. (1997). Cities and Growth: Theory and Evidence from France and Japan. *Regional Science and Urban Economics*, 27(4–5):443–474.

Eckey, H.-F., Horn, K., and Klemmer, P. (1990). *Abgrenzung von regionalen Diagnoseeinheiten für die Zwecke der regionalen Wirtschaftspolitik*. Brockmeyer, Bochum.

Eliason, M., Hensvik, L., Kramarz, F., and Nordstrom Skans, O. (2017). The causal impact of social connections on firms' outcomes. *CEPR Discussion Paper No. DP12135*.

Eliason, M., Hensvik, L., Kramarz, F., and Skans, O. N. (2023). Social connections and the sorting of workers to firms. *Journal of Econometrics*, 233(2):468–506.

ENRD (2017). Re-imagining rural business opportunities.

EU (2017). Socio-Economic challenges facing agriculture and rural areas.

EU (2021). Rural development programmes by country.

Eurostat (2021). Glossary: Tourism industries.

Faber, B. (2014). Trade integration, market size, and industrialization: evidence from china's national trunk highway system. *Review of Economic Studies*, 81(3):1046–1070.

Faber, B. and Gaubert, C. (2019). Tourism and economic development: Evidence from mexico's coastline. *American Economic Review*, 109(6):2245–93.

Fafchamps, M. and Quisumbing, A. R. (1999). Human Capital, Productivity, and Labor Allocation in Rural Pakistan. *Journal of Human Resources*, 34(2):369–406.

Faggio, G. and Overman, H. (2014). The effect of public sector employment on local labour markets. *Journal of urban economics*, 79:91–107.

Faggio, G. and Silva, O. (2014). Self-employment and entrepreneurship in urban and rural labour markets. *Journal of Urban Economics*, 84:67–85.

Findeisen, S. and Südekum, J. (2008). Industry Churning and the Evolution of Cities: Evidence for Germany. *Journal of Urban Economics*, 64(2):326–339.

Fons-Rosen, C. (2013). Knowledge flows through fdi: the case of privatisations in central and eastern europe. *Mimeograph Universitat Pompeu Fabra*.

Fons-Rosen, C., Kalemli-Ozcan, S., Sorensen, B. E., Villegas-Sanchez, C., and Volosovych, V. (2017). Foreign investment and domestic productivity: Identifying knowledge spillovers and competition effects. Technical report, National Bureau of Economic Research.

Fons-Rosen, C., Scrutinio, V., and Szemeredi, K. (2016). Colocation and knowledge diffusion: evidence from million dollar plants.

Fort, T. C., Pierce, J. R., and Schott, P. K. (2018). New perspectives on the decline of us manufacturing employment. *Journal of Economic Perspectives*, 32(2):47–72.

Fosfuri, A., Motta, M., and Rønde, T. (2001). Foreign direct investment and spillovers through workers' mobility. *Journal of International Economics*, 53(1):205–222.

Friebel, G., Heinz, M., Hoffman, M., and Zubanov, N. (2019). What do employee referral programs do? Technical report, National Bureau of Economic Research.

Gagliardi, L., Moretti, E., and Serafinelli, M. (2023). The World's Rust Belts. Unpublished journal article.

Ganguli, I., Lin, J., and Reynolds, N. (2020). The paper trail of knowledge spillovers: evidence from patent interferences. *American Economic Journal: Applied Economics*, 12(2):278–302.

Gathmann, C., Helm, I., and Schönberg, U. (2020). Spillover effects of mass layoffs. *Journal of the European Economic Association*, 18(1):427–468.

Gatzweiler, H. P. and Runge, L. (1984). *Aktuelle Daten zur Entwicklung der Städte, Kreise und Gemeinden 1984*, volume 17 of *Seminare, Symposien, Arbeitspapiere*. Bundesforschungsanstalt für Landeskunde und Raumordnung, Bonn.

