University of Siena

Doctoral School in Economics

Essays on labor mobility and network analysis

by

Carlo Gianelle

THESIS

SUBMITTED TO THE DEPARTMENT OF ECONOMICS

AND THE COMMITTEE ON GRADUATE STUDIES

OF SIENA UNIVERSITY

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY IN ECONOMICS

Supervisor: Prof. Francesca Bettio

Siena, Italy

September 2010

Acknowledgments

I would like to express my deepest gratitude to my advisor, Professor Francesca Bettio, and to Professor Giuseppe Tattara for their precious suggestions, insight, guidance, and constant support during my graduate studies and throughout the process of completing this Thesis.
I am truly indebted to Professor Andrea Ginzburg for first suggesting me to explore the literature on social networks; his original inspiration has led me to the invaluable experience of discovering an exciting research field.
The essay constituting the first Chapter of the Thesis, "Worker reallocation timing and the role of sector-specific skills. Evidence from microdata of labor mobility", has been written while I was visiting researcher at Laboratorio R. Revelli of Turin, whose hospitality I gratefully acknowledge. I would especially like to thank Professor Bruno Contini, the Director of Laboratorio R. Revelli, as well as the researchers Roberto Leombruni, Roberto Quaranta, Lia Pacelli, Francesco Devicienti, Matteo Richiardi, Claudia Villosio, and Edoardo Di Porto.
I would like to acknowledge and thank Professor Mauro Caminati for his advice during the very first steps of my research, and for providing me with the software used for modularity computation.
I also thank all the participants to the lunch seminar at the Research Department of the Bank of Italy on July 9th 2008.
The essays constituting the second and the third Chapters of the Thesis, respectively, "Discovering the network structure of labor mobility", and "Temporary employment agencies make the world smaller. Evidence from labor mobility networks", have been written while I was visiting researcher at the Center for Labor Economics of the University of California at Berkeley, which I gratefully acknowledge for hospitality. My sincere appreciation goes to Professor David Card for his kindness in giving me the opportunity to visit the Center for Labor Economics, and for his generous help and great academic advise.
I would like to thank Professor Giancarlo Ruffo for his encouragement to carry out this research. I am also thankful to Aaron Clauset, Cosma Rohilla Shalizi, and Mark Newman for making available the software used for the estimations of power-law distributions.
I am grateful to the participants to the 10th Trento Summer School on Networks and Innovation, and to the NetSci09 conference on network science.
A very special thank you to all my colleagues in the PhD program at the University of Siena, to all members of the Department of Economics, and to my numerous friends.
Last but not least, I would very much like to thank my parents, Gabriella and Tino, ant my girlfriend Roberta for their love and exceptional support.

Table of contents

Title page i

Acknowledgements iii

Table of contents v

List of figures vii

List of tables viii

Introduction ix

1 Worker reallocation timing and the role of sector-specific skills. Evidence from microdata of labor mobility 1

- 1.0 Abstract 1
- 1.1 Introduction 2
- 1.2 Theoretical background 5
- 1.3 The WHIP dataset 10
- 1.4 Reallocation timing and wage outcomes 12
- 1.5 Sectoral patterns of job change 18
- 1.6 Sectoral mobility and slow reallocation: a speculative interpretation 25
- 1.7 A network approach for identifying modular patterns of inter-sectoral mobility 29
- 1.8 Conclusions 34
- Appendix 1.1 36
- Appendix 1.2 40

2 Discovering the network structure of labor mobility 53

- 2.0 Abstract 53
- 2.1 Introduction 54
- 2.2 Theoretical insights on labor reallocation 56
- 2.3 Network definitions 59
- 2.4 Data and network construction 64
- 2.5 Small-world connectivity 65
- 2.6 A close look at the degree distribution 69
- 2.7 Hierarchical structure 75
- 2.8 The importance of hubs 77
- 2.9 Conclusions 82
- Appendix 2.1 85

3 Temporary employment agencies make the world smaller. Evidence from labor mobility networks 89

- 3.0 Abstract 89
- 3.1 Introduction 90

3.2 Outline of labor market intermediation …… 91
3.3 Temporary employment agencies in Italy (1997-2001) …… 94
3.4 Data: the Veneto Worker History panel …… 97
3.5 Network setup and empirical strategy …… 99
3.6 TEAs effect on job accessibility …… 104
3.6.1 Small-world analysis …… 104
3.6.2 Hub structure …… 111
3.7 Control over reallocation channels, and evolution of TEAs market power …… 114
3.7.1 Models of network formation …… 114
3.7.2 Empirical degree distributions …… 118
3.8 Conclusions …… 126
References …… 129

List of figures

Figure 2.1 Network with n=9, and m=10 ………………………………………………………..... 60

Figure 2.2 Strong components (blue, dotted), weak components (orange, dashed), and shortest path from vertex 6 to vertex 4 (green links) ……………………………………….. 61

Figure 2.3 Clustering coefficient: vertex 1 has max (a), intermediate (b), no clustering (c) 63

Figure 2.4 Complementary cumulative degree distributions and power-law fits ……………… 70

Figure 2.5 Hierarchical clustering …………………………………………………….....… 76

Figure 2.6 Impact of vertices removal on SCC coverage ……………………………………… 78

Figure 3.1 Vertices & links ……………………………………...…………………….. 106

Figure 3.2 Largest components (% coverage of the entire network) …………………………... 107

Figure 3.3 APL & ACC ………………………………………………………………….... 108

Figure 3.4 ACC (Y) *vs*. degree classes (X) ……………………………………...………….. 110

Figure 3.5 In-degree distributions, power-law fits …………………………………………….. 119

List of tables

Table 1.1 Relative wage outcomes related to job changes, OLS regression ………….....……... 16
Table 1.2 Frequency and incidence of sectoral changes ……………….....……………….......... 18
Table 1.3 Multinomial probit estimates of sector switches …………………………………… 24
Table A.1.2.1 Descriptive statistics ……...………………………………………………….... 40
Table A.1.2.2 OLS estimates of relative wage performances related to job change episodes ... 41
Table A.1.2.3 Community structure of quick-reallocation network …………………………... 42
Table A.1.2.4 Community structure of slow-reallocation network ………………………….... 46
Table 2.1 Network statistics ……………………………………………………………………... 66
Table 2.2 Power-law fit to actual data ………………………………………………...…..... 73
Table 2.3 Power law *vs*. alternative fat-tail distributions for discrete data …………………… 74
Table 2.4 The first 50 hubs by type of activity ……………………………….....…………... 79
Table A.2.1.1 Distributions ……………………………………………………………………… 88
Table 3.1 Total-degree distributions: main descriptive statistics ……………………...…… 111
Table 3.2 Ranking of the 10 biggest TEAs, according to total-degree ……………………….. 112
Table 3.3 Distribution fitting ………………………………………………………………….. 123

Introduction

This Thesis investigates the phenomenon of worker reallocation across firms, exploiting comprehensive matched employer-employee data, and making use of several analytical tools, especially, network analysis.

Two are the main strands of literature that constitute the background of the study: the investigation of labor market flows, based on administrative records tracking individual careers; and the research on the structure and dynamics of complex networked systems.

The flow approach to labor markets fully falls in the wake of labor economics, as the discipline has gradually developed over the past two decades, in response to an ever increasing availability of microdata which has pushed the search for new analytical methodologies suitable both to manipulate individual-level observations, and to extract information from huge amounts of data.

The analysis of complex networks is a truly multidisciplinary matter, with relevant applications in both social and exact sciences – e.g. sociology, political science, history, or physics, molecular biology, and computer science. Network studies were originally introduced in the first half of the past century by sociologists in search of an effective way for representing, and hence possibly at a glance grasping social interactions among small groups of people[1]. But the actual boost, that has allowed such methodologies to spread rapidly across field boundaries, dates back to the late 90s, when a bunch of great strides were made – mainly due to contributions from theoretical physics – that provided mathematical models, as well as statistical techniques allowing for the study of very large networks, driven by the opportunity, and by the necessity of studying global networks, such as the World Wide Web, involving thousands, or millions actors and interactions[2]. In recent years, economists too have been making increasingly use of network analysis tools, with prominent examples in game theory and innovation and business studies, yet, there are very few applications of networks to the investigation of labor markets and worker mobility[3].

At the origin of our work there is the intuition – at least the wish – of combining together the two afore mentioned threads of research, applying models of networks to worker mobility in the labor market; indeed, people moving between jobs can be naturally seen as links connecting together firms or sectors so as to form an intertwined system whose topology and functional properties can be quantitatively investigated.

---

[1] For instance, the seminal works of Jacob L. Moreno in the years 30s of the past century, William Lloyd Warner and Kurt Lewin in the 40s and 50s.

[2] The mathematical formalization of both the small-world model, by Duncan J. Watts and Steven H. Strogatz, and the power-law model, by Albert-László Barabási and Réka Albert, were developed in 1998-1999.

[3] Major contributions in game theory come from the work of Mattew O. Jackson; scholars using network analysis in innovation and business studies are Lee Fleming, Walter W. Powell, Jason Owen-Smith, just to mention a few.

Our endeavor is aimed at offering a detailed and perhaps unprecedented description of labor market structure at a very fine level of resolution, in order to usefully complement our actual understanding about how workers move between jobs, and more in general about how labor markets really work. In a network approach to employer-employee mobility, we recognize a particularly effective way for pinpointing micro-level dynamics of labor flows, and for enucleating emerging features of the worker reallocation process. Such elements – suitably organized and interpreted – may then provide useful indications for better policy design by the public authority.

Our interest in investigating worker reallocation does not merely stem from the evidence that worker mobility between jobs is a major feature of most contemporary labor markets in developed countries, but it is impelled by the awareness of the critical implications reallocation has both on individual working lives, and on the productivity of the economic system. Reallocation represents a fundamental passage in people's career, and at aggregated level, it is a key mechanism for augmenting productivity, that is the capacity of extracting value added from worker-employer matches[4]. The outcomes of both single workers and the entire economy are ultimately very strictly connected to the functioning of the reallocation process, and namely to its capacity of guaranteeing smooth transitions between jobs, quick adjustment of the labor market to changed macroeconomic conditions, and effective response to demand or technological shocks hitting industries selectively.

Issues connected with reallocation – its effects on workers and firms, the conduct of the economic actors involved, as well as the contractual forms and norms determining its licit boundaries – constitute a matter of harsh public debate in Italy, a country that has been characterized by high mobility of workers during the last decades, where substantial reforms of labor legislation have been invoked, announced, and partially realized, and where new actors – especially temporary employment agencies – have recently entered the market, modifying job searching strategies and recruitment behaviors. Yet, many aspects concerning the micro-dynamics of labor mobility are not known, and hence the need to devote new effort in investigating reallocation, devising novel ways to approach both the subject and the data.

To address comprehensively these topics implies setting a broad research agenda that encompasses very ambitious questions. With the work presented in this Thesis, we do not pretend to provide neither definitive answers to such questions, nor exhaustive systematization of such a complex matter; rather, we aim at achieving some specific and original results, in order to integrate the puzzle of labor market studies, in the hope of contributing with sensible and useful indications to the work of scholars and policy makers.

[4] The productivity-enhancing role of labor reallocation has been recently emphasized by Daron Acemoglu.

Throughout the study, our fundamental attitude of investigation is inspired by two principles: first, to provide – as much as possible, and to the extent allowed by the data at hand – multiple empirical results about a same phenomenon, exploring an extended range of interrelated occurrences to be evaluated in their mutual relationship, so as to possibly better orient economic interpretation; second, to rigorously test each piece of the proposed evidence, in order to substantially reduce the incidence of spurious and uncontrolled effects on the processes under scrutiny.

Our empirical investigation is based on administrative records from the Italian Social Security Institute. We employ two different databases, the Worker Histories Italian panel, WHIP, and the Veneto Worker Histories panel, VWH. Both databases are built on the same type of source data, covering private sector employees, and consist of employer-employee matched observations. WHIP is a 1:90 sample representative of the whole Italian population, and we especially utilize the annual files referred to the period 1987-1998; VWH covers the whole population of private workers in a region situated in the North East of Italy, Veneto, and we focus on the period 1991-2001.

The analytical toolbox we employ for investigation is quite varied, spanning from standard econometric techniques for assessing polytomous choice behaviors, structural measures aimed at revealing local and global topological features of large networks, tests for non-Gaussian statistical distributions, to algebraic algorithms designed for uncovering the block-model structure of a network from its matrix representation.

The Thesis is composed of three Chapters, corresponding to three different essays with the following titles:

1) "Worker reallocation timing and the role of sector-specific skills. Evidence from microdata of labor mobility";
2) "Discovering the network structure of labor mobility";
3) "Temporary employment agencies make the world smaller. Evidence from labor mobility networks".

The first Chapter, "Worker reallocation timing and the role of sector-specific skills. Evidence from microdata of labor mobility", utilizes the WHIP dataset, and focuses on the timing of reallocation, comparing two fundamental categories of job changes: those occurring with no intervening spell of unemployment, termed quick reallocations, and those in which two to twelve months elapse between separation and the next engagement, termed slow reallocations.

The literature background we rely upon comprises models of worker turnover over jobs at the individual level, search and matching models of equilibrium in the labor market, and empirical works on skill specificity at firm and/or industry level.

We systematically explore the complex web of correlations linking together reallocation timing and two particular dimensions characterizing job change events: wage outcomes, and sectoral switches.

Our analysis disproves the common presumption that slow reallocations are most likely due to displacement from previous jobs, while we show slow re-employments are associated to significantly worse wage performance, compared to job-to-job transitions. Moreover, we demonstrate that sectoral switches tend to worsen the wage performance of slow reallocations.

On this basis, we turn our attention to the inter-sector mobility patterns embedded in job changes, in the attempt to understand whether they can reveal some indications about the possible cause of long reallocation time. We find that the propensity to switch between narrowly defined industrial sectors is remarkably lower for people reallocating slowly, but conditional upon changing micro-level sector, the probability of switching macro-level sector is substantially higher for these people, than for job-to-job movers.

Finally, we employ a network-based algorithm in order to identify the cluster structure of sectoral mobility, and we find that quick reallocations tend to form smaller clusters of industries, which are homogeneous from a product/technology point of view, while slow reallocations give rise to larger and more variously assorted groups of sectors.

We propose a speculative interpretation of reallocation difficulties, that has the advantage of explaining the collected evidence all at once. We argue there must be a different distribution of sector-specific skills among individuals, that eventually plays an important role in determine reallocation outcomes. Specifically, we suggest that people experiencing slow reallocations are characterized by more sector-specific skills, compared to people realizing quick reallocations; the key difference between the two types of movers being that sector specificity manifests itself prevalently at 3-digit level for individuals reallocating slowly, while it is mostly related to wider economic areas for people reallocating quickly. Our conclusion is that professional profiles strongly dominated by skills which are specific to narrowly-defined sectors are likely to be a disadvantageous factor for people in search of new jobs.

Clear policy implications straightforwardly follow from such interpretation. Interventions should be explicitly devised in order to provide people with general education and general training off-the job, suitable to crystallize into skills portable across many jobs; at the same time, workers and their representatives should pay much attention to negotiate with employers a certain amount of general training on-the-job, that may turn out being an effective insurance against costly job search and prolonged reallocation time.

This is the first essay we carried out in our research, and it is mostly an exploratory study, as it is evident from the way the Chapter is conceived and structured: a progressive collection of stylized facts, knit together by a tentative interpretation. We took advantage of this study as an initial opportunity of training, in order for developing familiarity with the information contained in, or extractable from individual social security records, and for building the capacity for manipulating very large databases.

Network-based evidence is introduced just for complementing, and further proving the main results previously obtained by means of econometric analysis. Nevertheless, although network analysis is used as a minor source of information, the cluster-identification technique we employ represents one of the most advanced tools available to detect network partitions, and we provide an original adaptation of the Newman-Leich algorithm to the more general case of weighted networks.

The second Chapter, “Discovering the network structure of labor mobility”, focuses on worker reallocations between jobs from the VWH dataset, and it explores the web of interconnections linking together firms (vertices) by means of worker flows (links), with instruments typical of complex network analysis. Two are the main lines of enquiry: we test whether the labor network exhibits the features of a small world, then we estimate the statistical distribution of links over vertices, in order to assess the presence and functional role of hub firms.

The literature insights we start from in order to shape our empirical investigation span from the positive relationship between factor reallocation and economic growth, to the paucity of micro-level studies on worker reallocation in the current literature on applied labor economics, up to the importance of understanding micro-level reallocation mechanisms for designing effective welfare schemes aimed at supporting individual income during unemployment.

By examining an organized set of topological features, we are able to show the Veneto labor network clearly exhibits the nature of small world, i.e. it is an interconnected system, essentially dominated by local clustering, with a relatively few long-range links that act as shortcuts, connecting different bunches of vertices which otherwise would be much farther away from each other. The crucial functional significance of such an architecture is to guarantee high accessibility of network locations, i.e. to make it easy reaching a relatively large fraction of vertices from any initial position in the network. The small world is a well known network model, and in the specific context under scrutiny, it guarantees effective mobility of workers across the labor market.

In order to understand which key actors the small-world connectivity relies upon, we then shift the attention towards the statistical distribution of links over vertices, showing it is very unequal, with marked right-skewed shape, and demonstrating it is well approximated by a Pareto distribution. This means the small world of labor mobility is dominated by a few large hub firms, i.e. firms controlling many more reallocation channels than average, having the fundamental role of keeping the system integrated while also providing shortcuts for network traversal.

The main hub firms can be classified into three categories: (1) big and long-tradition manufacturing firms; (2) companies involved in services and commerce, typically organized into chains of stores, or performing services directly at the costumer's; (3) temporary employment agencies and cargo handling subcontractors.

For the labor network to maintain its small-world character, we should pay attention to preserving existing hubs, or to favoring the emergence of new hubs in substitution of those which close down. In particular, we should be concerned about the survival and performance of big, long-tradition manufacturing firms, and explicit strategies should be devised in order to achieve this goal. The failure of such firms – whose operations are today critically threaten by competition from low-wages countries, and by the worldwide economic crisis – might indeed result in the sudden occurrence of structural holes within the network, which in turn are most likely to hinder the reallocation mechanisms.

Another interesting result emerges from our analysis. The network exhibits two-regime hierarchical clustering, that is a two-slope negative relationship between the cluster coefficient and the number of vertex connections. Clustering scales down slower with connectivity for firms of small size, than for firms of medium and large size. This suggests that when designing policies aimed at favoring firms dimensional growth, we have to make sure we are providing firms with suitable tools in order to expand their labor markets beyond the boundaries of local communities.

This essay operationalizes a range of concepts and models of complex networks into the specific context of labor mobility, so laying down the foundations for the next Chapter. In particular, the functional significance of the small-world model is made explicit and extensively discussed, as well as the role of hubs, and the general meaning of right-skewed link distributions. The network tools we employ turn out to be useful in order to extract unprecedented information about labor market structure; moreover, they also prove themselves to be of significant help in the prospect of monitoring market trends, pinpointing potential policy targets with a level of detail up to the single firm.

The emergence of a special category of hubs, temporary employment agencies (TEAs), led us to focus our interest on the relationship between labor intermediation and the structure of labor networks. TEAs represent a relatively new phenomenon in the Italian labor market, and given their role of brokers of labor mobility, we expect they can significantly influence the process of worker reallocation. The third Chapter, “Temporary employment agencies make the world smaller. Evidence from labor mobility networks”, asks precisely how the labor market reform of 1997, that allowed for TEAs, has impacted on the worker reallocation network. Two are the main research questions we pose: (1) how, and to what extent intermediaries affect accessibility of jobs for people who reallocate within the market; (2) how the market power of intermediaries in controlling worker reallocation flows evolves over time, and which are the fundamental dynamics of such process.

Finding an answer to these questions is ultimately an attempt of identifying and measuring the terms of the trade off between the advantages of intermediation, given by increased information availability for the parties, resulting in higher accessibility of job opportunities, and the detriments associated to the concentration of labor transactions in the hands of intermediaries. Both effects are inherent in the activity of labor brokerage, and originate from the fact that people seek for most informed intermediaries, in order to take maximum advantage of intermediation services, while intermediaries obtain information through market transactions with customers, so that intermediaries with many customers tend to be more attractive, and the market evolves according to a cumulative-advantage logic that favors concentration, i.e. the emergence of a few big intermediaries dominating the market for reallocation services.

The literature we rely upon encompasses both studies on labor market intermediation and models of network structure and formation. The rationale for the existence of intermediaries is found in labor market imperfections that hamper an efficient matching between demand and supply of labor, hence leaving scope for profitably providing search and screening services to both workers and employers. As in the previous essay, we employ models of networks in order to understand the functional significance of mobility patterns, and to appreciate the role of TEAs within the system, aiming at possibly pinning down the fundamental mechanisms of labor mobility and network evolution.

We operationalize the notions of job accessibility and market concentration in the context of a labor mobility network. Our first choice is to evaluate job accessibility by quantifying the impact of TEAs on the small-world architecture of the network, interpreting the tendency of the world of worker mobility to become smaller as the signal of increased job accessibility, and vice versa. Next, we focus on the TEAs power of controlling hiring channels, as revealed by the number of incoming links of TEAs in the network; we assess the statistical distribution of connections over vertices, and we outline a process of network formation that can reproduce the main empirical findings.

What we do in this Chapter is to address a specific economic problem – labor market intermediation – by applying two network concepts – the small-world model, and the link distribution – that we have defined and discussed in the Chapter “Discovering the network structure of labor mobility". The two essays are indeed different stages of a unique research: the first step consisting of building up the analytical tools, and assessing their viability and performance in the specific context of labor mobility; the second step being the application of such tools to the analysis of a particular subject that is economically relevant.

We construct and examine a series of year networks obtained by mapping worker reallocations in the VWH dataset, and we calculate structural properties such as network size, components coverage, average clustering coefficient, and average path length. We find that, after the economic downturn of 1993, the complex web of labor mobility stably exhibits the features of a small world. Through counterfactual analysis, we further establish that TEAs, soon after their establishment, make the world of labor mobility significantly smaller, reducing average network distance and increasing clustering, hence making the labor market more accessible.

We then move on to the second research question. To this aim, we define the number of incoming links a firm has as the share of hiring channels the firm directly controls, hence obtaining a network-based measure of market power of each single employer. We find the distribution of links is right skewed, with a fat tail, and it is well approximated by a power-law or Pareto function all over the period considered.

Before the arrival of TEAs, the distribution stably exhibits a distinctive upper cutoff, meaning that there are some forces at play that effectively prevent single firms from controlling extremely massive shares of reallocation channels.

Soon after 1997, TEAs gather in the extreme tail of the link distribution, and they visibly modify its shape, pulling up the right tail even beyond the prediction of a pure power-law model. TEAs offset the forces producing the cutoff, and trigger a polarization of the market that can be precisely appreciated through statistical tests. Such evolution clearly reveals a process of concentration of the market for labor reallocations in the hands of a few TEAs.

We next introduce a model of network formation aimed at explaining attachment decisions, and hence at identifying the dynamics of the process by which TEAs drive the evolution of the link distribution. We assume workers are located in a space where there exist possible targets for reallocation moves; when reallocating, each worker establishes a link going from its initial location (firm) to the target one, so that it is possible to define a distribution of incoming links over locations. Workers look for targets that provide high location advantage, i.e. targets that have many connections, and which are reachable with low cost, i.e. targets that are close to the initial position in the space. Most relevant for us, such trade-off-optimization model gives rise to power-law distributed networks, where the exact shape of the link distribution depends crucially on the relative weighing between the cost variable (distance) and the benefit variable (connectivity).

Such model fits well the empirical distributions, and the impact of TEAs can be thought as equivalent to reducing the importance of attachment cost relative to connectivity advantage, hence making the connectivity variable to primarily drive reallocation decisions. According to the model, if the relative importance of attachment cost is sufficiently small, the system will evolve towards an extremely polarized configuration in which a small number of locations, or just one single location will attract all attachment decisions. In our case, this amounts to say a few TEAs would end up dominating the market for reallocations. Therefore, the correspondence between the empirical results and the theoretical predictions turns out having relevant implications for policy.

Since there are forces pushing reallocations in the hands of bigger intermediaries, we believe the evolution of intermediated labor markets should be monitored, and markets should be consequently regulated, in order to prevent the emergence of monopoly power that might offset the advantages of intermediation. Moreover, our analysis shows the system tends to evolve according to a cumulative-advantage logic; once in force, such a mechanism is very difficult to halt, or to mitigate, because the incentive structure at work is inherently self-reinforcing. It straightforwardly follows that regulatory interventions must be particularly prompt and vigorous, if we want them to be successful. This argument in turn reinforces the need for effective market monitoring.

We believe that – provided good and updated data are available for investigation purposes – an analytical strategy of the type presented in this essay can provide both effective monitoring of market conditions, and ways of evaluating relevant economic variables on which to base policy interventions.

1 Worker reallocation timing and the role of sector-specific skills. Evidence from microdata of labor mobility

1.0 Abstract

In this Chapter we present and interpret an organized set of stylized facts about the phenomenon of worker reallocation in the Italian labor market. We devote particular attention to job changes characterized by the presence of unemployment spells between subsequent employments, which we term slow reallocations, and which are contrasted with quick, job-to-job reallocations.
Job change events are recovered from social security records tracking down the work histories of a representative sample of employees in the private sectors during the period 1987-1998.
We find that slow reallocations are generally associated with worse wage outcomes, compared to quick transitions.
We then explore sectoral patterns of labor mobility, with the aim of casting light on the characteristics which may determine reallocation time. The propensity to switch between narrowly defined industrial sectors reveals to be remarkably lower for people reallocating slowly; but conditional upon changing micro-level sector, the probability of switching macro-level sector is substantially higher for these people, than for job-to-job movers. Moreover, quick reallocations tend to concentrate around smaller sectoral clusters, which are homogeneous from a product/technology point of view, while slow reallocations form larger and more variously assorted sectoral communities.
We speculate that the collected evidence is compatible with the idea that individual sector-specific skills are important in determining reallocation timing, with more specific skills ultimately determining higher reallocation difficulties.
The implications for policy that directly derive from such interpretation are clear, workers should bargain harder for general training on-the-job, while public authorities should be concerned by providing more portable skills, either through formal education, or through professional training off-the-job.

1.1 Introduction

The mobility of workers between jobs is a relevant feature of contemporary labor markets in most developed countries. The incidence of job changes over the lifecycle of individuals is typically very high in Anglo-Saxon countries, but it is quite significant also in some countries of continental Europe, like Italy and France (Contini and Pacelli, 2005). Employment relationships are mostly long-term, nevertheless, individual work histories are not simply a matter of getting hired in a job, when entering the labor market for the first time, and then holding it until retirement; more and more, working lives are punctuated by employment changes, sometimes with intervening periods of unemployment, temporary exit from the labor force, or sequences of very short employment spells in seasonal or time jobs.

Job changes affect workers in various ways, but their relationship with occupational outcomes is generally not clear cut a priori. On the one hand, job changes play a fundamental role in promoting individual careers, contributing to upgrade professional profiles, and to rise wages. The flowing of workers across jobs can be indeed viewed as a resource-reallocation mechanism that in principle allows to extract a higher value added from worker-employer matches, hence yielding higher payoffs for both parties. On the other hand, to move from one job to another may be difficult and costly for workers, requiring a prolonged period of search, either on- or off-the-job. In turn, when experiencing a long period of unemployment, and bearing substantial search effort, people may be more willing to mismatch, to the detriment of employment conditions. This is particularly true when labor demand is low, information about vacancies is hardly accessible, or when individual skills are specific to narrowly defined sectors, thus offering limited possibilities of re-employment. More in general, the matching process through which employee and employer establish a relationship is uncertain by nature, and it may result in bad matches, calling for further revision.

In the present Chapter we establish an organized set of empirical regularities – some of which are unprecedented in the literature, to the best of our knowledge – concerning job changes, with the primary aim of characterizing patterns of interrupted careers, or difficult reallocations, eventually inferring some plausible mechanisms at the root of such difficulties.

The first and most intuitive way in order to appreciate the success of job changes is to look at the *pace* of labor reallocation, that is to say whether individuals pass from one job to another with or without experiencing periods of unemployment. Unemployment is obviously harmful for workers, because it leaves people without salary, and it hampers the accumulation of pension requirements, bearing down on future income as well. Besides, unemployment is most likely to progressively induce people to adapt to worse and worse job conditions, and to accept wage cuts – this phenomenon is known as the "scarring" effect of unemployment[1]. In more general terms, unemployment and poor reallocation outcomes can be the simultaneous effects of a common cause, most likely an individual characteristic, for instance the lack of certain qualities, like professional skills, or entrepreneurial ability. Hence, periods of unemployment interrupting working careers may signal categories of workers which are particularly vulnerable and exposed to more bumpy, and less rewarding working-life paths.

Our measures of worker turnover in the private, dependent employment in Italy, referred to the period ranging from mid 80s to late 90s, show that 26% of the total sum of separations and engagements is accounted for by transitions from job to job, with at most one single month elapsing between separation and consequent engagement, 28% refers to reallocations occurring in two to twelve months, i.e. with career interruptions, 9% is related to workers engaging into new jobs one to two years after leaving old jobs, the rest being new accessions, retirements, and a minority of very long-term transitions[2]. The share of worker mobility explained by job changes taking place in two to twelve months is quite impressive, revealing that career interruptions are indeed a major phenomenon, punctuating people's working lives[3].

Career interruptions of the type mentioned above may in principle result from the deliberate choice of workers to leave the labor market for some time, remaining inactive, in the prospect of promptly finding a new job, when deciding to re-enter private employment. If this is the case, the observed re-entry times do not reflect actual difficulties in finding jobs, but rather voluntary unavailability of people to work. However, in a country like Italy, that has been affected by persistent, high unemployment all through the 90s, such occurrence appears to be unlikely, all the more that maternity and sick leaves – typically representing major reasons in order for temporarily stopping working – are acknowledge by law in all National Labor Contract[4]. It seems much more probable that the observed interruptions represent true unemployment episodes, stemming from job matches that have simply come to an end, owing to dismissals, or to workers' decisions to quit, possibly against their real will.

Building on such observations, we carry out an empirical investigation by first pinpointing career interruptions, based on reallocation timing, and then developing a comparison between quick and

---

[1], See for instance Arulampalam (2001), Gregory and Jukes (2001), Arranz *et al.* (2005), Garcia-Perez and Rebollo-Sanz (2005).

[2] Turnover measures are obtained from the administrative dataset that will be presented in the next Sections. A similar analysis can be found also in Leombruni and Quaranta (2005).

[3] In the sample of workers we consider hereafter, 5.8 months elapse, on average, from the separation to the following engagement, for people reallocating in two to twelve months; descriptive statistics are in Table A.1.2.1 of Appendix 1.2.

[4] Our study refers only to employment relationships in the private dependent employment, mostly governed by open-ended contracts negotiated at national level which provide substantial employment protection.

slow reallocations, encompassing the whole essay[5]. We devote most endeavor in exploring the complex web of correlations between reallocation timing, wage outcomes, and sectoral switching patterns. In particular, we believe the sectoral dimension of job changes can effectively hint at factors determining the short-term unemployment spells we observe in the data. At the root of such approach lies the idea that any diversity found in the sectoral patterns of slow reallocations, compared to quick reallocations, may reveal, albeit indirectly, some fundamental traits associated to reallocation difficulties, which are not otherwise directly observable in the data.

For instance, different patterns of sectoral mobility may hint at more or less sector-specific skill endowments, that in turn may result in sizably different chances of finding jobs in the labor market. Are people who maintain a close relationship with restricted clusters of productive sectors more successful than others in reallocating? Or alternatively, are the most furthered those who move across sectors, because of more portable competences that can be exercised and remunerated in different areas of the economy? Questions of the kind are of primary importance for our understanding of labor market functioning, and our investigation aims at producing useful clues, in order to find answers.

We are impelled to undertake this type of study also by a mass of research on real business cycle and macroeconomic fluctuations, indicating how frictions in the mechanism of labor reallocation, stemming from sectoral specialization of skills – that is sector-specific human capital – can significantly hamper the flowing of workers across sectoral employment basins, in response to asymmetric demand shocks, resulting in higher unemployment for workers dismissed from declining sectors[6]. The major difference between the present study and previous works, is that we consider all types of worker transfers that take place in the market, capturing reallocations not just originated from displacements and crises; hence, we are able to study sectoral mobility with respect to the bulk of labor mobility, exploring its relationship with reallocation timing.

Making use of Social Security longitudinal records, referred to a representative sample of Italian workers in the period 1987-1998, we are able to show that the sorting of workers according to whether they experience or not a spell of unemployment between subsequent jobs is not primarily determined by the dismissed/non-dismissed condition at the time of separation. Most indirect reallocations do not originate from layoffs, nevertheless, they prove to be associated to significant wage losses, compared to direct transitions.

[5] Henceforth, quick transitions are also referred to as *job-to-job* or *direct* reallocations; slow transitions are also termed *indirect* reallocations (more detailed definitions can be found in Section 1.4).

[6] See for instance Lilien (1982), Davis (1987), Davis *et al*. (1996), Haltiwanger and Schuh (1999). Theoretical models of labor reallocation which take explicitly into consideration the sectoral segmentation of the labor market as well as possible attritions in the inter-industry transitions have been proposed by Lucas and Prescott (1974), Langot (1997), and more recently, by Rogerson (2005).

We then set up a regression framework, aimed at evaluating how reallocation timing is correlated to the propensity of switching industrial sector of employment. Our key finding is that, compared to job-to-job movers, people experiencing career interruptions tend to remain more attached to the original micro-level industrial sector, but when leaving such economic branch, they are more willing to change macro-level sector.

Finally, we resort to a network-based methodology in order to discover and explore the group structure of inter-sectoral worker flows. Such analysis further reveals that job-to-job movements tend to concentrate around smaller clusters, that are somewhat homogeneous in terms of technology/products, while indirect reallocations group into larger, and more variously assorted communities of economic activities.

All findings appear to be consistent with the idea that reallocation difficulties may be caused, to a significant extent, by professional endowments being specific to very narrow sectoral labor markets. This speculative interpretation – besides being based on sensible and quite insightful principles, and also in accordance with findings well-established in the literature – appears to be very effective in explaining all at once the whole set of empirical results. Implications for policy are quite straightforward. In order to facilitate reallocation, and hence an efficient functioning of the labor market, public authorities should be concerned about providing workers with a good basis of general, or portable skills, either directly, through general education, or by promoting ad hoc off-the-job training. At the same time, workers and their organizations should be seeking for contracting on-the-job general training.

The Chapter is organized as follows: Section 1.2 reports and comments on some relevant contributions of the literature on worker turnover, job matching, and sectoral mobility of labor; Section 1.3 describes the administrative dataset we employ; Section 1.4 outlines the difference in the relative wage outcomes associated to direct and indirect job changes; Section 1.5 presents the estimates of the probabilities to change 3-, 2-, 1-digit sector in a logistic regression framework; Section 1.6 proposes a speculative interpretation of the evidence so far collected; Section 1.7 introduces the network-theoretic tool for the analysis of sectoral mobility, and discusses the results; finally, Section 1.8 concludes.

1.2 Theoretical background

The phenomenon of worker turnover has been addressed quite extensively in labor economics literature. Two are the main sources from which the flowing of workers across jobs originates:

(i) the reallocation of workers over existing jobs; (ii) the turnover of jobs generated by market forces, that in turn gives rise to workers reallocation from ceased to new jobs.

The *job-matching approach* to labor turnover offers a substantial body of theoretical research that provides an explanation for the turnover arising from the deliberate choice of one of the parties to cease an existing employment relationship. Essentially, separations – namely, the breakdown of employer-employee matches – of such kind are generated by the interest of the parties, worker and employer, in revising their match, whenever more valuable opportunities can be foreseen. Permanent separations occur any time entrepreneurs look for improving the productive assortment of their employees (layoffs or dismissals), or when people voluntarily leave their position, searching for a better job (quits).

A rationale for job turnover can be found in the domain of creative-destruction models of economic growth. In this view, endogenous innovations cause the displacement of less productive establishments in favor of more productive ones, generating a worker reallocation flow that goes in the same direction. Similarly, demand shifts trigger the reallocation of production and of the associated jobs from declining economic sectors to expanding ones.

Job-matching theory constitutes perhaps the most familiar setting for modeling individual worker turnover in micro-labor economics; at the same time, this theory is also the basis for the study of aggregate labor market dynamics, as in unemployment equilibrium models. The ultimate engine of turnover is assumed to be the variation in the value of labor productivity across different worker-job matches, and thus the variation in the payoffs of the parties involved. Models embedded in this tradition presuppose, on both sides of the market, imperfect information about the exact location of a worker optimal assignment; moreover, employers are allowed to contract with workers on an individual basis.

The classical framework proposed by Jovanovic (1979a) assumes that for each worker/employer a non-degenerate distribution of productivities across jobs/workers exists. The quality of the employer-worker match is initially uncertain, it is an “experience” good, in that the only way to determine it is to form the match, and experience it[7]. The real productivity of the match is then revealed gradually over time through an output signal. Assuming the parties share the value of labor productivity according to some predetermined and fixed rule, if the realized match quality turns out to be lower than the reservation match quality, worker and employer have the option of ending the match, and subsequently starting an employment relationship with a different counterpart. Hence, turnover arises as the optimal reassignment of workers to jobs, caused by the accumulation of new information about existing matches with the passage of time.

[7] The same notion is also used by Johnson (1978) in modelling job shopping over working life.

In Jovanovic's original formulation, workers receive the full value of their marginal productivity; firms are thus indifferent to whether workers stay or leave, and all relevant separation decisions are quit decisions. Moreover, only movements from job to job are considered, and no assumptions are made in order to explain how workers can locate alternative jobs. Nevertheless, this simple scheme accounts for a range of empirical findings about the correlation between tenure and turnover. Most importantly, the model predicts that the worker's probability of separation is a decreasing function of job tenure. This is because a worker-employer mismatch is more likely to be detected early than late, and bad matches are expected to end relatively quickly, once the low quality is acknowledged.

Building on the same basis, Farber (1999) notices that the gradual mechanism of information disclosure/detection also provides an explanation for the increase in monthly separation frequency observed very early in job relationships. At the very beginning of an employment relationship, uncertainty about match quality is likely to be very high, while quitting/dismissing can be costly; thus, there actually is option value in the match, and workers and employers may decide to continue with the relationship, despite some signals of poor match quality. Over the very first months after engagement, as the information about match quality is revealed, separation rates increase, and bad matches are dissolved. The remaining matches are then high quality matches, whose separation rates are low and decline in time.

Early on-the-job search models of individual turnover, like those proposed by Mortensen (1978) and Jovanovic (1979b), look at the matching process in a different way[8]. A worker-employer match is considered to be a "search" good, implying that existing matches dissolve due to the discovery (location) of new information about alternative opportunities, while the parties are assumed to be able to value any prospect match with certainty, once located. The search strategy consists of two components: a criterion for acceptance of alternative matching occasions, and a measure of search intensity, that ultimately determines the frequency with which alternatives are located. An established match survives until a better alternative is discovered by either agent. The main contribution we can grasp from such models is that the process of locating alternatives in the labor market is realistically costly and time consuming, generating a trade off between the benefits and costs of stronger search.

In another piece of work, Jovanovic (1984) goes a step further, merging together his classical matching model (Jovanovic, 1979a) and the search framework proposed by Burdett (1978), allowing for search both on- and off-the-job, and hence for moves from employment to employment, as well as from employment to unemployment, and vice versa. The resulting model provides two main contributions to the characterization of job-to-job movements. It predicts that

[8] For a survey of search-theoretic models of the labor market, see Rogerson *et al.* (2005).

workers are inclined to give up a job with a stable wage, in favor of a job with a lower initial wage, provided that the new job guarantees the chance of growing wages. Moreover, as tenure increases, workers can become more inclined to quit, as long as their wages remain constant, and their non-firm-specific productivity grows.