Glaeser, E. L. (2009). The death and life of cities. *Making cities work–prospects and policies for Urban America*, pages 22–62.

Glass, A. and Saggi, K. (2002). Multinational firms and technology transfer. *The Scandinavian Journal of Economics*, 104(4):495–513.

Glitz, A. (2017). Coworker networks in the labour market. *Labour Economics*, 44(C):218–230.

Glitz, A. and Vejlin, R. (2019). Learning through coworker referrals. *IZA Discussion Paper*.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624.

Greenstone, M., Hornbeck, R., and Moretti, E. (2010). Identifying agglomeration spillovers: Evidence from winners and losers of large plant openings. *Journal of political economy*, 118(3):536–598.

Griliches, Z., Hall, B. H., and Pakes, A. (1991). R&d, patents, and market value revisited: is there a second (technological opportunity) factor? *Economics of Innovation and new technology*, 1(3):183–201.

Gualdani, C. (2020). An econometric model of network formation with an application to board interlocks between firms. *Journal of Econometrics*.

Guilluy, C. (2019). *Twilight of the Elites: Prosperity, the Periphery, and the Future of France*. Yale University Press, New Haven; London.

Guryan, J., Kroft, K., and Notowidigdo, M. J. (2009). Peer effects in the workplace: Evidence from random groupings in professional golf tournaments. *American Economic Journal: Applied Economics*, 1(4):34–68.

Gyetvai, A. and Zhu, M. (2020). Coworker networks and the role of occupations in job finding.

Hall, B. H., Jaffe, A., and Trajtenberg, M. (2005). Market value and patent citations. *The RAND Journal of Economics*, 36(1):16–38.

Hall, B. H., Jaffe, A. B., and Trajtenberg, M. (2001). The nber patent citation data file: Lessons, insights and methodological tools. Technical report, National Bureau of Economic Research.

Hall, B. H., Lotti, F., and Mairesse, J. (2008). Employment, innovation, and productivity: evidence from italian microdata. *Industrial and corporate change*, 17(4):813–839.

Hausman, J., Hall, B. H., Griliches, Z., et al. (1984). Econometric models for count data with an application to the patents-r&d relationship. *Econometrica*, 52(4):909–938.

Heblich, S., Seror, M., Xu, H., and Zylberberg, Y. (2022). Industrial clusters in the long run: evidence from million-rouble plants in china. Technical report, National Bureau of Economic Research.

Henry, N. and Pinch, S. (2000). Spatialising knowledge: placing the knowledge community of motor sport valley. *Geoforum*, 31(2):191–208.

Hensvik, L. and Skans, O. N. (2016). Social Networks, Employee Selection, and Labor Market Outcomes. *Journal of Labor Economics*, 34(4):825–867.

Hornbeck, R. and Moretti, E. (2022). Estimating who benefits from productivity growth: local and distant effects of city productivity growth on wages, rents, and inequality. *The Review of Economics and Statistics*, pages 1–49.

Horton, J. J. (2017). The effects of algorithmic labor market recommendations: Evidence from a field experiment. *Journal of Labor Economics*, 35(2):345–385.

Huang, K., Moretti, E., and Xia, X. (2020). Does college expansion enrollment stimulate innovation? *Mimeograph*.

INSEE (1987). *Le Découpage des Vingt-Deux Régions en 365 Zones d'Emploi*. Institut National de la Statistique et des Études Économiques (INSEE), Centre d'Étude Statistique du Développement Régional (CESDR), Paris.

Jaravel, X., Petkova, N., and Bell, A. (2018). Team-specific capital and innovation. *American Economic Review*, 108(4-5):1034–73.

Kaiser, U., Kongsted, H. C., and Rønde, T. (2015). Does the mobility of r&d labor increase innovation? *Journal of Economic Behavior & Organization*, 110:91–105.

Kantor, S. and Whalley, A. (2014). Knowledge spillovers from research universities: evidence from endowment value shocks. *Review of Economics and Statistics*, 96(1):171–188.