Both Jovanovic (1979a, 1979b) and Mortensen (1978) explain the negative, structural relationship between separation probability and job tenure, by means of the accumulation of firm-specific human capital[9]. Match quality depends on characteristics both of worker and employer, hence it is inherently match specific, and therefore, it can be viewed as a form of firm-specific human capital. High quality means there is something valuable in the match between worker and firm, that has no value outside the relationship; in this case, neither party has incentives to end the match.

In general, specific capital of the kind so far discussed accumulates over time, as result of non-recoverable investments in the employment relationship. A typical example is the training of workers in particular skills that have a role in the firm, but no value elsewhere. Then, the meaning of the matching models proposed by Jovanovic and Mortensen can be rephrased as follows: as tenure increases, firm-specific capital accumulates and, consequently, the likelihood of separation decreases. High levels of specific capital can explain the existence of long-term employment relationships, while low levels can be compatible with more frequent separations. However, as highlighted by Farber (1999), it is difficult to empirically validate the specific-capital interpretation, because specific capital is not observed directly, and the wage need not reflect productivity, when there is specific capital.

The single-agent models so far mentioned define the essential incentive scheme for individual turnover, and they are the base of the equilibrium approach to matching in labor markets, used in macroeconomics. Models belonging to this latter strand focus on aggregate job flows, as opposed to individual turnover; a well-known example is the equilibrium unemployment model developed by Mortensen and Pissarides (1994). In their framework, the process of matching takes place between job vacancies and unemployed workers, no on-the-job search is considered, and worker flows are generated only by job turnover. Jobs are created or destroyed, according to idiosyncratic productivity shocks arriving randomly. Job turnover hence arises as a consequence of varying uncertainty in match productivities.

Pissarides (1994) also proposes a search-equilibrium setting that allows for both on- and off-the-job search. More recently, Moscarini (2005) brings together the microeconomic and the

[9] In Jovanovic (1979a), specific capital has the form of information about the quality of the worker-employer match. The process of accumulation of specific capital over time is symbolized in this case by the progressive revelation of information about match quality.

macroeconomic views of matching in labor markets, nesting a job matching model *à la* Jovanovic (1984) into a Mortensen and Pissarides (1994) equilibrium search environment.

As far as sectoral mobility of workers is concerned, Parnes (1954) is probably the first author to provide a systematic contribution on this topic. The author introduces explicitly the difference between reallocations involving a change of employer, but not of the type of work, and reallocations characterized by changing both employer and type of tasks performed. Parnes also provides some empirical evidence showing that the latter type of job changes is more frequent among young workers, who also engage in a higher number of changes.

The distinction introduced by Parnes is used by Neal (1999) to study job changes among young workers, and for developing a two-stage model of job search. Workers first search for career type, and once they have found it, they look for a firm match. Changes in type of job are thus more likely to occur early in working life, while, as experience accumulates, workers are more likely to search over employers, within the same career. It straightforwardly follows that the probability to observe cross-industry mobility declines, as working experience increases. Using data from the National Longitudinal Survey of Youth in the US, Neal offers some evidence in direct support of this interpretation, showing that more than half job changes made by young men involve both a change in job and a movement across sectors.

Jovanovic and Moffit (1990), and more recently Greenaway, Upward, and Wright (2000), argue that inter-sectoral mobility is due more to job-worker mismatches, than to sectoral shocks. A large fraction of job creation/destruction and of job changes occurs within narrowly defined industries, and therefore, the prevailing forces driving reallocation flows are likely to be firms and workers idiosyncratic differences. Demand shocks that impact on sectors differentially generate a net flow between sectors only through a wage effect: an unfavorable shock in a given sector produces a cut in the wage firms are disposed to pay, consequently workers start looking for more appealing jobs in expanding sectors. Of course, such a reasoning applies only in labor markets where wages are highly flexible and are allowed to adjust downward.

Using Quarterly labor Force Survey data for the UK, Elliott and Lindley (2001) explore the consequences of within- and between-industries adjustment on individual wages, and on the transition into and out of unemployment. They find that the wage differential received by between-industry movers is lower than the one obtained both by within-industry movers and by stayers, suggesting that workers who change industry – especially manual workers – are more exposed to wage losses, as a consequence of loss in industry-specific human capital. The authors also find it is not always the case that workers with lower qualification are less mobile between industries.

The multi-sectoral model of job search and matching proposed by Moscarini and Vella (2000), predicts mobility across sectors is negatively affected by skill specialization, and positively affected by depressed labor market conditions. In a recent work, Golan, Lane, and McEntarfer (2007) address directly the issue of sectoral changes, using matched employer-employee data drawn from the Longitudinal Employer-Household Dynamics Programme of the US Census Bureau. The authors find that workers who are employed in industries providing low returns to tenure are much more likely to reallocate across industries, implicitly supporting the idea that accumulation of industry-specific human capital has a negative effect on cross-sectoral mobility.

Haynes, Upward, and Wright (2000) compare US and UK data to test the "smooth adjustment hypothesis", that states intra-industry reallocations are less costly than inter-industry ones. They find that workers employed in declining sectors are more mobile in both countries, and in general, individuals are more likely to switch sector the longer they are unemployed. Moscarini and Vella (2008) focus on occupations, rather than on industrial sectors, and based on matched monthly files from the Current Population Survey in the US, they find that occupational mobility declines with age, family commitments, and education. But high aggregate unemployment somewhat offsets the role of such variables in the choice of career. The idea conveyed is that, when few jobs are available, workers accept any job that comes along, and they are willing to mismatch, whereas when jobs are easy to find, individual comparative advantages matter more, and unemployed workers search more selectively, and mismatch less.

1.3 The WHIP dataset

We base our investigation on the Work Histories Italian Panel, WHIP in short, a longitudinal panel made up of administrative records covering both firms and workers, obtained from Inps, the Italian Social Security Institute[10]. The original Inps archives comprise private firms active in industrial and service sectors, with at least one employee; agricultural firms are excluded, but services and other activities connected with agriculture are included. The central administration of the State is entirely absent from the archives; mail services, state school teachers, administration of justice, army, and government agencies are excluded as well. However, the archives cover companies owned or controlled by the State, and public utilities (water, electricity, energy supply, municipal transportation). Apart from services offered directly by the central administration of the State, then, an almost complete coverage is granted for dependent employment in industrial and service sectors.

[10] The WHIP database is developed by the Laboratorio R. Revelli – Center for employment studies, based in Turin, Italy: http://www.laboratoriorevelli.it/whip.

Each year and for each employee, the following information are available: place of work, months for which wages are paid, number of weeks and days actually worked, date of closure of the relationship with the current employer, total wage received, type of occupation (apprentice, blue collar, white collar, manager).

Inps archives keep track of the individual wage on which social security contributions apply, which in most cases comprises of the amount of money a worker receives while actually supplying labor (including overtime, night shifts, and holidays work bonuses), as well as certain non monetary benefits like meals, and possible supplements due by employers. Such amount constitutes the basic workers earnings.

For each employer, the following data are recorded: firm location, dates of beginning and closing down of activity, code of the main economic activity. Besides, each month for each employer, the average number of employees by occupation, and the total wage bill by occupation are recorded.

The WHIP database is a representative sample of the Italian working population, in the economic areas covered by Inps. The longitudinal sample is obtained as follows: for each calendar year in the period 1985-2001, the records of the employees born on the 10th of March, June, September and December are selected. In this way, a sequence of roughly 1:90 systematic samples of the Italian population is formed. Each year sample includes approximately 100,000 workers. Using available identifiers (Tax Identification Number and Social Security Code), individual longitudinal data are generated for each sampled worker, relative to all period 1985-2001, and various events characterizing individual working careers are meticulously reconstructed. Univocal identifiers ensure the linkage between workers and firms, so that firms history and attributes can be attached to each worker file present in the sample. A comparably valuable firm-worker connection is provided in Italy only by VWH panel, based on the same Inps source data.

There is no attrition in the WHIP panel, excluding minor updating problems, e.g. delays in the acquisition of information from the firms.

For the purposes of the present investigation, we select from the WHIP annual files job change events referring to workers for which we can observe two consecutive job spells in the period 1987-1998, net of transitions occurring between seasonal jobs in the tourist trade sector[11]. We consider individuals of both sexes, aged 15 to 65.

[11] To identify consecutive experiences in seasonal jobs we require that, limited to the tourist trade sector, the job spells last less than six months, and that more than six months elapse between them. With respect to 1998, the Italian National Institute of Statistics (ISTAT) estimates seasonal jobs to account for less than two percent of all jobs.

1.4 Reallocation timing and wage outcomes

We begin our empirical research by evaluating the relative wage performance related to job change episodes, with respect to three relevant dimensions: career interruptions, displacement condition, and sector switches. We first describe how these information are extracted from the Social Security data; then, we draw attention to the fact that career interruptions do not seem to be determined by displacements; and finally, we run a wage regression over a set of control variables, that allows to measure the wage differentials between the groups of interest, net of several observable characteristics that might otherwise blur the comparison.

The initial phase of analysis amounts to identify the fundamental statistical units, i.e. job change episodes, and to classify them, according to whether transitions occur with or without an intervening spell of interruption. For each individual experiencing two consecutive job spells, the information contained in the administrative archives allow to measure accurately the number of months elapsing between the first separation and the subsequent engagement. We can hence observe the re-entry time into dependent employment in the private sector, but we do not have explicit information about the workers actual status during inactivity; we only know that in the time span between separation and engagement, individuals are not employed in the private sector.

In principle, during observed inactivity, four different events can occur: (1) the individual is unemployed; (2) he/she is temporarily out of the labor force; (3) he/she works as self-employee; (4) he/she works in the public sector. But such events are not equally probable.

From previous studies, we know that event (3) on average involves less than 10% of all separations (Contini *et al.*, 1996), and conditional upon workers re-entering private employment, it is even less likely to happen. As for event (4), re-entering the private sector after moving to the public one is very unlikely in Italy, where public employment is usually a lifetime event (Leombruni and Quaranta, 2002).

As already mentioned in the introduction, we choose to focus our work on two particular categories of job transitions: job-to-job moves, in which at most one month intervenes between separation and engagement[12], and transitions in which two to twelve months elapse between separation and engagement[13]. In the latter case, the twelve-months threshold restricts investigation to only relatively short-term transitions, further curbing the likelihood of occurrences (3) and (4).

---

[12] In the administrative archives, the information about separation/engagement dates are recorded with one-month granularity. This means that one to 60 days can actually elapse between separation and engagement for reallocations classified as job-to-job.

[13] We have carried out a sort of sensitive analysis, allowing for different definitions of the reallocation categories; namely, we have comprised in the job-to-job definition also reallocations occurring within two or three months, and the results have proven to be very similar to those presented henceforth.

Moreover, under this condition, event (2) turns out to be much less probable as well[14]. Overall, we believe our particular choice of reallocation categories allows us to think of inactivity spells mostly as true unemployment. Of course, this does not imply that the costs and detriments of unemployment are equal for all unemployed people, nor that they have the same urgency to find a job, nor that they all search with the same intensity.

We now want to put in relation our two reallocation categories with a fundamental dimension of job change, that is its voluntary or involuntary nature. Some transitions indeed arise from the deliberate choice of workers of leaving unsatisfactory positions, some others are the consequence of (possibly unexpected) dismissals[15].

In the Social Security archives, no information about the nature of separations is recorded, and hence we cannot directly distinguish between quits and layoffs. But taking advantage of other, detailed information contained in the dataset, we can identify displacements indirectly, and then use this information as a proxy for detecting involuntary movers.

Displacements usually originate from three types of events: (1) firm closures; (2) collective layoffs; (3) individual layoffs. Unfortunately, in the data at hand there is not a reliable way for identifying displacements related to cause (3), but this should pose much of a minor problem, as Italian employment protection legislation makes this kind of discharges generally difficult[16]. On the contrary, episodes related to causes (1) and (2) can be recognized under plausible assumptions.

As for displacements due to cause (1), we identify all people separating from their job in the same year in which firms close down and exit the market. In order to minimize the possibility of capturing spurious displacements in the presence of company transformations, we also add the condition that workers do not immediately engage in newly established enterprises. As for displacements due to cause (2), we select workers separating from businesses that have reduced the labor force by more than 20%, between the year of separation and the year before. These criteria together lead to our more stringent definition of displaced workers[17]. We consider also a looser

[14] Workers may be willing to stop working, in order to attend a period of formal education, aimed at improving their professional profiles, or in order to look after children or family. But formal training, and maternity or sick leaves are well acknowledged by all National Labor Contracts, so that such events cannot be considered common reasons for permanent separations.
Moreover, it is worth stressing that, conditional upon re-entering private employment, even assuming that workers temporarily leave the labor force, it is a fact that they must spend some time searching actively for a job, during the short period of non-employment that we observe, hence qualifying as unemployed.

[15] The first occurrence is a case of job-match revision from part of the worker; the second may be due either to job-match revision from part of the employer, or to the destruction of that particular job, by the action of market forces.

[16] In firms with more than 15 employees, individual dismissals are allowed only with "good cause", as disposed by the Paragraph 18 of the Workers' Statute, adopted in 1970. See also Contini and Morini (2007).

[17] Out of caution, we also exclude from the category of displaced workers people who ended the old job while being in a wage supplementation regime (the so called CIG or CIGS), and who then reallocate job-to-job. These people, possibly working zero hours at the time of separation, are actually in a subsidized condition that at least partly cancels out displacement detriments.

definition, which also includes individuals who possibly anticipate a future layoff by leaving their job during the year just before firm closure. These definitions lead to quite similar results.

The first possible explanation for the materialization of unemployment between jobs is the involuntary nature of the separation at the origin of the worker reallocation. We may indeed expect displaced workers to reallocate mostly slowly, because they are more exposed to the eventuality of engaging in job search after separation. But taking into account that layoffs are usually notified to workers some months in advance, it is in principle possible for a displaced worker to search and find a new job while still employed, entering the new job soon after separation, hence, without experiencing unemployment. Moreover, a worker facing the shock of being laid off may be more willing to search harder for new employment, thus showing a higher propensity to reallocate quickly (Reyneri, 2002). So that the relation between displacement and reallocation timing cannot be fully predicted in advance.

In the sample of job change events we consider, applying the strict definition provided above, displacements account for 22.5% of total reallocations, and 62% of laid-off workers reallocates job-to-job, whereas the remaining 38% reallocates in two to twelve months. Using the less stringent definition of displacement, layoffs account for 24.5% of total movements, with 61% of workers experiencing job-to-job transitions, and 39% reallocating slowly. This evidence is of central importance for our study, because it clearly shows that it is not the displaced condition that mostly determines the sorting of workers into the category of indirect reallocations. Indeed, strict displacements give rise prevalently to job-to-job transitions, and account for approximately one fifth only of total movements.

Keeping in mind such evidence, the wage outcome related to job change episodes can be assessed, according to various dimensions of interest, namely, the presence of spells of unemployment between jobs, the displacement condition (less stringent definition), and change of the economic sector of activity. Our straightforward strategy consists in running an OLS regression of wage variations on a vector of individual characteristics, a vector of firm characteristics, and time dummies.

The basic statistical unit is the change in log-wage before and after job transition, that we call wage outcome. The sample we use is made up of 159,493 observations related to 76,347 individuals, hence, we deal with repeated observations at individual level. Job-to-job transitions account for 51% of total changes, the remaining being reallocations taking place in two to twelve months. Slow reallocations, as well as displacements and sector switches, are identified by means of dummy variables[18]; all other covariates are evaluated at the time of separation.

We focus on wage dynamics in the neighborhood of job changes, comparing the salary received during the last period spent in the old job, with the salary obtained during the first period in the new job. It is important stressing that we only account for short term loss/gain due to the differential between exit and entry wages, while we do not consider possible wage progression in the new job; hence, our conclusions about wage outcomes are limited to short-period horizon.

In the Social Security archives, salaries come in annual amounts, we thus consider the average weekly wage received in the years of separation and engagement[19]. If separation (engagement) occurs between January and June (July and December), and therefore we observe less than six months of potential tenure, we additionally average over the year before (after) the year of separation (engagement)[20]. Salaries are taken in real terms. In order to limit the influence of outliers, we exclude from the analysis all observations yielding a wage differential comprised in the two extreme tails of the overall distribution of wage differentials, i.e. we exclude observations below the 5th and above the 95th percentiles[21].

To control for composition effects across the groups of observations we want to compare, we incorporate among the covariates a set of individual characteristics, including gender, age (3 classes), qualification (4 categories), tenure (6 classes)[22]. We also add a dummy identifying permanent movers, that is people who have already changed job at least three times before the current observation. Some characteristics of the old firm are also considered, comprising location (4 areas), industry (10 macro-sectors), and firm dimension (5 classes). Finally a vector of year dummies is incorporated, to account for cyclical fluctuations at economy-wide level. Unfortunately, in the archives there is no information about schooling. To partly get round this limitation, we include as regressor the average week wage before separation, as a rough proxy for attained education, and more in general, for the skill level acknowledged by the firm.

In the OLS setup, we technically face a problem of endogenous selection due to unobserved heterogeneity of workers, that is likely to simultaneously affect wage outcomes, reallocation timing, and also the sectoral patterns of job change. The propensity to reallocate slowly can in fact be

---

[18] See Section 1.4 for more detailed information about the classification of economic activities adopted hereafter.

[19] When dealing with Italian Social Security data about salaries, Contini, Filippi and Malpede (2000) suggest to employ week wages instead of day wages, in order to reduce overestimation risk, due to the tendency – especially diffuse among employers in the south of Italy – of declaring less working days than the real weekly amount.

[20] Hence, the span of potential tenure considered for average wage computation ranges from a minimum of 24 to a maximum of 72 weeks.

[21] This is a common procedure when working with Social Security data on wages.

[22] Tenure is left truncated at 1985, we thus consider six discrete classes of observed tenure, the lowest being “one month”, and the highest being “equal to or more than 24 months”.

correlated to the regression residuals, if there are individual unobservable traits affecting both the probability of experiencing unemployment and reallocation outcomes. This is likely to be the case, for instance, whenever workers have different skill endowments which are not directly observable. A problem of endogeneity arises also in the case of sectoral switches, as far as individual unobservables manifest their effects according to the sectoral dimension of reallocation. Besides, the wage level in the old job is likely to be endogenously determined too, since it reflects the past working history of the worker, which is influenced by unobservable individual ability, talent, and professional attitudes in general.

Hence the OLS coefficients of the independent variables of interest cannot be given a causal interpretation, and consequently, at this stage of the analysis, we can just appraise the intensity of the correlation between dependent and independent variables. Next Section will then be devoted to investigate more in detail the relationship between reallocation timing and sectoral patterns of job change, in search of interpretable behaviours that can actually reveal some particular, unobserved, individual trait suitable for determining the observed correlations. Here, we simply go on estimating the wage equation, bearing in mind that the magnitude of the coefficient of the reallocation dummy will reflect the compound effect of all factors affecting wages *trough* and *in association to* careers interruptions.

Tab. 1.1 – Relative wage outcomes related to job changes, OLS regression

	type of transition/status	change in Δwage (logs) *robust std. error*	t-stat. *p*-value
model I	slow reallocation	-0.0830 *0.0013*	-63.25 *0.000*
	displacement	-0.0069 *0.0014*	-4.90 *0.000*
	switch 3-digit	-0.0069 *0.0013*	-5.45 *0.000*
model II	slow reallocation	-0.0582 *0.0020*	-29.50 *0.000*
	displacement	-0.0003 *0.0017*	-0.16 *0.873*
	switch 3-digit	0.0132 *0.0016*	8.21 *0.000*
	displacement*slow reallocation	-0.0121 *0.0027*	-4.48 *0.000*
	switch 3-digit*slow reallocation	-0.0393 *0.0024*	-16.20 *0.000*

Model I: n° of obs: 159,493; R-squared: 0.3361; Std. errors adjusted for clusters at individual level.
Model II: n° of obs: 159,493; R-squared: 0.3373; Std. errors adjusted for clusters at individual level.
Control variables and constant omitted.