Kilkenny, M. (2010). Urban/Regional Economics And Rural Development. *Journal of Regional Science*, 50(1):449–470.

Kim, S. and Margo, R. A. (2004). Historical Perspectives on U.S. Economic Geography. In Henderson, J. V. and Thisse, J.-F., editors, *Handbook of Regional and Urban Economics*, volume 4, chapter 66, pages 2981–3019. Elsevier.

Kline, P. (2012). The impact of juvenile curfew laws on arrests of youth and adults. *American Law and Economics Review*, 14(1):44–67.

Kline, P. and Moretti, E. (2014). People, Places, and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs. *Annual Review of Economics*, 6(1):629–662.

Kline, P., Petkova, N., Williams, H., and Zidar, O. (2019). Who profits from patents? rent-sharing at innovative firms. *The Quarterly Journal of Economics*, 134(3):1343–1404.

Korchowiec, B. (2019). To work or to network? - a study of co-worker link heterogeneity and firm hiring decisions. *Mimeograph Universitat Autònoma de Barcelona*.

Kramarz, F. and Skans, O. N. (2014). When strong ties are strong: Networks and youth labour market entry. *Review of Economic Studies*, 81(3):1164–1200.

Kramarz, F. and Thesmar, D. (2013). Social networks in the boardroom. *Journal of the European Economic Association*, 11(4):780–807.

Lanjouw, J. . and Lanjouw, P. (2001). The Rural Non-Farm Sector: Issues and Evidence from Developing Countries. *Agricultural Economics*, 26:1–23.

Li, H. and Liang, X. (2022). Responses of housing price under different directions of population change: Evidence from china's rust belt. *Chinese Geographical Science*, 32(3):405–417.

Maliranta, M., Mohnen, P., and Rouvinen, P. (2009). Is inter-firm labor mobility a channel of knowledge spillovers? evidence from a linked employer-employee panel. *Industrial and Corporate Change*, 18(6):1161–1191.

Man, S., Wu, X., Yang, Y., and Meng, Q. (2021). An assessment approach to urban economic resilience of the rust belt in china. *Complexity*, 2021:1–16.

Marin, G. and Lotti, F. (2016). Productivity effects of eco-innovations using data on eco-patents. *Industrial and corporate change*, page dtw014.

Markusen, J. (2001). Contracts, intellectual property rights, and multinational investment in developing countries. *Journal of International Economics*, 53(1):189–204.

Mas, A. and Moretti, E. (2009). Peers at work. *American Economic Review*, 99:112–145.

McCann, P. (2016). *The UK Regional-National Economic Problem: Geography, Globalisation and Governance*. Routledge, London, New York.

McCann, P. (2020). Perceptions of Regional Inequality and the Geography of Discontent: Insights from the UK. *Regional Studies*, 54(2):256–267.

Michaels, G., Rauch, F., and Redding, S. J. (2012). Urbanization and Structural Transformation. *Quarterly Journal of Economics*, 127(2):535–586.

Mohnen, M. (2018). Stars and brokers: knowledge spillovers among medical scientists. *Unpublished, University of Essex*.

Moretti, E. (2010). Local multipliers. *American Economic Review*, 100(2):373–77.

Moretti, E. (2021). The effect of high-tech clusters on the productivity of top inventors. *American Economic Review*, 111(10):3328–3375.

Moretti, E. and Thulin, P. (2013). Local multipliers and human capital in the united states and sweden. *Industrial and Corporate Change*, 22(1):339–362.

Moser, P., Voena, A., and Waldinger, F. (2014). German jewish émigrés and us invention. *American Economic Review*, 104(10):3222–55.

Neumark, D. and Simpson, H. (2015). Place-Based Policies. In Duranton, G., Henderson, V. J., and Strange, W., editors, *Handbook of Regional and Urban Economics*, volume 5B, chapter 18, pages 1197–1287. Elsevier, Amsterdam.