Table 1.1 reports the OLS regression results relative to the three crucial dimensions we want to focus our attention on, all other covariates are omitted for brevity[23]. Two different specifications of the wage equation are shown. In the first one (model I), the variables of interest enter the equation separately; in the second (model II), we also include an interaction term obtained by combining the reallocation variable with the other two variables, so that the impact of displacement and sector switches in association with slow reallocation can be appreciated, hence, model II has a *DIFF-IN-DIFF* form. The reported coefficients can be interpreted as percentage differences between the wage outcomes of the two categories identified by the corresponding dummy variables, net of the effect of other variables.

Let us first focus on model I. After controlling for several observable characteristics, people moving job-to-job realize a wage outcome more than 8% higher, than people who experience a short spell of unemployment between jobs; thus, an interruption of the working career seems to be generally associated to considerably worse wage performances. This in turn supports the idea that reallocations involving unemployment can indeed push people to adapt to worse wage conditions, perhaps in order to avoid remaining unemployed for an even more prolonged time[24]. At the same time, switching 3-digit sector, as well as displacement, seem to have only a limited impact on wage differentials: in both cases, outcomes are negatively affected by nearly 0.7%.

A different picture emerges when the interaction term is included in the model, as reported in the second part of Table 1.1. Displacement alone seems not to affect wage outcome appreciably, so it does not seem to be a major cause of relative wage losses when changing job, but it yields a negative, although moderate effect when associated to slow reallocation (-1.2%). As for the sectoral dimension of mobility, the estimates now show that industry changes alone are associated with positive, moderate impact on wage outcomes (+1.3%, highly significant), but again, when in association with career interruptions, sector switches determine negative outcomes, this time lowering wage differentials by nearly 4%.

Summing up, the analysis presented in this Section brings to light two important facts. First, slow reallocations cannot be explained by worker displacement. Second, the presence of a spell of unemployment between jobs has a strong connection with significantly poorer wage performances. Moreover, our calculations reveal quite different correlation patterns between sectoral mobility and wage outcomes, according to job transitions being direct or indirect, suggesting that a deeper analysis of sectoral mobility is needed, in order to uncover possible explanations for reallocation difficulties.

---

[23] The complete results are reported in Table A.1.2.2 of Appendix 1.2.

[24] See for example Contini and Morini (2007, p. 8) who argue that: "in Italy the large majority of workers will take whatever position is in sight, no matter how bad, rather than staying unemployed".

1.5 Sectoral patterns of job change

This Section provides estimates of the propensity to switch industrial sector when changing job, either for people experiencing an interruption between successive employments, and for people moving directly from one job to another. We adopt an econometric approach based on multinomial probit regression.

We focus on the full sample of job change events in the period 1987-1998, made of 188,728 observations, related to 85,216 individuals. For each employment spell recorded in the administrative archives, the sector of activity of the corresponding firm is reported. Such information is contained in the five-digit Statistical Contributive Code, reflecting the 1971 Census classification developed by the National Statistical Institute on the basis of the General Industrial Classification of Economic Activities, known as NACE 70, adopted by the European Communities in 1970. In order to make the classification more tractable and suitable to our aims, we re-code the original five-digit taxonomy into the 3-digit Census classification Ateco81 adopted in 1981, which in turn is compatible with NACE standards. Accordingly, the 586 five-digit classes reported in the WHIP annual files, are aggregated into 172 groups (3-digit level)[25]; groups are then further aggregated according to the Census Classification Ateco91 adopted in 1991, obtaining 24 industries (2-digit level), and 10 macro-sectors (1-digit level)[26]. Table 1.2 provides the absolute frequency and incidence of sector switches for direct and indirect reallocations.

Tab. 1.2 – Frequency and incidence of sectoral changes

sectoral disaggregation	mobility	quick reallocations (%)	slow reallocations (%)
1-digit (10 sectors)	stay	64,489 (67.5)	64,424 (69.1)
	switch	31,015 (32.5)	28,800 (30.9)
	total	95,504 (100)	93,224 (100)
2-digit (24 sectors)	stay	50,735 (53.1)	56,780 (60.9)
	switch	44,769 (46.9)	36,444 (39.1)
	total	95,504 (100)	93,224 (100)
3-digit (168 sectors)	stay	36,794 (38.5)	48,205 (51.7)
	switch	58,710 (61.5)	45,019 (48.3)
	total	95,504 (100)	93,224 (100)

[25] Four groups do not give rise to job movements and they are not used in the analysis.
[26] It is worth noticing that all aggregations proposed are ultimately based on the old 1971 Census classification, which is not exhaustive for services and tertiary sector, while it is quite well detailed for manufacturing. Hence, especially when pushed at the maximum level of disaggregation, the analysis will tend to provide more detailed results for manufacturing industry.

Noticeably, within-industry flows always represent a conspicuous fraction of movements, accounting for one to two thirds of total changes, depending on the level of disaggregation considered. This fact can be due to the existence of industry-specific skills, that workers exploit by seeking for within-industry careers, but it may result also from asymmetric information about job opportunities among workers. Workers are likely to know better the sectoral labor market in which they are or have been employed, having more opportunities to be informed of possible job vacancies in firms similar or related to their current or former one, and knowing better the formal mechanisms through which one gains access to jobs.

When evaluated at low level of disaggregation (1-digit), within- and between-industry flows appear to be quite similar for quick and slow reallocations, with approximately two thirds of transitions remaining within the broad boundaries of macro-sectors. The picture radically changes when considering greater levels of detail. At 2-digit, on average more than half job transitions ends up in the same sector of origin, but slow transitions appear to be significantly more attached to the original sector (61%), than quick transitions (53%); such trend is confirmed also at the finest level of disaggregation (3-digit), with slow transitions manifesting an even more marked tendency to remain within the same sector of origin (52%), compared to job-to-job transitions (38.5%).

This last result is somewhat surprising, and denotes a considerably lower cross-industry mobility for movers experiencing unemployment spells; most importantly, sectoral attachment manifests itself in industries very narrowly defined, apparently contrasting with the common-sense idea that the longer workers are unemployed, the more they become willing to mismatch, hence, to switch sector. As far as short term interruptions are concerned, our data seem to disprove this hint. The discrepancy between direct and indirect moves at high level of sectoral disaggregation suggests that the similarity observed at low level of disaggregation may in fact hide some more complex dynamics, that cannot be grasped at a first glance.

In order to appreciate more precisely the dynamics of sectoral mobility, our strategy consists now in two steps: first, defining a set of different feasible moves, based on the notion of sectoral distance embedded in the Census classification; second, evaluating how the likelihood to carry out different types of moves varies, according to whether workers reallocate directly or indirectly.

We can distinguish different mobility events, according to how many industry boundaries people must cross in order to complete the reallocation move; we contrast different possible choices, according to the following scheme[27]:

[27] The number of group boundaries an individual crosses when reallocating can be thought as a measure of "distance" between the old and the new job; it is worth noticing that such distance is just obtained on the basis of a classification essentially centred on product and/or technological affinity between sectors. Such technological distance leaves out of consideration any geographical considerations of job location.

1) remaining in the 3-digit sector of origin;

2) switching 3-digit, remaining in the same 1-digit sector;

3) switching 1-digit sector.

Alternative (1) comprises 84,999 observations, and in our classification it represents the extreme case of sectoral attachment, alternative (2) covers 43,914 events, while alternative (3) represents the extreme case of switching behaviour, covering 59,815 events.

To evaluate how sectoral mobility relates to the timing of reallocation, we look at these three mobility outcomes as the possible states of a response variable to be expressed as a function of some explanatory factors, including reallocation timing. In order to allow high flexibility in mobility behaviours, we choose not to impose an order among the realizations of the response variable, and we resort to a multinomial probit model. Such technique is suitable for polytomous dependent variables with less than 5 response categories, as it is in our case, and, compared to other similar techniques, as for instance multinomial logit, it has the advantage of relaxing the restrictive behavioral assumption of independence of irrelevant alternatives. The maximization of the likelihood function of a multinomial probit model may be computationally demanding (McCulloch and Rossi, 1994), hence, in our estimation procedure, we allow different maximization algorithms, in order to achieve convergence of the likelihood function to a minimum[28].

The statistical units of analysis are job change events; for each job change episode i we define a latent processes of sectoral mobility, conditional upon separation

$$\mathrm{SECT}_i^* = x_i'\beta + \varepsilon_i \ , \tag{1}$$

where SECT_i^* is a latent variable, capturing the individual propensity to switch, or to stay in a given sector; x_i is a vector of explanatory variables, evaluated at the time of separation; β is the unknown parameter vector of interest; and ε_i denotes some zero-mean error term. The latent measure of sectoral mobility is not observed, and we conduct our analysis on the observed measures $\mathrm{SECT}_i = m$, where m assumes the following values:

$m = 0$ if job change entails remaining in the same 3-digit sector;

$m = 1$ if job change entails changing 3-digit sector, remaining in the same 1-digit sector;

$m = 2$ if job change entails changing 1-digit sector;

[28] This procedure is common among scholars, and we implemented it in the software package Stata; for details see Gould *et al*. (2006).

and where

$$\text{SECT}_i = \mathbb{I}\{\ \text{SECT}_i^* > \underline{\text{SECT}}(m)\}\ , \tag{2}$$

which says that the latent variable is above some minimum thresholds $\underline{\text{SECT}}(m)$, and SECT_i is observed in the absence of any additional censoring mechanisms. The multinomial probit regression then consists in the simultaneous estimation of different sets of coefficients (i.e. different equations) corresponding to each outcome category. We take $\text{SECT}_i = 1$ as reference category, that is we set $\beta^{(m=1)} = 0$, and we estimate two sets of coefficients $\beta^{(m=0)}$, and $\beta^{(m=2)}$; each of such vectors gives us impacts on the corresponding outcome, relative to the impacts on the reference outcome.

We attempt to specify sectoral mobility as a function of reallocation timing, whether quick or slow, and of a bunch of observable characteristics, which we think may have a role in determining the observed patterns, and which we are actually able to measure in the data. In particular we examine three different families of explanatory factors[29]:

1) worker characteristics evaluated at the time of separation;
2) characteristics of the firm from which the worker separates;
3) economy and labor market aggregate factors[30].

We consider a vector p_i of worker characteristics, including gender, age (2 dummies: young, and mature; the benchmark category being prime-age), qualification in the old job (3 dummies: apprentice, blue collar, and manager; the reference group being white collar), tenure in the old job (5 dummies: 1 month, 2-3 months, 4-6 months, 13-24 months, and more than 24 months; the benchmark class being 7-12 months), and a dummy denoting the displacement/non displacement status (identified using the less stringent definition provided in Section 1.4).

In order to take into account individual heterogeneity arising from different preferences towards change/stability and risk, we incorporate in p_i a group of covariates containing information about individuals past working life: a dummy variable identifying permanent movers, and a dummy indicating whether workers have already switched 3-digit sector in the past. Among the elements of

---

[29] Moscarini and Vella (2008), in a slightly different setting, suggest to specify the mobility decision as a function of worker characteristics evaluated at the time of separation, and aggregate labor market conditions.

[30] The state of the labor market indeed interferes with worker sorting. Moscarini (2001) spells out the mechanism according to which workers sort ex ante across different types of jobs, based on information they know in advance. When few jobs are available, workers accept any job that comes along and they are willing to mismatch. When jobs are easy to find, individual comparative advantages matter more, unemployed workers search more selectively, and they mismatch less.

vector p_i we also include the average weekly wage in the old job, as a proxy for general educational attainment, and for the skill level acknowledge by the employer at the time of separation.

We then construct a vector q_i, whose elements represent characteristics specific to the firm from which a worker separates, including industry (2 dummies: manufacturing and transportation, and building; with services and commerce as benchmark sectors), location (3 dummies: North-East, Centre, South; with North-West as reference area), and firm dimension (4 dummies: 0-9 employees, 10-49, 250-999, and more than 1000; with 50-249 employees as reference category).

Finally, let r_i be a vector of economy and labor market aggregate factors, that may affect the individuals propensity to change sector, including 11 year dummies (the benchmark year being 1987) aimed at capturing macroeconomic fluctuations, and an indicator of sectoral occupational trends[31], incorporated in order to absorb the effects of cyclical shocks (as for instance demand trend variations) that hit micro-level sectors selectively, having direct repercussions on the likelihood of re-employment in the same sector.

Quick and slow reallocations are identified by a dummy variable (*SREALL*), taking value one if the individual comes into the new employment via a spell of unemployment, and zero otherwise.

The model we estimate is thus[32]

$$\mathrm{SECT}_i = \gamma SREALL_i + p_i'\eta + q_i'\delta + r_i'\lambda + \varepsilon_i \ , \tag{3}$$

where coefficients γ, $\boldsymbol{\eta}$, $\boldsymbol{\delta}$, and $\boldsymbol{\lambda}$ are estimated using maximum likelihood, and the standard errors are calculated taking into account the grouped structure of the data, that is the presence of repeated observations at individual level, assuming observations are independent across groups (individuals), but not necessarily within groups.

Table 1.3 reports estimates of model (3). As usual in the estimation of multinomial probit models, coefficients are expressed as Z-scores, i.e. standard normal scores; positive (negative) coefficients indicate of how many standard deviation units the Z-score associated to a given outcome increases (decreases) relative to the reference case, as result of a one-unit increase in the independent variable, controlling for the other covariates.

[31] Such indicator is defined – for each job change event, and with respect to the old job spell – as the variation in the 3-digit employment stock, between the year of separation and the year before.

[32] Clearly, unobserved heterogeneity, affecting both the probability of experiencing a spell of unemployment and the choice of sectoral moves, is a potential source of endogeneity bias for the coefficient of the reallocation dummy. So that the parameter γ of *SREALL* cannot be given a causal interpretation, it will simply offer an indication of the sign and intensity of the correlation between reallocation timing and sectoral moves.

The econometric investigation yields several, interesting results. We notice that young people are less inclined to remain in the original 3-digit industry, and more inclined to switch macro-level sectors, while the opposite is true for old people, a pattern that can be intuitively explained by time accumulation of skills which are specific to a given job or to a small sector[33]. Apprentices also show a marked inclination to remain within the narrow boundaries of small industries, avoiding moving far away of their initial sector, most probably due to the training they are receiving in a specific job or task. Women show a significantly higher propensity to remain within the original 3-digit sector, compared to longer moves, and even more so do permanent movers. People who have previously switched 3-digit sector are much more inclined to switch 3-digit sector again, also aiming at switching macro-level sectors.

The most important evidence for us is anyway related to the impact of slow reallocation (first line of Table 1.3). People reallocating in two to twelve months show a remarkably higher propensity to remain in the original 3-digit sector. But conditional upon switching 3-digit sector, people experiencing a spell of unemployment tend to switch more 1-digit sector, compared to people reallocating directly. Specifically, a slow reallocation increases the Z-score associated to outcome 1 (remaining in the original 3-digit sector) by 0.4 standard deviation points, while it also increases the Z-score associated to outcome 3 (switching 1-digit) by 0.23 standard deviations. All results are statistically significant, and reveal a quite definite dual pattern of sectoral mobility for people experiencing a spell of unemployment between jobs.

When thinking of these results, it is important to bear in mind the wage outcomes related to switching 3-digit sector we discussed in the previous Section. Sector changes entail a significantly worse (short-term) wage performance when associated to slow reallocations. Combining such evidence to the data of Table 1.3, it seems that individuals who remain unemployed for a while adopt two different behaviors: some prefer to search for a relatively higher-wage within the original micro-sector, while some others search at a greater distance, ending up accepting more penalizing employment conditions.

On the whole, people experiencing a spell of unemployment between jobs appear to be either more conditioned by concerns specific to the original sector they belong to, or not concerned at all about sectors, and in this case they obtain the poorest outcomes. In the next Section, we try to systematize the whole evidence collected so far, in order to identify a possible cause of long reallocation times, and poor reallocation outcomes.

[33] See also Moscarini and Vella (2008), who show how occupational mobility declines with age.

Tab. 1.3 – Multinomial probit estimates of sector switches

	outcome (0) – remaining in 3-digit		outcome (1) – switching 1-digit	
	coefficient *robust std. error*	z-stat. *p-value*	coefficient *robust std. error*	z-stat. *p-value*
slow reallocation	0.4047 *0.0110*	36.73 *0.000*	0.2331 *0.0112*	20.81 *0.000*
young	-0.1802 *0.0132*	-13.69 *0.000*	0.0976 *0.0140*	7 *0.000*
old	0.2139 *0.0197*	10.87 *0.000*	-0.0886 *0.0221*	-4.01 *0.000*
apprentice	0.2421 *0.0241*	10.03 *0.000*	-0.0488 *0.0245*	-1.99 *0.047*
blue collar	0.3621 *0.0155*	23.41 *0.000*	0.1132 *0.0157*	7.22 *0.000*
manager	0.0837 *0.0617*	1.36 *0.175*	0.2004 *0.0661*	3.03 *0.002*
female	0.3820 *0.0135*	28.36 *0.000*	0.0405 *0.0139*	2.91 *0.004*
permanent mover	0.3359 *0.0158*	21.24 *0.000*	-0.0721 *0.0165*	-4.36 *0.000*
displaced	0.0576 *0.0127*	4.55 *0.000*	-0.1221 *0.0129*	-9.45 *0.000*
previous switch 3-digit	-0.9049 *0.0123*	-73.38 *0.000*	0.0482 *0.0112*	4.29 *0.000*
wage level at separation	0.0370 *0.0135*	2.74 *0.006*	-0.1513 *0.0131*	-11.54 *0.000*
Δ occupation 3-digit	0.1737 *0.1105*	1.57 *0.116*	0.4883 *0.1146*	4.26 *0.000*
north east	0.1003 *0.0139*	7.19 *0.000*	-0.0151 *0.0145*	-1.04 *0.298*
centre	0.3240 *0.0163*	19.93 *0.000*	0.0379 *0.0170*	2.23 *0.026*
south	0.4688 *0.0176*	26.66 *0.000*	-0.1059 *0.0192*	-5.52 *0.000*
dimension 0-9	0.0339 *0.0164*	2.07 *0.038*	-0.0463 *0.0163*	-2.85 *0.004*
dimension 10-49	-0.0094 *0.0159*	-0.59 *0.554*	-0.0884 *0.0158*	-5.59 *0.000*
dimension 250-999	0.0736 *0.0248*	2.97 *0.003*	0.0825 *0.0244*	3.38 *0.001*
dimension 1000+	0.1012 *0.0291*	3.48 *0.000*	0.0882 *0.0286*	3.09 *0.002*
tenure 1	-1.3192 *0.0137*	-96.55 *0.000*	-1.5006 *0.0135*	-111.09 *0.000*
tenure 2-3	-0.3225 *0.0186*	-17.36 *0.000*	-0.8319 *0.0193*	-43.22 *0.000*
tenure 4-6	0.0407 *0.0204*	2 *0.046*	0.0982 *0.0203*	4.83 *0.000*
tenure 13-23	0.1502 *0.0204*	7.38 *0.000*	0.1062 *0.0206*	5.16 *0.000*
tenure 24+	0.0742 *0.0204*	3.64 *0.000*	0.0269 *0.0209*	1.29 *0.197*

Note: time dummies and constant are included in the regressions, but for brevity they are not reported.

1.6 Sectoral mobility and slow reallocation: a speculative interpretation

We think the empirical facts found in the previous Sections – if properly organized – can reveal some possible explanations for reallocation difficulties; specifically, we believe they can help identifying what sort of individual attributes may ultimately result in such difficulties. Unfortunately, the data at hand are quite poor in terms of individual characteristics, and hence it is inherently difficult to directly assess the determinants of reallocation outcomes. Nonetheless, the information so far uncovered offer substantial support to one particular explanation, that we thoroughly discuss in what follows. Our argument is going to be essentially speculative – although supported by a mass of empirical evidence, as well as by relevant, theoretical results – and its actual significance, in our view, is primarily that of offering a compelling suggestion about where to direct subsequent research.

The core idea is that there must be a different distribution of sector-specific skills among individuals, that eventually determine reallocation success/difficulty. In particular, we argue that people experiencing unemployment spells are characterized by more sector-specific skills, compared to job-to-job movers; the key difference between the two types of movers being that sector specificity manifests itself prevalently at 3-digit level, for individuals reallocating slowly, while it is mostly related to wider economic areas, for people reallocating directly.

Skill endowments specific to narrow industrial sectors are compatible with all the empirical facts emerged up to now, that is:

- longer reallocation time for people who try to remain into the same sector, because single-sector labor markets are on average small;
- more frequent re-employment into the original sector for workers who bear the risk of prolonged periods of search (unemployment), and/or are not willing to adapt to worse employment options;
- more frequent long-distant switches for workers who cannot bear the risk of very long unemployment, and soon become willing to accept whatever job, even if it yields comparatively lower salary.

In a mirror-like way, people endowed with skills which are comparatively more portable across sectors have more chances to reallocate quickly, because they have larger labor markets where to search for matches. Moreover, they face less wage losses, even when reallocating afar from the original sector. Reallocations are anyway more likely to take place within groups of sectors which are somewhat affine, according to technology/product, so that some degree of specificity exists, but it manifests itself at lower level of sectoral disaggregation.

To better understand the rationale behind the proposed interpretation, let us briefly review some important contribution in labor economics literature, in order to appreciate how the idea of sector-specific skills has been introduced and framed. Starting from the seminal work of Neal (1995), several authors have recognized, and demonstrated, that workers receive compensation for some skills that are neither completely general nor firm-specific, but rather specific to their industry or sector[34]. Neal suggests that returns to tenure measured in most standard wage equations are capturing the remuneration of industry, rather than firm-specific skills, and he verifies that in case of exogenous displacement, individual wage loss varies, according to whether workers are able to reallocate in the same industry or not. Using data on US displaced workers, Neal compares industry switchers and stayers, finding that the wage difference between current and pre-displacement jobs is negative, and higher for switchers than for stayers. He also finds a positive correlation between wage fall and the level of pre-displacement experience and firm-specific tenure, again higher for industry switchers[35].

More recently, the topic has been addressed by Lamo, Messina and Wasmer (2006), who focus on the process of transition of eastern European countries in the late 90s, highlighting the role of specific skills on the lack of mobility across jobs. They contrast the positive role of general education on workers mobility in the labor market, with the negative role of vocational education. Notably, to appreciate the costs of reallocation, the authors consider unemployment spells between subsequent jobs and transition towards inactivity, and they quantify wage mobility and wage losses after job separation. They find that age, tenure and, above all, vocational education are associated with higher wage losses, higher unemployment duration, and a higher likelihood to exit the labor market[36].

The main fact stemming from these considerations is that, when the remuneration of skills and working experience has a sector-specific component, the sector a worker belongs to automatically

34 Parent (2000), using data from the National Longitudinal Survey of Youth (US), finds that what matters most for wage profiles of young workers is industry-specificity, not firm-specificity. Dustman and Meghir (2005), based on administrative data from Germany, document the importance of acquisition of sector-specific skills for wage growth of skilled workers early on in career.

35 For instance, a displaced worker having accumulated 10 years of tenure in the same firm would experience a wage fall of 23% in case he/she switches industry, but only 11% if he/she is able to reallocate in the same industry. These differences, the author argues, must be capturing some industry-specific skills losses (Neal, 1995).

36 The authors carry out a comparative study of Poland and Estonia, and examine the probability of re-entering employment after job separation, conditional on having experienced an unemployment spell. They find that in both countries, each additional year of education raises the probability of re-entering employment by about 10% to 11%, whereas holding basic vocational, or secondary vocational degrees reduce it by 12% to 16%.

defines the perimeter of the labor market that, in principle, guarantees him/her the highest remuneration when reallocating.

The role of sector specificity of skills can hence be framed as follows. Let us simply assume that, net of cyclical trends, in each given time unit vacancies open up in the economy at a frequency that is proportional to the occupational stock. In addition, let assume that workers searching for a new job are selective, and enter an employment relationship only if the prospective salary is above – preferably much above – their reservation wage. Then, the higher sector-specificity is, the smaller is the labor market able to offer "good" employment opportunities, and the smaller is also the likelihood of matching a satisfactory job offer in each time unit. On the contrary, to the extent that skills are portable across different sectors, the market that can in principle provide the highest level of remuneration is by definition larger, and the probability of finding and accepting a job in a given time unit is higher, holding all other factors fixed. According to this simple logic, we expect people holding comparatively more sector-specific skills to take longer for finding a job, and to reallocate more frequently within the same industrial sector, once the cyclical fluctuations at both macro and micro level are taken into account. Our empirical findings point in the direction of such predictions.

Besides and importantly, sector specificity of skills can also explain the behavior of people who reallocate slowly and show a higher propensity to switch industry at progressively lower level of sectoral disaggregation. Some individuals may in fact choose to renounce the remuneration of the specific component of their skill profile, in exchange for a relatively more rapid re-employment. These are people who are most hurt by unemployment, and even more so by the prospect of very long unemployment, hence being particularly sensitive to unemployment duration, so that after a period of unsuccessful search, they rapidly diminish their reservation wage at such a point that it makes for them acceptable jobs outside their original sector.

Compared to people endowed with skills which are more portable across 3-digit sectors, individuals having skills which are specific to single 3-digit sectors are thus expected *either* to reallocate more slowly, and to remain more attached to their original sector, *or* to reallocate more slowly, and to move more faraway from their original sector. This is exactly what we observe empirically.

As further proof in support of this explanation, the data reveal that, among people experiencing a spell of interruption two to twelve months long, workers who choose to change 3-digit sector reallocate on average in 5.2 months, while workers who re-enter the same sector reallocate more slowly, in 6.4 months on average. Such a piece of evidence suggests that the former group of workers may prefer a relatively faster, and less remunerative reallocation to a more remunerative, and slower one; while the latter group may be more disposed to face unemployment in exchange for preserving the rewarding of sector-specific skills[37]. These findings confirm our conjectures.

Moreover, in the estimates reported in Table 1.3, the coefficients of the variable indicating previous sectoral switches reveals that, in general, people who do not switch 3-digit sector, have switched less also in the past. This additional element is also in accordance with the general idea that sector specificity matters. Our view is even further corroborated by the fact that the same sectoral patterns highlighted in Table 1.3 emerge also when the regression analysis is performed on several, relevant sub-samples of workers[38].

An aspect of the above reasoning that is worth stressing, is that people may not be completely conscious of the quality of their skills, before experiencing job search, and just when actually searching, they may progressively come to discover the real perimeter and the characteristics of their main labor market, adjusting their expectations consequently.

Another possible explanation for the observed results relies on asymmetric information about job vacancies. This view is to a great extent complementary to sector-specificity of skills, implying that workers endowed with stronger sector-specific skills are more likely to be scarcely informed about job opportunities outside their sector, and they are also less familiar with the formal mechanisms that allows to enter in contact with such external job prospects. On the contrary, people characterized by more transferable skills are more likely to be part of an information network that cut-across sectors, providing access to a wider range of labor market opportunities.

In order to provide additional support to the sector-specificity explanation, we next make a step further in the analysis, trying to assess whether people switching 3-digit sector move according to some cluster or *modular* pattern, and how such pattern varies according to reallocation timing. The expression modular pattern corresponds to the idea that cross-sectoral flows are likely to link together some sectors more tightly than others, originating more densely connected groups of economic activities, with sparser connections between groups. The sector-specificity approach predicts that people characterized by more sector-specific skills, once renounced the remuneration of their specific component, should exhibit weaker sectoral preferences. So that, for these people, we expect to observe a higher propensity to reallocate at a greater distance from the original

[37] A difference of one month may seem small, but we should also bear in mind that the semester is likely to coincide with a specific psychological threshold, according to which, exceeded the first six months of unemployment, the fear of long-term unemployment increases rapidly (with special focus on the Italian labor market, see also the discussion in Contini and Morini, 2007).

[38] Namely: people aged 15-29, or 30-44, or 45-65, or 25-65; male or female workers; manufacturing workers; blue or white collars; people with firm tenure in the old job higher than six months long; displaced or non-displaced workers. Moreover, the results reveals to be robust also with respect to the inclusion among the covariates of 168 sectoral dummies at 3-digit level.

position, and also to reallocate more sparsely across different industries. The next Section is devoted to address precisely this issue.

1.7 A network approach for identifying modular patterns of inter-sectoral mobility

We now explore job-change patterns by way of a network-based methodology, that allows to identify the modular architecture of inter-sectoral transitions. This analytical endeavor represents a first experimentation of how network-analysis techniques can help extracting new information from labor mobility data, supplementing the empirical evidence collected so far.

Essentially, a network is a set of entities, called vertices, connected in pairs by lines, called links. If lines are of different intensity, i.e. they carry weights, the network is said to be weighted; if lines point in only one direction the network is called directed. We specifically consider weighted, directed networks, whose vertices are industrial sectors at 3-digit level, and whose links represent flows of workers between sectors; we compare two networks, originated by quick or slow reallocations, seeking for identifying characteristics of and differences in the respective *community structures*.

The community structure of a network is defined to be a particular partition of the set of vertices into non-overlapping groups, exhibiting an appreciably higher density of links within, than between them. The ability to detect and characterize such groups is of significant, practical importance for our purpose of investigation. In our setting, communities would identify sets of sectors within which worker mobility is particularly intense, offering an immediate indication of how the labor market is actually segmented. The assortment of sectors comprised in each community can then reveal to what extent workers move across sectors that are similar, from the point of view of technology and/or product. Holding fixed network size, fewer and more heterogeneously assorted communities in general hint that reallocations are less constrained by sectoral boundaries, hence, the labor market is less segmented.

In order to detect relevant communities, we resort to a spectral algorithm, originally formulated by Newman (2006a) for unweighted, undirected networks, and then extended to directed networks by Newman and Leicht (2008). We slightly enhance the algorithm, in order to allow for weights on links; and we characterize the centre-periphery architecture of each community, according to the *community centrality index* proposed by Newman (2006b). As far as we know, this is the first study trying to analyze large-scale labor mobility data by means of network-based techniques.

Formally, a directed network of labor mobility across sectors can be represented as a graph, and denoted as $G(V, L)$, where $V=\{i: 1, 2, ..., n\}$ is a finite set of vertices denoting industrial sectors, and $L = \{l_{ij}\}$ is a set of links denoting labor flows between sectors[39]. A vertex is referred to by its order i in the set V; a link pointing from i to j is defined by the ordered pair (i, j) and denoted by l_{ij}. The graph $G(V, L)$ can be fully described by its *adjacency* matrix A, a $n \times n$ square matrix whose entry a_{ij} (with $i, j = 1, \ldots, n$) is equal to one when the link l_{ij} is active, and zero otherwise. In our specific case, since we consider only inter-sectoral mobility, the diagonal of the adjacency matrix contains all zeros, that is $a_{ii} = 0$. Moreover, since the network is directed, A is not necessarily symmetric.

This notation allows only for a network of binary nature, where links between vertices are either present or not. But our goal is to describe a network characterized by flows of workers, hence by links of different magnitude, according to how many workers actually cover a given link. We thus introduce the notion of directed weighted network $G(V, L, W)$, where W is an $n \times n$ matrix of weights, that are real values attached to links. The entry w_{ij} is the weight of the link connecting vertex i to vertex j, and $w_{ij} = 0$ if i and j are not connected, i.e. $w_{ij} = 0$ if $a_{ij} = 0$.

In our context, in-/out-flows of workers to/from sectors can be quite different in absolute size across sectors. This occurs for the evident reason that, at each point in time, sectors have different occupational stocks, that in turn give rise to different turnover in absolute terms; moreover, net of such stock effect, sectors can be characterized by different structural turnover, due either to distinct institutional settings, or to different responses to business cycle fluctuations. In order to be able to compare different flows within the system, we resort to a normalization of reallocation flows. Let us define the element w_{ij} of the weight matrix in the following way

$$w_{ij} = \frac{f_{ij}}{F_i^{out}} \; , \tag{4}$$

where f_{ij} is the absolute number (frequency) of reallocations from sector i to sector j, and $F_i^{out} = \Sigma_j f_{ji}$ is the total number of reallocations from sector i towards all other sectors. The entry w_{ij} of the weight matrix thus represents the share of workers reallocating from sector i to sector j, calculated with respect to the total out-flow from sector i. In this way, w_{ij} captures the relative importance of sector j as labor market of destination for workers separating in sector i.

In the following analysis, the notion of vertex *degree* plays a fundamental role. The degree k_i of vertex i is defined to be the number of links connecting that vertex with other vertices in the network. In a directed graph, the degree of a vertex has two components: the number of out-going links, and the number of in-going links. In terms of the weight matrix W these two measures are

[39] A thorough review of network theory can be found in Boccaletti *et al*. (2006).

defined as $k_i^{out} = \Sigma_j w_{ij}$ and $k_i^{in} = \Sigma_j w_{ji}$, respectively. Notice that, by the definition of weights afore introduced, in our mobility network $k_i^{out} = \Sigma_j w_{ij} = 1$.

Among scholars, the problem of community structure identification has been the centre of great interest in the last years. The most challenging aspect of such a topic is that the number and size of groups is given by the network itself, and not by the experimenter, so that ad hoc techniques have to be implemented, in order to detect existing communities. Mark Newman, one leading figure in this field of research, has recently proposed a spectral algorithm for community detection, that has revealed to perform particularly well in several, different real situations, being at the same time based on sensible statistical principles. The intuitive concept of network community proposed by Newman can be effectively grasped from his own words: "a good division of a network into communities is not merely one in which there are few links between communities; it is one in which there are *fewer than expected* links between communities" (Newman, 2006a, p. 2). This idea is formalized using a benefit function known as *modularity* (Newman and Girivan, 2004). Modularity is defined, up to a multiplicative constant, as the number of links falling within communities, minus the expected number of such links in an equivalent network with links randomly placed. Modularity is denoted with Q, and it can be written as follows

$$Q = \text{(fraction of links within communities)} - \text{(expected fraction of links within communities)}. \quad (5)$$

Positive values of Q indicate the presence of community structure, with larger values denoting a stronger, more definite structure. The problem of communities detection can thus be solved by looking for the partition of the network that yields the largest, positive value of modularity. The key contribution of Newman is the reformulation of modularity in terms of network spectral properties, yielding a computationally feasible way to actually address the problem of community identification. Making use of the algorithms described in Appendix 1.2, we can assign each vertex in the network to a precise community, also providing a measure – the community centrality index *CI* – of how central or peripheral vertices are in the respective communities[40].

We consider labor reallocations between industrial sectors at 3-digit level, hence dealing with networks formed by 168 vertices, and we make use of all information contained in the archives, considering the job change events taking place in the period 1986-1999, referred to people aged 15

[40] The *CI* index varies between 0 and 1, with lower values indicating more peripheral positions, and greater values indicating core positions.

to 65, excluding only transitions between seasonal jobs in the tourist trade sector[41]. The job-to-job network is formed by 68,253 individual moves, while the slow-reallocation network is formed by 53,023 moves. Tables A.1.2.3 and A.1.2.4 in Appendix 1.2 show the complete lists of sectors, grouped according to the identified communities.

Our algorithm identifies 7 distinct communities in the job-to-job network, and 5 communities in the slow-reallocation network. In both cases, within-group mobility represents only a fraction of total movements; namely, within-group flows account for 37% of transitions in the job-to-job network, and for 43% in the slow-reallocation network, the remaining movements taking place between communities. The size of groups ranges from 15 to 31 sectors for quick reallocations, to 16 to 58 for slow reallocations.

In the job-to-job network, the most central sectors in each community are found to be:

1) building (*CI* = 0.6667);
2) firm services (0.4311);
3) garment manufacturing (0.2858);
4) commercial concerns and hotel trade (0.2494);
5) machine shops (0.1965);
6) machine tools for metalwork (0.0306);
7) transformation of plastic materials (0.0155).

In the slow-reallocation networks the most central sectors are:

1) building (*CI* = 0.5523);
2) garment manufacturing (0.2946);
3) commercial concerns and hotel trade (0.2441);
4) machine shops (0.1066);
5) machine tools for food industry (0.0156).

Let us focus specifically on the job-to-job network. If we look at the sectoral composition of each single community, we immediately notice that groups appear to be substantially homogeneous, from the point of view of technology and/or product. Labor flows at 3-digit level tend to link sectors according to a few well-understood product branches, which can be characterized by looking at the

[41] The time span considered here is two years larger than those considered in the analysis carried out in the previous Sections; we make this choice so as to be able to utilize a greater mass of information available in the WHIP supply at hand, while the key results change only very slightly, when shorter periods are considered.

sectors with highest centrality values, obtaining the following 7-group taxonomy: (1) building, energy and transportation; (2) firm services, banking and ICT; (3) textile-clothing and footwear; (4) personal services, commerce, and hotel trade; (5) metallurgy and machine shops; (6) machine tools; (7) chemicals and plastic.

Within-group homogeneity is especially notable in the textile-clothing and footwear community, grouping all the 21 micro-level sectors – on a total of 22 – traditionally pertaining to the garment value chain. These are all sectors having well-known product linkages, sharing some important aspects of the organization of labor, with mostly female workforce, characterized by skills and know-how largely portable across sectors.

As a general feature, it is evident at a glance that the results tend to be somewhat “manucentric”, due to the already mentioned nature of the Census classification we employ, which details relatively poorly services and high-technology sectors. Nevertheless, the 7-group partition appears to be extremely sensible, especially if we bear in mind the historical product specialization of the Italian economy. Indeed, Italy has always been a manufacturing country, specialized in the so called light industry, that is textile-clothing and footwear, and in the mechanical industry in general. During the 90s, the machine tools business has progressively become a primary exporting sector, although accounting for a minor share of manufacturing production and employment. Moreover, the last decade of the past century witnessed a continuous growth of the building sector, which was, and still is one of the pillars of the Italian economy. All these factors are mirrored quite clearly in the network partition.

As for the slow-reallocation network, the first thing to notice is that the core of the community structure (sectors with the highest *CI*) seems to resemble quite closely the pattern emerged in the job-to-job network. In 4 groups out of 5, the most central sectors are the same as in the quick reallocation case, so that communities can be characterized similarly: (1) building, energy and transportation; (2) textile-clothing and footwear; (3) personal services, commerce and hotel trade; (4) metallurgy and machine shops; while community (5) exhibits a more mixed assortment. The job-to-job communities with the lowest average centrality measures, i.e. machine tools and chemicals, disappear in the slow-reallocation network, and notably, most machine tool sectors are located in the periphery of the metallurgy community, while chemicals sectors are dispersed in all other groups. Sectors pertaining to firm services, banking, and ICT are included in the expanded periphery of the community centered on personal services, commerce and hotel trade.

Despite the core of the modular architecture reveals to be relatively similar for both mobility categories, slow reallocations exhibit much fewer communities, characterized by larger, much more heterogeneous peripheries. This evidence reveals that, compared to people moving job-to-job, when leaving the original micro-level sector, people experiencing a spell of unemployment, not only move more faraway from it, but also show more varied behaviors, that can be interpreted as a signal of weaker sectoral preferences. People facing unemployment, once decided to leave the original micro-level sector, indeed seem to be more willing to accept whatever job in the economy. We believe this finding supports the idea that people reallocating slowly are prevalently characterized by skills which are valuable prevalently within the 3-digit sector of origin, so that when decided to leave the original sector, they end up moving according to less structured patterns.

1.8 Conclusions

In this Chapter we investigate the phenomenon of worker reallocation in the Italian labor market, with a special focus on the pace of the reallocation process.

Difficulties in switching from one job to another, which manifest themselves in short spells of unemployment, are a widespread phenomenon that appears to depend on displacements only to a minor extent. To understand which factors contribute to determine the numerous, short-term unemployment spells we observe in the data, we investigate sectoral mobility patterns, with the idea that such structures may reveal, albeit indirectly, some individual characteristics of workers experiencing different types of reallocations.

We centre our empirical investigation on the comparison between two categories of reallocations: direct transitions, that is job changes taking place within one month at most, and reallocations occurring with an intervening spell of interruption two to twelve months long. Using administrative microdata that track down individual work histories in the private dependent employment, we show that, compared to job-to-job transitions, career interruptions reveal to be associated with considerably worse wage performances. In addition, sectoral switches evaluated at 3-digit level of disaggregation have a considerably worse impact on the wages of people experiencing a period of unemployment, compared to people reallocating directly.