Ngai, L. R., Pissarides, C. A., and Wang, J. (2019). China's mobility barriers and employment allocations. *Journal of the European Economic Association*, 17(5):1617–1653.

OECD (1994). *Creating Rural Indicators for Shaping Territorial Policy*. Organisation for Economic Co-operation and Development (OECD), Paris.

OECD (2018). *OECD Regions and Cities at a Glance 2018*. OECD, Paris.

Osman, T. and Kemeny, T. (2022). Local job multipliers revisited. *Journal of Regional Science*, 62(1):150–170.

Parrotta, P. and Pozzoli, D. (2012). The effect of learning by hiring on productivity. *The RAND Journal of Economics*, 43(1):167–185.

Pellizzari, M. (2010). Do friends and relatives really help in getting a good job? *ILR Review*, 63(3):494–510.

Piore, M. (2009). Conceptualizing the dynamics of industrial districts. In *The Handbook of Industrial Districts*. Cheltenham, Edward Elgar.

Piore, M. and Sabel, C. (1984). Italian small business development: Lessons for u.s. industrial policy. *American Industry in International Competition. Cornell University Press*, John Zysman and Laura Tyson (eds.).

Pischke, J.-S. and Velling, J. (1997). Employment Effects of Immigration to Germany: An Analysis Based on Local Labor Markets. *Review of Economics and Statistics*, 79(4):594–604.

Poole, J. P. (2013). Knowledge transfers from multinational to domestic firms: evidence from worker mobility. *Review of Economics and Statistics*, 95(2):393–406.

Reardon, T., Stamoulis, K., and Pingali, P. (2007). Rural Nonfarm Employment in Developing Countries in an Era of Globalization. *Agricultural Economics*, 37(S1):173–183.

Reckwitz, A. (2019). *Das Ende der Illusionen: Politik, Ökonomie und Kultur in der Spätmoderne*. Suhrkamp, Berlin.

Redding, S. J. and Sturm, D. M. (2008). The Costs of Remoteness: Evidence from German Division and Reunification. *American Economic Review*, 98(5):1766–1797.

Redding, S. J. and Turner, M. A. (2015). Transportation Costs and the Spatial Organization of Economic Activity. In Duranton, G., Henderson, J. V., and Strange, W. C., editors, *Handbook of Regional and Urban Economics*, volume 5, chapter Ch. 20, pages 1339–1398. Elsevier, Amsterdam.

Rodríguez-Pose, A. (2018). The Revenge of the Places That Don't Matter (and What to Do About It). *Cambridge Journal of Regions, Economy and Society*, 11(1):189–209.

Ronsac, J.-J. (1994). Le Nouveau Découpage en Zones d'Emploi: Un Outil Pour la Connaissance et l'Action. *Courrier des Statistiques*, 70:33–35.

Rosenthal, S. S. and Ross, S. L. (2015). Change and Persistence in the Economic Status of Neighborhoods and Cities. In Duranton, G., Henderson, V. J., and Strange, W., editors, *Handbook of Regional and Urban Economics*, volume 5B, chapter 16, pages 1047–1120. Elsevier, Amsterdam.

San, S. (2020). Who works where and why? parental networks and the labor market.

Saxenian, A. (1994). *Regional Advantage: Culture and Competition in Silicon Valley and Route 128*. Harvard University Press.

Saygin, P. O., Weber, A., and Weynandt, M. A. (2019). Coworkers, networks, and job-search outcomes among displaced workers. *ILR Review*, page 0019793919881988.

Schmitt, K., Rattinger, H., and Oberndörfer, D. (1994). District Data (Censuses 1950–1987). ZA2472 Data File Version 1.0.0, GESIS Data Archive.

Schmutte, I. M. (2015). Job referral networks and the determination of earnings in local labor markets. *Journal of Labor Economics*, 33(1):1–32.