We then set up a multinomial probit regression, in order to directly appreciate sectoral mobility patterns. For people experiencing career interruptions, we document a higher propensity to reallocate within the original 3-digit industrial sector, and at the same time, conditional upon moving outside the initial micro-level sector, we estimate a higher propensity to switch wide economic branches. These findings are both statistically significant and of relevant magnitude, and are not driven by observable individual characteristics, or by cyclical fluctuations at sector-, or economy-wide level.

Furthermore, we adopt an original network-based approach to labor mobility, aimed at detecting and characterizing the community structure of cross-sectoral movements. We find that people who reallocate slowly and switch 3-digit sector tend to move within broader and more variously assorted sectoral clusters, compared to job-to-job movers, and we interpret such behavior as a signal of weaker sectoral preferences.

We believe the collected findings are consistent, all at once, with the existence of sector-specific skills that cause superior reallocation difficulties to people endowed with skill profiles specific of narrower sectors. Besides, this mechanism appears to be operating irrespective of the reasons that give rise to separation. The rationale behind all this is that individuals endowed with skills and professional experience which are valuable only within the boundaries of narrow labor markets, generally have smaller chance to match an acceptable job offer in a given unit of time. Then, when reallocating, workers with more sector-specific skills essentially have two alternatives. After some unsuccessful search, they can decide to give up their sector-specific skill endowment, together with the associated remuneration, in exchange of a more rapid re-employment wherever in the economy; or they can hold on searching nearby the original sector, and wait longer in order to eventually match a job offer, that allows them to possibly preserve most remuneration components. As a general rule, when individual skills depend heavily on sector-specific components, reallocations may reveal to be costly, both in terms of unemployment, and of prospective wages, due to higher likelihood to mismatch.

Investigating the determinants of the pace of labor reallocation is a matter of particular relevance, especially in a time of increasing flexibility of employment conditions, when people are called to change jobs many times in their working life. In such a context, for workers of whatever category it is more and more crucial having competencies that can be transferred, and perhaps enhanced, across sectors. Skill portability allow individuals to choose among a wider range of job opportunities, being less exposed to unemployment and pejorative wage outcomes. Consequently, general training on-the-job should be for workers a major goal of contractual bargaining, because it represents a form of unemployment insurance destined to play crucial role in times of job change. Besides, general education, as well as general training off-the-job, should be provided by public authorities, in order to guarantee an efficient functioning of the reallocation process, and hence of the labor market as a whole.

Appendix 1.1

Community identification algorithm

Let us approach the question of how to optimally identify network communities by steps, and focus initially on the problem of dividing the network into just two groups.

To calculate modularity, we first need to define a suitable null network against which to compare the actual one. To this end, we generate a network with the same number of vertices, *n*, as the original one, and where the expected degree of each vertex is equal to the actual degree of the corresponding vertex in the real network; then, we randomly place links between vertices. Therefore, in the null network the expected weight of the link going from vertex *i* to vertex *j* is equal to $k_i^{out}k_j^{in}/r$, where $r = \Sigma_{ij}w_{ij}$ is the sum of link weights all over the network. In our case, $k_i^{out}k_j^{in}/2r = k_j^{in}/r$, meaning that the expected weight of the link going form *i* to *j* depends only on the in-degree of *j*, that is on its capacity of attracting workers from other sectors. Given these notions, and closely following Newman and Leicht (2008), modularity *Q* can be written

$$Q = \frac{1}{r}\sum_{ij}\left[w_{ij} - \frac{k_j^{in}}{r}\right]\delta_{C_i,C_j} \ , \qquad (1a)$$

where $\delta_{Ci,Cj}$ is the Kronecker delta symbol, and c_i is the label of the community to which vertex *i* is assigned. At this point, it is possible to start searching for a division of the network into (two) communities $\{c_i\}$ that maximizes *Q*. Let be $s_i = 1$ if vertex *i* belongs to community 1, and $s_i = -1$ if it belongs to community 2, then: $\delta_{Ci,Cj} = 1/2(s_i s_j + 1)$ and

$$Q = \frac{1}{2r}\sum_{ij}\left[w_{ij} - \frac{k_j^{in}}{r}\right](s_i s_j + 1) = \frac{1}{2r}\sum_{ij} s_i B_{ij} s_j = \frac{1}{2r}\mathbf{s}^T\mathbf{Bs} \ , \qquad (2a)$$

where **s** is the vector whose elements are the s_i, and **B** is the *modularity matrix*, with elements

$$B_{ij} = w_{ij} - \frac{k_j^{in}}{r} \ . \qquad (3a)$$

The network can be optimally divided into two communities by choosing the index vector **s** that maximizes Q for a given **B**. For directed networks, the modularity matrix is not in general symmetric, but the implementation of the spectral algorithm for community detection requires a symmetric modularity matrix. Fortunately, this problem can be solved by adding to **B** its own transpose, to have

$$Q = \frac{1}{4r}\mathbf{s}^T\left(\mathbf{B} + \mathbf{B}^T\right)\mathbf{s} \ . \tag{4a}$$

The matrix ($\mathbf{B}+\mathbf{B}^T$) is now symmetric and we focus on this form hereafter; notice that the constant term $1/4r$ makes no difference in the position of the maximum of Q, hence we can omit it. In order to make the maximization problem more treatable, the key intuition of Newman is to express vector **s** as a linear combination of the eigenvectors $\mathbf{u}_i$ of the matrix ($\mathbf{B}+\mathbf{B}^T$), in the following way: $\mathbf{s} = \Sigma_i v_i \mathbf{u}_i$, where $v_i = \mathbf{u}_i^T\mathbf{s}$. So that equation (4a) can be written as follows

$$Q = \sum_i v_i \mathbf{u}_i^T\left(\mathbf{B} + \mathbf{B}^T\right)\sum_j v_j \mathbf{u}_j = \sum_i \beta_i\left(\mathbf{u}_i^T\mathbf{s}\right)^2 \ , \tag{5a}$$

where β_i is the eigenvalue of ($\mathbf{B}+\mathbf{B}^T$) associated to the eigenvector $\mathbf{u}_i$. Expression (5a) is the basic equation of the network partition algorithm. Let us assume that eigenvalues are labelled in decreasing order: $\beta_1 \geq \beta_2 \geq ... \geq \beta_n$. For maximizing Q, we have to find an appropriate **s**, so as to concentrate as much weight as possible in the terms of the sum (5a) that involves the largest positive eigenvalue β_1. This can be done by choosing **s** proportional to the eigenvector $\mathbf{u}_1$, but this solution is normally forbidden by the constraint $s_i = \pm 1$, so Newman proposes to proceed by approximation, making **s** as parallel as possible to $\mathbf{u}_1$. This means choosing $s_i = +1$ if $u_i^{(1)} > 0$ and $s_i = -1$ if $u_i^{(1)} < 0$, where $u_i^{(1)}$ is the ith element of $\mathbf{u}_1$ (if $u_i^{(1)} = 0$, $s_i = \pm 1$ are equally good solutions). Finally, the algorithm can be summarized as follows: we calculate the eigenvector corresponding to the largest positive eigenvalue of ($\mathbf{B}+\mathbf{B}^T$), and then we assign vertices to communities according to the sign of the corresponding elements of the eigenvector.

To divide the network into more than two communities, we proceed by repeated bisection: we first divide the network in two groups, and then divide each group and so forth; the process stops when it reaches a point at which a further division does not increase the total modularity.

The subdivision of a community which is part of a larger network requires a generalization of the method so far explained. Consider the additional contribution to total modularity ΔQ, obtained when a community g within it is subdivided. Defining s_i as before for vertices in g, we have

$$\begin{aligned}\Delta Q &= \frac{1}{2r}\left[\sum_{i,j\in g}(B_{ij}+B_{ji})\frac{s_i s_j+1}{2}-\sum_{i,j\in g}(B_{ij}+B_{ji})\right]\\ &= \frac{1}{4r}\sum_{i,j\in g}\left[(B_{ij}+B_{ji})-\delta_{ij}\sum_{k\in g}(B_{ik}+B_{ki})\right]s_i s_j \\ &= \frac{1}{4r}\mathbf{s}^T(\mathbf{B}^{(g)}+\mathbf{B}^{(g)^T})\mathbf{s}\end{aligned} \tag{6a}$$

where we define a new modularity matrix $\mathbf{B}^{(g)}$, that is a sub-matrix of $\mathbf{B}$ corresponding to the sub-graph g with the sum of each row subtracted from the corresponding diagonal element. The expression (6a) is equivalent to (4a), and we can thus apply the spectral method; notice that if the sub-graph is undivided, the contribution ΔQ to total modularity is correctly equal to zero.

The complete algorithm for network partitioning can be now summarized as follows. First, we construct the modularity matrix (3a) and find the largest positive eigenvalue β_1 of the symmetric matrix ($\mathbf{B}$+$\mathbf{B}^T$) and the corresponding eigenvector $\mathbf{u}_1$. Second, we assign vertices to communities according to the sign of the corresponding elements in the leading eigenvector. Third, in the same way we subdivide each communities, making use of the generalized formula (6a). The algorithm ends when communities cannot be further subdivided giving a positive value of ΔQ.

The procedure presented above makes explicit use only of the sign of the elements of the leading eigenvector, but the magnitudes of these elements contain useful information as well. In particular, vertices corresponding to elements of great magnitude make larger contributions to overall modularity. On the contrary, vertices corresponding to small eigenvector's elements make only a little contribution to Q, and consequently moving them from one group to another has a limited impact on modularity. In turn this means that the magnitudes of the eigenvector's elements offer a measure of how strongly the corresponding vertices belong to their assigned communities. Vertices with large elements have thus a very 'central' position in their communities, while vertices with elements close to zero are on the borderline between groups. To capture this idea in more formal terms, Newman (2006b) proposes a measure of the strength of community membership, called community centrality, that makes use of the information contained in potentially all the eigenvectors associated to positive eigenvalues of the matrix ($\mathbf{B}$+$\mathbf{B}^T$). We can define the community centrality *CI* of vertex *i* as follows

$$CI_i = \sum_{j=1}^{h} (\sqrt{\beta_j} u_{ij})^2 \quad , \tag{7a}$$

where h is the number of positive eigenvalues of the symmetrized modularity matrix, β_j is the jth positive eigenvalue, and u_{ij} is the ith component of the eigenvector corresponding to eigenvalue β_j. Making use of the index CI, it is possible to order vertices within communities according to a continuous scale that varies between zero and one, telling us how central (values close to one), or peripheral (values close to zero) vertices are in their respective groups. To simplify computation a bit, we actually derive the centrality index only on the basis of the information conveyed by the first 5 positive eigenvalues of the symmetrized modularity matrix, i.e. in our calculations we have h=5.

Appendix 1.2

Tab. A.1.2.1 – Descriptive statistics

	quick reallocations		slow reallocations		full sample	
	value	%	value	%	value	%
N° of observations (job changes)	95,504	100	93,224	100	188,728	100
male	68,661	71.89	62,659	67.21	131,320	69.58
female	26,843	28.11	30,565	32.79	57,408	30.42
young	51,688	54.12	56,162	60.24	107,850	57.15
prime-age	31,531	33.02	26,019	27.91	57,550	30.49
old	12,285	12.86	11,043	11.85	23,328	12.36
non-displaced	67,304	70.47	75,091	80.55	142,395	75.45
displaced	28,200	29.53	18,133	19.45	46,333	24.55
non-permanent mover	78,366	82.06	72,057	77.29	150,423	79.70
permanent mover	17,138	17.94	21,167	22.71	38,305	20.30
apprentice	6,598	6.91	10,520	11.28	17,118	9.08
blue collar	64,880	67.94	67,653	72.57	132,533	70.22
white collar	23,002	24.09	14,773	15.85	37,775	20.02
manager	1,016	1.06	269	0.29	1,285	0.68
north West	35,181	36.84	23,398	25.10	58,579	31.04
north East	29,659	31.06	26,103	28.00	55,762	29.55
centre	17,809	18.65	18,704	20.06	36,513	19.35
south	12,845	13.45	25,011	26.83	37,856	20.06
dimension 0-9	37,737	39.51	43,807	46.99	81,544	43.21
dimension 10-49	32,305	33.83	27,437	29.43	59,742	31.66
dimension 50-249	15,660	16.40	12,505	13.41	28,165	14.92
dimension 250-999	5,873	6.15	5,306	5.69	11,179	5.92
dimension 1000+	3,929	4.11	4,169	4.47	8,098	4.29
tenure 1	10,355	10.84	18,103	19.42	28,458	15.08
tenure 2-3	9,211	9.64	18,124	19.44	27,335	14.48
tenure 4-6	10,132	10.61	14,325	15.37	24,457	12.96
tenure 7-12	11,301	11.83	11,230	12.05	22,531	11.94
tenure 13-23	16,391	17.16	12,970	13.91	29,361	15.56
tenure 24+	38,114	39.91	18,472	19.81	56,586	29.98
Avg. week wage at separation (Euros at 2003 prices). *std. dev.*	361.90 *0.9599*		309.94 *0.8421*		336.23 *0.6423*	
Avg. months elapsing between separation and engagement. *std. dev.*			5.85 *0.0097*			

Tab. A.1.2.2 – OLS estimates of relative wage performances related to job change episodes

	model I		*model II*	
	coefficient *robust std. error*	t-stat. *p-value*	coefficient *robust std. error*	t-stat. *p-value*
slow reallocation	-0.0830 *0.0013*	-63.25 *0.000*	-0.0582 *0.0020*	-29.5 *0.000*
displaced	-0.0069 *0.0014*	-4.9 *0.000*	-0.0003 *0.0017*	-0.16 *0.873*
switch 3-digit	-0.0069 *0.0013*	-5.45 *0.000*	0.0132 *0.0016*	8.21 *0.000*
displaced*slow reallocation			-0.0121 *0.0027*	-4.48 *0.000*
switch 3-digit*slow reallocation			-0.0393 *0.0024*	-16.20 *0.000*
wage level at separation	-0.6237 *0.0032*	-193.03 *0.000*	-0.6250 *0.0032*	-193.49 *0.000*
permanent mover	0.0145 *0.0017*	8.66 *0.000*	0.0142 *0.0017*	8.51 *0.000*
gender	-0.0639 *0.0016*	-41.03 *0.000*	-0.0639 *0.0015*	-41.27 *0.000*
young	-0.0339 *0.0014*	-23.69 *0.000*	-0.0337 *0.0014*	-23.65 *0.000*
old	0.0056 *0.0022*	2.61 *0.009*	0.0054 *0.0022*	2.52 *0.012*
apprentice	-0.1790 *0.0032*	-56.32 *0.000*	-0.1794 *0.0032*	-56.48 *0.000*
blue collar	-0.1106 *0.0019*	-57.65 *0.000*	-0.1105 *0.0019*	-57.7 *0.000*
manager	-0.0585 *0.0382*	-1.53 *0.126*	-0.0582 *0.0382*	-1.52 *0.128*
north East	-0.0097 *0.0015*	-6.39 *0.000*	-0.0097 *0.0015*	-6.43 *0.000*
centre	-0.0208 *0.0018*	-11.79 *0.000*	-0.0204 *0.0018*	-11.61 *0.000*
south	-0.0304 *0.0020*	-15.24 *0.000*	-0.0319 *0.0020*	-16.07 *0.000*
dimension 0-9	-0.0236 *0.0020*	-11.88 *0.000*	-0.0235 *0.0020*	-11.85 *0.000*
dimension 10-49	-0.0138 *0.0020*	-6.87 *0.000*	-0.0134 *0.0020*	-6.73 *0.000*
dimension 250-999	0.0159 *0.0033*	4.86 *0.000*	0.0155 *0.0033*	4.76 *0.000*
dimension 1000+	0.0294 *0.0039*	7.53 *0.000*	0.0284 *0.0039*	7.34 *0.000*
tenure 1	0.0024 *0.0026*	0.94 *0.347*	0.0029 *0.0026*	1.13 *0.257*
tenure 2-3	-0.0076 *0.0024*	-3.21 *0.001*	-0.0081 *0.0024*	-3.43 *0.001*
tenure 4-6	0.0009 *0.0023*	0.38 *0.707*	0.0004 *0.0023*	0.18 *0.859*
tenure 13-23	0.0084 *0.0021*	3.94 *0.000*	0.0084 *0.0021*	3.98 *0.000*

tenure 24+	0.0281	14.43	0.0281	14.46
	0.0019	*0.000*	*0.0019*	*0.000*
constant	3.7743	191.83	3.7666	191.72
	0.0197	*0.000*	*0.0196*	*0.000*

Model I: N ° of observations: 159,493; N° of individuals: 76,347; R-squared: 0.3361.
Model II: N ° of observations: 159,493; N° of individuals: 76,347; R-squared: 0.3373.
All regressions include sector dummies at 1-digict level, and year dummies.
R-squared adjusted for clusters at individual level.

Tab. A.1.2.3 – Community structure of quick-reallocation network

community centrality	Ateco81 code	community slow reall.	Ateco definition
			(1) Building, energy, and transportation
0.6667	501	1	Costruzione d'immobili (per abitazione ed altri)
0.2642	502	1	Genio civile: costruzione di strade, ponti, ferrovie, ecc.
0.2459	132	5	Estrazione e depurazione di gas naturale
0.0582	504	1	Attività di finitura dell'edilizia
0.0488	162	1	Officine del gas; distribuzione del gas
0.0467	231	1	Estrazione di materiali da costruzione e di terre refrattarie e per ceramica
0.0428	243	1	Fabbricazione di materiali per costruzione in calcestruzzo, cemento e gesso
0.0346	979	5	Servizi ricreativi n.d.a.
0.0309	720	1	Altri trasporti terrestri (urbani, su strada, ecc.)
0.0305	242	1	Fabbricazione di cemento, calce e gesso
0.0286	503	2	Installazione
0.0284	163	1	Produzione e distribuzione di vapore, acqua calda, aria compressa, calore
0.0206	245	1	Lavorazione della pietra e di prodotti minerali non metallici
0.0177	429	3	Industria del tabacco
0.0159	170	2	Raccolta, depurazione e distribuzione d'acqua
0.0131	348	4	Montaggio, lavori di impianto tecnico (escluse le installaz. elettriche per l'edilizia)
0.0113	411	1	Industria dei grassi vegetali e animali
0.0110	750	5	Trasporti aerei
0.0106	740	1	Trasporti marittimi e cabotaggio
0.0089	984	5	Servizi personali n.d.a.
0.0077	415	5	Fabbricazione di conserve di pesce e di altri prodotti del mare
0.0058	161	1	Produzione e distribuzione di energia elettrica
0.0050	412	5	Macellazione del bestiame, preparazione e conservazione della carne
0.0039	134	2	Ricerca di petrolio e gas naturali
0.0029	613	1	Commercio all'ingrosso del legname e di materiali da costruzione
0.0029	241	2	Fabbricazione di materiali da costruzione in laterizio

0.0025	462	2	Fabbricazione di prodotti semifiniti in legno
0.0024	461	1	Taglio e preparazione industriale del legno
0.0019	131	2	Estrazione di petrolio
0.0016	416	1	Lavorazione delle granaglie
0.0013	239	1	Estrazione di altri minerali; torbiere
			(2) Firm services, banking and ICT
0.4311	839	1	Altri servizi prestati alle imprese
0.3332	232	5	Estrazione mineraria di sali di potassio e di fosfati di calce naturali
0.2158	975	5	Spettacoli (esclusi cinema e sport)
0.1944	493	5	Laboratori fotografici e cinematografici
0.1733	810	5	Istituti di credito
0.0915	812	1	Altri istituti monetari
0.0680	330	5	Costruzione di macchine per ufficio e macchine e impianti per l'elaborazione dei dati
0.0523	630	5	Intermediari del commercio
0.0238	820	5	Assicurazioni, escluse le assicurazioni sociali obbligatorie
0.0231	790	5	Comunicazioni
0.0190	730	5	Trasporti fluviali
0.0143	345	5	Costruzione di apparecchi elettronici, radioriceventi, televisori, nastri magnetici
0.0096	474	5	Editoria
0.0085	653	5	Commercio al minuto di carburanti e lubrificanti
0.0067	344	4	Fabbricazione di apparecchi per telecom., contatori, di misura, elettromedici
0.0059	257	5	Fabbricazione di prodotti farmaceutici
0.0059	364	5	Costruzione e riparazione di aeronavi
0.0046	111	1	Estrazione e agglomerazione del carbon fossile
0.0024	374	5	Fabbricazione di orologi e loro pezzi staccati
0.0022	120	1	Cokerie
			(3) Textile-clothing and footwear
0.2858	453	3	Confezione (produzione in serie) di articoli di abbigliamento e accessori
0.1729	454	3	Fabbricazione su misura di abiti, biancheria e capelli
0.1162	436	3	Fabbricazione di tessuti di maglia, maglieria, calze
0.0652	439	3	Altre industrie tessili
0.0644	431	3	Industria laniera
0.0364	437	3	Finitura di tessili
0.0339	432	3	Industria cotoniera
0.0289	438	3	Fabbricazione di tappeti, di linoleum e di copripavimento, nonché di tele cerate
0.0280	456	3	Fabbricazione di pellicce e articoli in pelo
0.0259	451	3	Fabbricazione a macchina di calzature (tranne quelle in gomma o in legno)
0.0241	442	3	Fabbricazione di articoli in cuoio e affini
0.0230	434	3	Industria del lino, della canapa e del ramié
0.0212	452	3	Fabbricazione a mano di calzature (comprese le calzature ortopediche)