Sforzi, F. (1997). *I Sistemi Locali del Lavoro 1991*. Istituto Nazionale di Statistica (ISTAT), Rome.

Song, Z., Storesletten, K., and Zilibotti, F. (2011). Growing like china. *American economic review*, 101(1):196–233.

State Stat. Office of Bavaria (1981). *Statistisches Jahrbuch für Bayern 1981*. Fürth.

State Stat. Office of Hesse (1981). Die Bevölkerung der kreisfreien Städte und Landkreise Hessens am 31.12.1980 nach Alter und Geschlecht. Statistische Berichte / A / 1 / 3 / A 1 4, Wiesbaden.

State Stat. Office of Schleswig-Holstein (1981). *Statistisches Jahrbuch Schleswig-Holstein 1981*. Kiel.

State Stat. Office of Schleswig-Holstein (1990). Die Bevölkerung in Schleswig-Holstein nach Alter und Geschlecht 1990. Statistische Berichte / A / 1 / 3, Kiel.

Stoyanov, A. and Zubanov, N. (2012). Productivity spillovers across firms through worker mobility. *American Economic Journal: Applied Economics*, 4(2):168–198.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199.

Tattara, G. and Valentini, M. (2010). Turnover and excess worker reallocation. the veneto labour market between 1982 and 1996. *Labour*, 24(4):474–500.

Taylor, J. E. and Martin, P. L. (2001). Human Capital: Migration and Rural Population Change. In Gardner, B. and Rausser, G., editors, *Handbook of Agricultural Economics*, volume 1, part a 9, pages 457–511. Elsevier.

Terluin, I. J. (2003). Differences in Economic Development in Rural Regions of Advanced Countries: An Overview and Critical Analysis of Theories. *Journal of Rural Studies*, 19:327–344.

Terluin, I. J. and Post, J. H., editors (2000). *Employment Dynamics in Rural Europe*. CAB International, Wallingford.

Topa, G. (2011). Labor markets and referrals. In *Handbook of social economics*, volume 1, pages 1193–1221. Elsevier.

Trigilia, C. (1990). Work and politics in the third italy's industrial districts. *Industrial Districts and Inter-Firm Co-operation in Italy, Geneva: International Institute for Labor Studies*, F. Pyke, G. Becattini and W. Sengenberger (eds.):160–184.

Trigilia, C. (2020). Innovazione e territorio. *Podcast DIST - Lezioni Italiane, Puntata 5*.

UNESCO (2020). Socio-Economic Impacts of World Heritage Listing.

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.

Waldinger, F. (2010). Quality matters: The expulsion of professors and the consequences for phd student outcomes in nazi germany. *Journal of Political Economy*, 118(4):787–831.

Waldinger, F. (2012). Peer effects in science: Evidence from the dismissal of scientists in nazi germany. *The Review of Economic Studies*, 79(2):838–861.

Wang, T. and Chanda, A. (2018). Manufacturing growth and local employment multipliers in china. *Journal of Comparative Economics*, 46(2):515–543.

Weston, T. B. (2004). The iron man weeps: Joblessness and political legitimacy in the chinese rust belt 1. In *State and Society in 21st-century China*, pages 67–86. Routledge.

Whitford, J. (2001). The decline of a model? challenge and response in the italian industrial districts. *Economy and Society*, 30(1):38–65.

Willis, S. (2022). Workplace segregation and the labour market performance of immigrants.

Wuthnow, R. (2018). *The Left Behind: Decline and Rage in Rural America*. Princeton University Press, Princeton; Oxford.

Zacchia, P. (2019). Knowledge Spillovers through Networks of Scientists. *The Review of Economic Studies*. rdz033.

Zhu, X. (2012). Understanding china's growth: Past, present, and future. *Journal of Economic Perspectives*, 26(4):103–124.

Zinovyeva, N. and Bagues, M. (2015). The role of connections in academic promotions. *American Economic Journal: Applied Economics*, 7(2):264–92.