0.0202	616	3	Commercio all'ingrosso di prodotti tessili, abbigliamento, calzature, articoli in cuoio
0.0189	433	3	Industria della seta
0.0160	981	3	Lavanderia, tintoria e servizi affini
0.0158	455	3	Confezione di altri articoli tessili (senza tessitura integrata)
0.0158	672	3	Riparazioni di calzature ed altri articoli in cuoio
0.0058	466	3	Fabbricazione di articoli in sughero, paglia, giunco e vimini, spazzole e pennelli
0.0056	435	3	Industria delle iuta
0.0038	365	5	Costruzione di mezzi di trasporto n.d.a.
0.0037	441	3	Concia delle pelli e del cuoio
			(4) Personal services, commerce, and hotel trade
0.2494	660	5	Pubblici esercizi e esercizi alberghieri
0.2234	830	5	Ausiliari finanziari e delle assicurazioni, affari immobiliari, servizi alle imprese
0.1677	970	5	Servizi ricreativi e altri servizi culturali
0.0728	640	5	Commercio al minuto di alimentari
0.0691	923	5	Servizi di pulizia
0.0349	921	1	Servizi di nettezza urbana, servizi di disinfezione e servizi analoghi
0.0274	650	5	Commercio al minuto di veicoli
0.0267	617	5	Commercio all'ingrosso di prodotti alimentari, bevande e tabacco
0.0246	770	5	Agenzie di viaggio, intermediari dei trasporti, magazzini di custodia e deposito
0.0236	419	5	Panetteria, pasticceria, biscottificio
0.0168	760	5	Attività connesse ai trasporti
0.0147	423	5	Fabbricazione di prodotti alimentari vari
0.0114	983	5	Studi fotografici
0.0102	619	5	Altri commercio all'ingrosso specializzati e commercio all'ingrosso di prodotti vari
0.0099	418	5	Industria dei prodotti amilacei
0.0095	982	5	Saloni di parrucchiere e istituti di bellezza
0.0090	611	5	Commercio all'ingrosso di materie prime agricole, animali vivi, materie prime tessili
0.0090	417	5	Fabbricazione di paste alimentari
0.0089	618	5	Commercio all'ingrosso di prodotti farmaceutici, sanitari, di bellezza e di detersivi
0.0076	233	2	Estrazione di sale
0.0070	421	5	Industria del cacao e cioccolato, caramelle e gelati
0.0067	414	5	Preparazione di conserve di frutta e ortaggi
0.0062	615	1	Commercio all'ingrosso di mobili, articoli per la casa e ferramenta
0.0058	612	5	Commercio all'ingrosso di combustibili, minerali e prodotti chimici
0.0052	614	5	Commercio all'ingrosso di macchine, di materiale e di veicoli
0.0047	473	5	Stampa e industrie affini
0.0043	674	5	Riparazioni di orologi; gioiellerie
0.0031	422	1	Fabbricazione di prodotti alimentari per la zootecnia (ivi compresa la farina di pesce)
0.0026	413	1	Industria casearia
0.0008	424	5	Industria degli alcool etilici di fermentazione

0.0000	340	5	Costruzione elettrica ed elettronica
			(5) Metallurgy and machine shops
0.1965	319	2	Officine meccaniche n.d.a.
0.0696	314	2	Costruzione metalliche (ivi compresa la relativa posa)
0.0409	244	2	Fabbricazione di articoli in amianto (ad esclusione degli articoli in amianto-cemento)
0.0358	328	2	Costruzione di altre macchine e apparecchi meccanici
0.0253	224	2	Produzione e prima trasformazione dei metalli non ferrosi
0.0201	312	2	Fucinatura, stampaggio, imbutitura, tranciatura e lavorazione a sbalzo
0.0155	325	2	Costruzione di macchinario per miniere, industrie siderurgiche, genio civile
0.0147	211	1	Estrazione e preparazione di minerale di ferro
0.0123	313	2	Seconda trasformazione, trattamento e rivestimento dei metalli
0.0111	220	2	Produzione e prima trasformazione dei metalli
0.0111	311	2	Fonderie
0.0098	315	2	Costruzione di caldaie e serbatoi
0.0087	223	2	Trafilatura, stiratura, laminazione di nastri, profilatura a freddo dell'acciaio
0.0080	671	2	Riparazioni di autoveicoli e biciclette
0.0069	212	1	Estrazione e preparazione di minerali metallici non ferrosi
0.0069	362	2	Costruzione di materiale rotabile a scartamento normale e a scartamento ridotto
0.0059	467	3	Industria del mobile in legno
0.0058	491	5	Bigiotteria, oreficeria, argenteria e taglio delle pietre preziose
0.0057	361	2	Costruzione navale, riparazione e manutenzione di navi
0.0045	463	2	Fabbricazione in serie di elementi di carpenteria, falegnameria, pavimenti in legno
0.0045	341	3	Fabbricazione di fili e cavi elettrici
0.0022	420	5	Industria zuccheriera
0.0017	464	2	Fabbricazione di imballaggi in legno
0.0006	428	5	Industria delle bevande analcoliche e delle acque gassate
			(6) Machine tools
0.0306	322	2	Costruzione di macchine utensili per la lavorazione dei metalli, utensili per macchine
0.0261	316	2	Fabbricazione di utensili e articoli finiti in metallo, escluso materiale elettrico
0.0225	324	4	Costruzione di macchine e apparecchi per le industrie alimentari, chimiche e affine
0.0153	343	4	Fabbricazione di materiale elettrico di uso industriale, di pile ed accumulatori
0.0153	353	4	Fabbricazione di apparecchiature, accessori e pezzi staccati per automobili
0.0149	342	2	Fabbricazione di motori, generatori, trasformatori, interruttori e altro materiale elettr.
0.0135	373	3	Fabbricazione di strumenti ottici e di apparecchiature fotografiche
0.0130	352	2	Costruzione di carrozzerie, rimorchi e cassoni mobili
0.0101	327	4	Costruzione di altre macchine e apparecchi specifici
0.0099	371	5	Fabbricazione di strumenti di precisione, di apparecchi di misura e controllo
0.0097	323	2	Costruzione di macchine tessili e di loro accessori, macchine per cucire
0.0089	326	5	Fabbricazione di organi di trasmissione
0.0080	321	2	Costruzione di macchine e trattori agricole

0.0075	351	2	Costruzione e montaggio di autoveicoli (compresi i trattori stradali) e relativi motori
0.0062	363	4	Costruzione di cicli, motocicli e loro parti staccate
0.0062	222	2	Fabbricazione di tubi di acciaio
0.0058	346	3	Fabbricazione di apparecchi elettrodomestici
0.0054	492	4	Fabbricazione di strumenti musicali
0.0037	427	2	Produzione di birra e malto
0.0034	347	5	Fabbricazione di lampade e apparecchi per illuminazione
0.0025	247	2	Industria del vetro
0.0022	465	2	Fabbricazione di altri oggetti in legno (mobili esclusi)
0.0012	372	4	Fabbricazione di materiale medico-chirurgico e apparec. ortopedici (scarpe escluse)
0.0011	248	4	Fabbricazione di prodotti in ceramica
0.0005	425	5	Industria del vino e delle bevande a base di vino
			(7) Chemicals and plastic
0.0155	483	4	Trasformazione delle materie plastiche
0.0127	251	5	Fabbricazione e trasformazione di prodotti chimici di base
0.0063	140	1	Industria petrolifera
0.0053	256	5	Fabbricazione di altri prodotti chimici destinati all'industria e all'agricoltura
0.0044	259	4	Fabbricazione di altri prodotti chimici destinati al consumo privato e all'uso d'ufficio
0.0038	260	2	Fabbricazione di fibre artificiali e sintetiche
0.0030	255	2	Fabbricazione di mastici, pitture, vernici e inchiostri da stampa
0.0022	258	5	Fabbricazione di sapone e detergenti sintetici, profumeria
0.0021	481	4	Industria della gomma
0.0018	490	2	Industrie manifatturiere diverse
0.0015	482	1	Rigenerazione e riparazione di pneumatici
0.0014	620	1	Recupero
0.0014	246	4	Produzione di mole e altri corpi abrasivi applicati
0.0011	472	4	Trasformazione della carta e del cartone, fabbricazione di articoli in pasta-carta
0.0009	471	4	Fabbricazione della pasta-carta, della carta e del cartone

Tab. A.1.2.4 – Community structure of slow-reallocation network

community centrality	Ateco81 code	community quick reall.	Ateco definition
			(1) Building, energy and transportation
0.5523	501	2	Costruzione d'immobili (per abitazione ed altri)
0.5018	245	2	Lavorazione della pietra e di prodotti minerali non metallici
0.4886	720	2	Altri trasporti terrestri (urbani, su strada, ecc.)
0.4613	111	4	Estrazione e agglomerazione del carbon fossile

0.4019	163	2	Produzione e distribuzione di vapore, acqua calda, aria compres.; produz. di calore
0.2750	502	2	Genio civile: costruzione di strade, ponti, ferrovie, ecc.
0.1123	120	4	Cokerie
0.1088	211	1	Estrazione e preparazione di minerale di ferro
0.0764	504	2	Attività di finitura dell'edilizia
0.0556	231	2	Estrazione di materiali da costruzione e di terre refrattarie e per ceramica
0.0291	812	4	Altri istituti monetari
0.0259	242	2	Fabbricazione di cemento, calce e gesso
0.0254	243	2	Fabbricazione di materiali per costruzione in calcestruzzo, cemento e gesso
0.0162	416	2	Lavorazione delle granaglie
0.0138	411	2	Industria dei grassi vegetali e animali
0.0134	239	2	Estrazione di altri minerali; torbiere
0.0115	212	1	Estrazione e preparazione di minerali metallici non ferrosi
0.0112	740	2	Trasporti marittimi e cabotaggio
0.0102	161	2	Produzione e distribuzione di energia elettrica
0.0085	921	3	Servizi di nettezza urbana, servizi di disinfezione e servizi analoghi
0.0075	839	4	Altri servizi prestati alle imprese
0.0063	422	3	Fabbricazione di prodotti alimentari per la zootecnia (compresa la farina di pesce)
0.0053	461	2	Taglio e preparazione industriale del legno
0.0049	140	6	Industria petrolifera
0.0036	162	2	Officine del gas; distribuzione des gas
0.0036	620	6	Recupero
0.0033	615	3	Commercio all'ingrosso di mobili, articoli per la casa e ferramenta
0.0019	613	2	Commercio all'ingrosso del legname e di materiali da costruzione
0.0017	482	6	Rigenerazione e riparazione di pneumatici
0.0004	413	3	Industria casearia
			(2) Textile-clothing and footwear
0.2946	453	5	Confezione (produzione in serie) di articoli di abbigliamento e accessori
0.1543	454	5	Fabbricazione su misura di abiti, biancheria e capelli
0.0749	436	5	Fabbricazione di tessuti di maglia, maglieria, calze
0.0510	451	5	Fabbricazione a macchina di calzature (tranne quelle in gomma o in legno)
0.0348	429	2	Industria del tabacco
0.0333	456	5	Fabbricazione di pellicce e articoli in pelo
0.0331	672	5	Riparazioni di calzature ed altri articoli in cuoio
0.0263	442	5	Fabbricazione di articoli in cuoio e affini
0.0254	452	5	Fabbricazione a mano di calzature (comprese le calzature ortopediche)
0.0246	438	5	Fabbricazione di tappeti, di linoleum e di copripavimento, nonché di tele cerate
0.0198	981	5	Lavanderia, tintoria e servizi affini
0.0181	439	5	Altre industrie tessili
0.0162	431	5	Industria laniera

0.0142	437	5	Finitura di tessili
0.0136	455	5	Confezione di altri articoli tessili (senza tessitura integrata)
0.0103	616	5	Commercio all'ingrosso di prodotti tessili, abbigliamento, calzature e art. in cuoio
0.0074	434	5	Industria del lino, della canapa e del ramié
0.0073	433	5	Industria della seta
0.0052	432	5	Industria cotoniera
0.0050	435	5	Industria delle iuta
0.0036	341	1	Fabbricazione di fili e cavi elettrici
0.0035	373	7	Fabbricazione di strumenti ottici e di apparecchiature fotografiche
0.0035	466	5	Fabbricazione di articoli in sughero, paglia, giunco e vimini, spazzole e pennelli
0.0031	441	5	Concia delle pelli e del cuoio
0.0023	346	7	Fabbricazione di apparecchi elettrodomestici
0.0019	467	1	Industria del mobile in legno
			(3) Personal services, commerce and hotel trade
0.2441	660	3	Pubblici esercizi e esercizi alberghieri
0.1203	830	3	Ausiliari finanziari e delle assicurazioni, affari immobiliari, servizi alle imprese
0.1011	975	4	Spettacoli (esclusi cinema e sport)
0.0990	970	3	Servizi recreativi e altri servizi culturali
0.0951	493	4	Laboratori fotografici e cinematografici
0.0549	640	3	Commercio al minuto di alimentari
0.0515	340	3	Costruzione elettrica ed elettronica
0.0319	979	2	Servizi ricreativi n.d.a.
0.0295	983	3	Studi fotografici
0.0266	650	3	Commercio al minuto di veicoli
0.0225	419	3	Panetteria, pasticceria, biscottificio
0.0195	630	4	Intermediari del commercio
0.0171	730	4	Trasporti fluviali
0.0154	421	3	Industria del cacao e cioccolato, caramelle e gelati
0.0147	330	4	Costruzione di macchine per ufficio, macchine e impianti per l'elaborazione dei dati
0.0140	923	3	Servizi di pulizia
0.0120	770	3	Agenzie di viaggio, intermediari dei trasporti, magazzini di custodia e deposito
0.0118	982	3	Saloni di parrucchiere e istituti di bellezza
0.0118	750	2	Trasporti aerei
0.0116	417	3	Fabbricazione di paste alimentari
0.0110	345	4	Costruzione di apparec. elettron., radioriceventi, televisori, dischi e nastri magnetici
0.0100	423	3	Fabbricazione di prodotti alimentari vari
0.0085	790	4	Comunicazioni
0.0084	810	4	Istituti di credito
0.0079	418	3	Industria dei prodotti amilacei
0.0076	820	4	Assicurazioni, escluse le assicurazioni sociali obbligatorie

0.0075	760	3	Attività connesse ai trasporti
0.0075	374	4	Fabbricazione di orologi e loro pezzi staccati
0.0072	364	4	Costruzione e riparazione di aeronavi
0.0072	326	7	Fabbricazione di organi di trasmissione
0.0071	365	5	Costruzione di mezzi di trasporto n.d.a.
0.0068	371	7	Fabbricazione di strumenti di precisione, di apparecchi di misura e controllo
0.0066	415	2	Fabbricazione di conserve di pesce e prodotti del mare per alimentazione umana
0.0066	474	4	Editoria
0.0061	617	3	Commercio all'ingrosso di prodotti alimentari, bevande e tabacco
0.0061	653	4	Commercio al minuto di carburanti e lubrificanti
0.0056	619	3	Altri commercio all'ingrosso specializzati e commercio all'ingrosso di prodotti vari
0.0051	984	2	Servizi personali n.d.a.
0.0048	414	3	Preparazione di conserve di frutta e ortaggi
0.0048	491	1	Bigiotteria, oreficeria, argenteria e taglio delle pietre preziose
0.0034	618	3	Commercio all'ingrosso di prodotti farmaceutici, sanitari, di bellezza e di detersivi
0.0033	614	3	Commercio all'ingrosso di macchine, di materiale e di veicoli
0.0032	674	3	Riparazioni di orologi; gioiellerie
0.0029	611	3	Commercio all'ingrosso di materie prime agricole, animali vivi, mat. prime tessili
0.0028	473	3	Stampa e industrie affini
0.0028	257	4	Fabbricazione di prodotti farmaceutici
0.0027	612	3	Commercio all'ingrosso di combustibili, minerali e prodotti chimici per l'industria
0.0025	420	1	Industria zuccheriera
0.0022	258	6	Fabbricazione di sapone e detergenti sintetici nonché di altri prodotti per l'igiene
0.0020	424	3	Industria degli alcool etilici di fermentazione
0.0018	347	7	Fabbricazione di lampade e apparecchi per illuminazione
0.0017	425	7	Industria del vino e delle bevande a base di vino
0.0012	251	6	Fabbricazione di prodotti chimici di base
0.0011	412	2	Macellazione del bestiame, preparazione e conservazione della carne
0.0007	428	1	Industria delle bevande analcooliche e delle acque gassate
0.0003	256	6	Fabbricazione di altri prodotti chimici destinati all'industria e all'agricoltura
0.0000	132	2	Estrazione e depurazione di gas naturale
0.0000	232	4	Estrazione mineraria di sali di potassio e di fosfati di calce naturali
			(4) Metallurgy and machine shops
0.1066	319	1	Officine meccaniche n.d.a.
0.0994	314	1	Costruzione metalliche (ivi compresa la relativa posa)
0.0413	233	3	Estrazione di sale
0.0406	503	2	Installazione
0.0234	131	2	Estrazione di petrolio
0.0229	328	1	Costruzione di altre macchine e apparecchi meccanici
0.0145	427	7	Produzione di birra e malto

0.0138	322	7	Costruzione di macchine utensili per la lavorazione dei metalli, utensileria e utensili
0.0137	134	2	Ricerca di petrolio e gas naturali
0.0123	315	1	Costruzione di caldaie e serbatoi
0.0120	316	7	Fabbricazione di utensili e articoli finiti in metallo, escluso materiale elettrico
0.0113	244	1	Fabbricazione di articoli in amianto (escluso articoli in amianto-cemento)
0.0100	325	1	Costruzione di macchinario per le miniere, le industrie siderurgiche e le fonderie
0.0098	342	7	Fabbricazione di motori, generatori, trasformatori, interruttori e materiale elettrico
0.0090	490	6	Industrie manifatturiere diverse
0.0082	323	7	Costruzione di macchine tessili e di loro accessori; macchine per cucire
0.0079	311	1	Fonderie
0.0077	313	1	Seconda trasformazione, trattamento e rivestimento dei metalli
0.0069	321	7	Costruzione di macchine e trattori agricole
0.0067	671	1	Riparazioni di autoveicoli e biciclette
0.0064	220	1	Produzione e prima trasformazione dei metalli
0.0059	312	1	Fucinatura, stampaggio, imbutitura, tranciatura e lavorazione a sbalzo
0.0057	224	1	Produzione e prima trasformazione dei metalli non ferrosi
0.0056	241	2	Fabbricazione di materiali da costruzione in laterizio
0.0052	222	7	Fabbricazione di tubi di acciaio
0.0051	223	1	Trafilatura, stiratura, laminazione di nastri, profilatura a freddo dell'acciaio
0.0041	260	6	Fabbricazione di fibre artificiali e sintetiche
0.0040	362	1	Costruzione di materiale rotabile a scartamento normale e a scartamento ridotto
0.0037	462	2	Fabbricazione di prodotti semifiniti in legno
0.0036	352	7	Costruzione di carrozzerie, rimorchi e cassoni mobili
0.0030	351	7	Costruzione e montaggio di autoveicoli (compresi i trattori stradali) e relativi motori
0.0025	361	1	Costruzione navale, riparazione e manutenzione di navi
0.0015	464	1	Fabbricazione di imballaggi in legno
0.0014	255	6	Fabbricazione di mastici, pitture, vernici e inchiostri da stampa
0.0013	170	2	Raccolta, depurazione e distribuzione d'acqua
0.0012	463	1	Fabbricazione in serie di elementi di carpenteria, falegnameria, pavimenti in legno
0.0009	465	7	Fabbricazione di altri oggetti in legno (mobili esclusi)
0.0003	247	7	Industria del vetro
			(5) Mixed group
0.0156	324	7	Costruzione di macchine e apparecchi per le industrie alimentari, chimiche e affine
0.0118	483	6	Trasformazione delle materie plastiche
0.0084	327	7	Costruzione di altre macchine e apparecchi specifici
0.0082	343	7	Fabbricazione di materiale elettrico di uso industriale, di pile ed accumulatori
0.0075	353	7	Fabbricazione di apparecchiature, accessori e pezzi staccati per automobili
0.0068	348	2	Montaggio, lavori di impianto tecnico (escluse installazioni elettriche per l'edilizia)
0.0063	363	7	Costruzione di cicli, motocicli e loro parti staccate
0.0055	492	7	Fabbricazione di strumenti musicali

0.0047	246	6	Produzione di mole e altri corpi abrasivi applicati
0.0044	344	4	Fabbricazione di apparecchi per telecomunicazioni, contatori, apparec. elettromed.
0.0041	259	6	Fabbricazione di altri prodotti chimici principalmente destinati al consumo privato
0.0025	372	7	Fabbricazione di materiale medico-chirurgico e apparec. ortopedici (scarpe escluse)
0.0014	471	6	Fabbricazione della pasta-carta, della carta e del cartone
0.0013	248	7	Fabbricazione di prodotti in ceramica
0.0010	472	6	Trasformazione della carta e del cartone, fabbricazione di articoli in pasta-carta
0.0008	481	6	Industria della gomma

2 Discovering the network structure of labor mobility

2.0 Abstract

This Chapter explores the network topology of inter-firm labor mobility in the Italian region of Veneto, during the 90s. Drawing upon a matched employer-employee dataset that covers the universe of private dependent workers, we map individual job changes onto a directed graph, where vertices indicate firms, and links denote transfers of workers between firms.

Three are our major empirical findings: (1) the network is a small world; (2) the degree distribution is well approximated by a power law in the tail; (3) the overall architecture is denoted by hierarchical clustering. High level of interconnection, redundancy of paths at local scale, and small average distances all contribute to guarantee mutual accessibility to a large fraction of labor market locations. We show that the measured connectivity crucially depends on the presence of hubs that span the network from side to side, bridging together different local clusters by means of long-distance links. The main hubs are found to be large firms, belonging to three categories: (1) temporary jobs agencies; (2) long-tradition manufacturing companies; (3) chains of department stores, supermarkets, and companies providing services directly at the costumer's.

We argue that public authorities should devote special care to hubs. In particular, long-tradition manufacturers – nowadays facing tough competitive pressure from low-wages countries – should be supported, since their failure would lead to an unprecedented lack of interconnectivity in the labor market, hampering labor flows. Besides, particular attention should be placed on the emergence of temporary employment agencies, not much as gatherers of precarious employment, rather as effective labor market integrators. We believe network analysis, of the sort discussed in the present study, can be an extremely effective tool, in order of monitoring labor market functioning, identifying potential weaknesses, and locating precise targets for policy interventions.

2.1 Introduction

The object of investigation of the present Chapter is the firm-to-firm network formed by worker reallocations. Our analysis moves on two levels. First, we perform a systematic exploration of the network structure of labor mobility, so as to provide a description of the reallocation market that is totally unprecedented, because of both the dimension explored (network), and the fine level of data disaggregation (individual reallocations). Second, we categorize network properties according to functional significance, so as to identify their implications for labor market functioning, ultimately aiming at identifying the critical elements – either single firms or connectivity structures – that should be protected, or promoted, in order for reallocations to occur smoothly and efficiently.

Our work complements the traditional *flow approach* to labor markets, by way of considering individual firm-to-firm transitions, and then positioning each of them into a more and more complex mobility pattern. We use employer-employee matched data referring to the whole population of private dependent workers in a highly industrialized region of Italy, Veneto. We single out worker reallocations occurred during the 90s, and map them onto a directed graph, whose vertices represent employers, and whose links symbolize passages of workers from one employer to another. We explore in detail a variety of local and global properties of the graph, uncovering firm-to-firm pathways and characterizing the employers partaking into such circuits, and we discuss how the collected evidence is related to specific forms of industrial organization[1].

Veneto represents a sort of ideal setting for studying labor reallocation. Firms are quite fairly distributed over the entire territory, and they are organized around a plurality of small and medium urban centers, so that, a priori, there is no single industrial concentration able to capture a majority portion of mobility flows, i.e. there are no clear cut center-periphery patterns. Besides, throughout the 90s, Veneto labor market has been characterized by a relevant, positive rate of job creation in both manufacturing and services, and by almost frictional unemployment. Consequently, soon as vacancies open up, they are very likely to be filled with people from the pool of employed people, hence originating firm-to-firm switches, and giving rise to proper chains of substitutions, known as vacancy chains (Contini and Revelli, 1997). In such a context, the micro-level structure of labor mobility turns out to be particularly important in determining the aggregate behavior of the reallocation market.

[1] Importantly, our research effort is not aimed at assessing whether and to what extent reallocations are good for the economy or individuals. In the analysis we perform, the amount of labor mobility is taken as an exogenous factor, and the focus is on the global arrangement of individual job transitions. The key research question is rather, given a certain demand and supply of reallocations, in turn originating a certain level of worker mobility, what features or elements of the connectivity structure, revealed by individual moves, have an impact on the functioning of the reallocation market. Understanding what is the optimal amount of worker turnover in the economy is a question that goes beyond the scope of our current work.

The study draws upon the VWH database[2], a longitudinal panel that presents the unique feature of covering the entire population of private sector workers and employers in Veneto, so allowing to recover virtually all individual transitions between firms. Moreover, the administrative nature of VWH ensures that the network we construct is a reliable representation of the true fabric of labor mobility, since very little is the ambiguity in the data about what a change of employer actually is, and quite small is the actual uncertainty as to whether a worker has moved or not from one firm to another.

Worker reallocation is quantified by counting individual firm-to-firm passages. This type of mobility arises in two cases: when workers resign to form a new job match, whatever the reason at the origin of such decision; or when workers find another job, after being fired by employers aiming at modifying the workforce assortment, or at reducing employment level. In all cases, in order to properly speak of reallocation, the period of non-employment intervening between subsequent job spells must be reasonably short.

In this essay we consider all employment transitions occurred over a whole decade, the 90s, so as to capture patterns of mobility not influenced by short-term fluctuations of the business cycle. We take account of job switches generated both by quits and dismissals, imposing the relatively loose condition that the transition is accomplished within 12 months. Most importantly, we focus on the *unweighted* network, exploring the arrangement and direction of links, without paying attention to how many workers actually pass through each link; a future study of the weighted network will then benefit from the knowledge of the underlying unweighted structure.

In the following analysis, a key concept is that of *path*, that is an uninterrupted chain of links connecting several firms in sequence. Based upon the existence of paths – especially short paths – and on their layout, we evaluate the extent to which different locations (employers) are accessible from a given position in the network. The key idea is that paths are not mere displays of independent, unrelated mobility episodes, but rather, they signal effectively practicable routes to navigate across the labor market.

This view is strongly supported by empirical evidence about the dominant role vacancy-chain-driven reallocations played in the very tight labor market characterizing Veneto during the 80s and the 90s[3]. A vacancy chain denotes a succession of substitutions of workers into jobs, which is

[2] VWH is the acronym for Veneto Worker Histories, a matched employer-employee dataset developed at the Department of Economics of the University of Venice “Ca’ Foscari”, on the ground of administrative records from the Italian Social Security Institute; see Occari *et al*. (2001).

[3] Based on an earlier version of the VWH dataset, Tattara and Valentini (2004) show that the share of employer-to-employer transitions accomplished within 4 months, accounted for by vacancy-chain processes, is on average 88%. Taking into account the further tightening of Veneto labor market, throughout the second half of the 90s, we believe in our setting the share of employer-to-employer transitions explained by vacancy chains is unlikely to be much lower than the one calculated by Tattara and Valentini.

ultimately made possible by the existence of a non trivial degree of overlapping among the sets of tasks, skills, and professional profiles offered and demanded by firms located along the chain. Insofar as paths embody substitution chains, they hence represent channels through which a given worker can potentially flow through. In turn, this means that the network, i.e. the arrangement of all paths, can be viewed as a sort of infrastructure that is capable of supporting and directing worker flows. Our task is then to study the properties of such infrastructure.

The measures we present in the next Sections are essentially aimed at gauging to what extent it is possible to move from one vertex to another following a connected path, and understanding which elements guarantee such connectivity. In particular, we investigate three fundamental issues:

1) the level of network interconnection and the existence of a *small-world* effect;
2) the shape of the probability distribution of vertex links, the so called *degree distribution*[4];
3) the characteristics of the most connected vertices, *hubs*, and their impact on connectivity.

The reminder of the Chapter is organized as follows. Section 2.2 gives a brief account of the economic importance of factor reallocation, with special focus on labor markets; Section 2.3 provides the formal definitions of the labor mobility network, and of the metrics we use to define its structure; Section 2.4 describes the dataset and the sample selection criteria, also providing some notions about Veneto economy; Section 2.5 discusses network connectivity and the small-world characteristics; Section 2.6 analyzes the degree distribution; Section 2.7 focuses on the hierarchical structure of the network; Section 2.8 highlights the properties of the most important vertices; finally, Section 2.9 concludes.

2.2 Theoretical insights on labor reallocation

The mobility of workers between employers is a distinctive feature of most contemporary labor markets. Quite intuitively, both the success of individual work histories and firms performance rely

[4] The organizations (vertices) populating our network differ substantially in employment size, and such characteristic plays a relevant role in determining the number of connections each vertex can support, as a pure consequence of its dimension; see the discussion in Watts (2004, p. 255-56). That is to say, the process generating the observed link distribution is likely to be influenced by the (unknown) process governing the size distribution of firms. To disentangle the complex relationships linking together these two dimensions is far beyond the scope of the present essay; here, we analyze exclusively labor mobility patterns, and then discuss the results making use of all the information available, including firm size. As we show in Section 2.6, vertex degree and firm size are correlated, but the intensity of such linkage is only moderate and, thus, it is far from being conclusive, leaving good autonomy to the analysis we perform. On the size distribution of firms, see the pioneering article of Simon and Bonini (1958), and more recently Luttmer (2007), and Buldyrev *et al*. (2007).

critically on the characteristics of the labor reallocation process; therefore, to understand the mechanisms underlying such phenomenon represents a major interest for policy makers, in order to devise appropriate measures for boosting economic growth and community welfare.

In market economies, growth – especially long-term growth – is widely understood to rest on two pillars: innovation and reallocation of production factors (Acemoglu, 2009). Let us imagine output is obtained by means of combinations of factors, capital and labor; more specifically, assume production takes place through matching units of labor (workers) with units of capital (technologies, firms). Many units of capital and labor exist, each characterized by specific attributes, hence, several different matches of labor and capital – yielding different productivity – are feasible, of which some do exist at any given point in time.

Weitzman (1998) coined the term “recombinant growth”, referring to the possibility of rising value added by means of looking for new, productivity-enhancing combinations/matches of factors, obtained through dissolving already existing matches, and forming new ones, suitable of generating higher product. In other words, under the play of selective forces stemming from market competition, growth can be viewed as a process of constant recombination of factors into new productive configurations with increased “fitness”.

This process is propagated by reallocation. Reallocation of factors between concurrent uses, in particular labor transfers between industries or firms, is a counterpart of growth. Indeed, growth usually takes place together with output, labor, and capital moving away from given companies towards their competitors, and from sectors in which the economy ceases to have comparative advantage, towards those where advantages are stronger. In real markets, existing firms, procedures, and products are continuously replaced by new ones, while capital is diverted between alternative investments, and workers transfer across firms – much in the Schumpeterian spirit of creative destruction.

Small improvement in technology, or increase in individual skills within a given production configuration have a positive, direct effect on productivity, but their potential impact can in principle better unfold if the production configuration, formed by labor and capital, is allowed to change, for instance by dissolving current employer-employee matches and forming new ones. Of course, this process implies a cost associated to match breaking, namely, potential unemployment for workers, and long-lasting vacancies for employers, but positive effects overcome negative ones in the long term, according to most literature[5].

[5] Of course, the extent to which the potential for productivity-enhancing reallocation is realized is likely to be a function of a number of factors. Existing theoretical models tend to emphasize frictions in product and factor markets (Caballero and Hammour, 1996), externalities associated with innovation (Aghion and Howitt, 1992), or the impact of international trade (Melitz, 2003).

The relationship between growth and reallocation is particularly evident in times of economic crisis or industrial restructuring, and it has been extensively studied with reference to transition countries, or to major trade reforms[6]. Most dynamic market economies have been shown to exhibit significant rates of resource reallocation across production units, and across economic sectors[7]. In labor economics, workers turnover over jobs has been the object of extensive investigation both on theoretical and on empirical sides. Applied analyses focus mostly on the dynamics of aggregate employment flows, according to business cycle fluctuations, exploring occupational and sectoral dimensions as well. Some studies go further, addressing the relationship between worker engagements (separations), and job creation (destruction) at the employer level[8].

Most of the creative destruction process, thus most reallocation, takes place at micro level, that is at establishment level; therefore, the bulk of our attention as researchers should be devoted to exploring reallocation at a very disaggregated level of analysis. But the micro-level structure of labor mobility – in particular the complex web of connections between firms each worker contributes to weave as the result of changing employer – has never been thoroughly investigated[9].

At firm-level resolution, the fabric of labor mobility emerges as the combination of different individual transitions into longer paths, linking together many firms in sequence. We may think of each link as a door opened by the passage of one or more workers, and we may look at a chain of links as a corridor with many doors, along which reallocations progressively both come into being, and find an outlet, being fed by multiple sources, and branching off into different directions along the way. At firm-level resolution, worker reallocation looks like a gradual process of percolation through a porous material, and the microscopic architecture of this material is what ultimately determines direction and timing of the flows we usually observe at some higher level of aggregation.

Understanding the micro-level structure of labor reallocation, and the related dynamics of worker transfers from job to job, is relevant also to welfare decisions. In Italy, at present time, this topic is of particular interest, since the political arena is now engaged into an animated debate about the possible transition from a welfare system for labor based essentially on high firing costs, strong

---

[6] On transition economies, see for instance Brown and Earle (2004); on trade reforms, see the recent paper by Kambourov (2008).

[7] The empirical regularities of these processes have been extensively documented in studies of job reallocation, such as those by Davis and Haltiwanger (1990, 1992, 1999). The relationship between reallocation and productivity has been analyzed by Baily, Hulten, and Campbell (1992), Bartelsman and Dhrymes (1998), and Foster, Haltiwanger, and Krizan (2001), among others.

[8] For a comprehensive review of the so called flow approach to labor markets, see Schettkat (1996). With reference to the U.S., flow analyses can be found for instance in Fallick and Fleishman (2004), and in Yashiv (2007), occupational and sectoral mobility are discussed in Moscarini and Thomsson (2007), and in Kambourov and Manovskii (2008), while recent examples of employer-level studies are those of Cooper *et al*. (2007), and Davis *et al.* (2006, 2009).

[9] To the best of our knowledge, the only attempt to explore this phenomenon is the study of Currarini and Feri (2006).

employment protection, and social security cushions associated to job maintenance (wage supplementation schemes, as CIG, CIGS, or CIG in deroga), towards a welfare system of "flexsecurity" (Ichino, 2009).

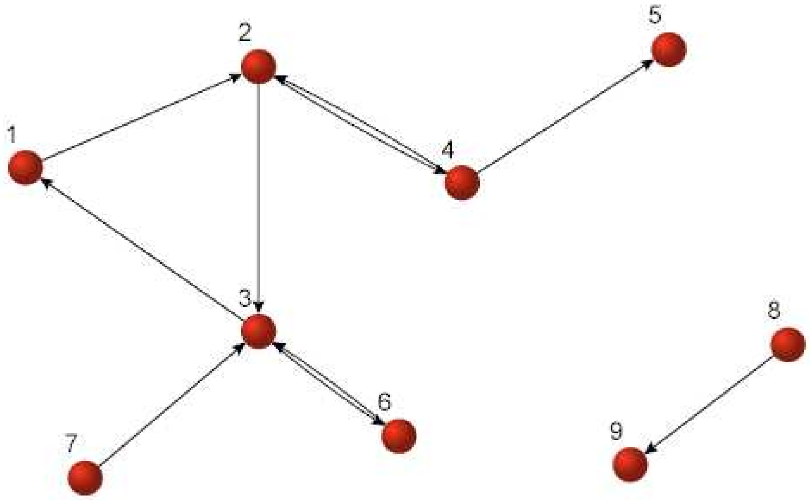
Flexsecurity is essentially based on two simultaneous mechanisms: high unemployment subsidies, being able of effectively supporting individual and household income, and active reallocation policies, substituting for high employment protection and wage supplementation schemes (De Vos, 2009). The aim of such a system is to combine benefits for firms, stemming from employment flexibility, with substantial income protection for workers. At the very core of the idea of flexsecurity lays the worker reallocation process: a smooth and efficient reallocation of workers across jobs represents the key for successful and sustainable labor welfare policies, also allowing for productivity enhancement, according to recombination of production factors. Therefore, reallocation can be regarded as the crucial dimension governing the relationship between welfare choices and productivity paths.

The possibility of designing successful welfare policies and promoting growth largely resides in our ability of pinpointing the fundamental patterns of labor mobility, up to a highly disaggregated level of resolution, in order to extract valuable hints about how reallocation actually work. Network analysis applied to employer-worker linked data gives us a unique chance of exploring in detail the structure of worker reallocation, about which we have still very little empirical knowledge, and almost no priors about what to expect from what we do not know.

2.3 Network definitions

This Section provides the formal definitions of the graph-theoretic concepts we are going to use throughout the study. Let $V = \{i\text{: } 1, 2, ..., n\}$ be a finite set of firms, representing network vertices. For each ordered pair of firms (i, j), with $i, j \in V$ and $i \neq j$, let $l_{ij} \in \{0,1\}$ be a link pointing from i to j, with $l_{ij} = 1$ if at least one worker has passed from firm i to firm j (active link), and $l_{ij} = 0$ otherwise (inactive link); let then $L = \{l_{ij}\}$ be the collection of such links. The set of firms and the set of links form the binary, directed labor mobility network $G(V, L)$, of which an instructive graphical example is given in Figure 2.1. The total number of vertices is n; the number of active links is $m = \sum_{i \in V} \sum_{j \in V} l_{ij}$; the number of active links divided by the total number of links then gives the network *density*, denoted by $\delta(G) = m/n(n-1)$. Henceforth, with the word links we refer to just active links.

Figure 2.1 – Network with *n*=9, and *m*=10



Note: firms 2 and 4, as well as 3 and 6, directly exchange workers in both directions.

We define *in-degree* of vertex *i* the number of links pointing towards *i*, and we denote it by k_i^{in}; similarly, we define *out-degree* of vertex *i* the number of links originating from *i*, and we denote it by k_i^{out}. The *total-degree* of vertex *i*, indicated by k_i^{tot}, is then the sum of in-degree and out-degree. In formal terms we can write the following expressions[10]

$$k_i^{in} = \sum_{j \in V} l_{ji} \quad , \tag{1a}$$

$$k_i^{out} = \sum_{j \in V} l_{ij} \quad , \tag{1b}$$

$$k_i^{tot} = k_i^{in} + k_i^{out} \quad . \tag{1c}$$

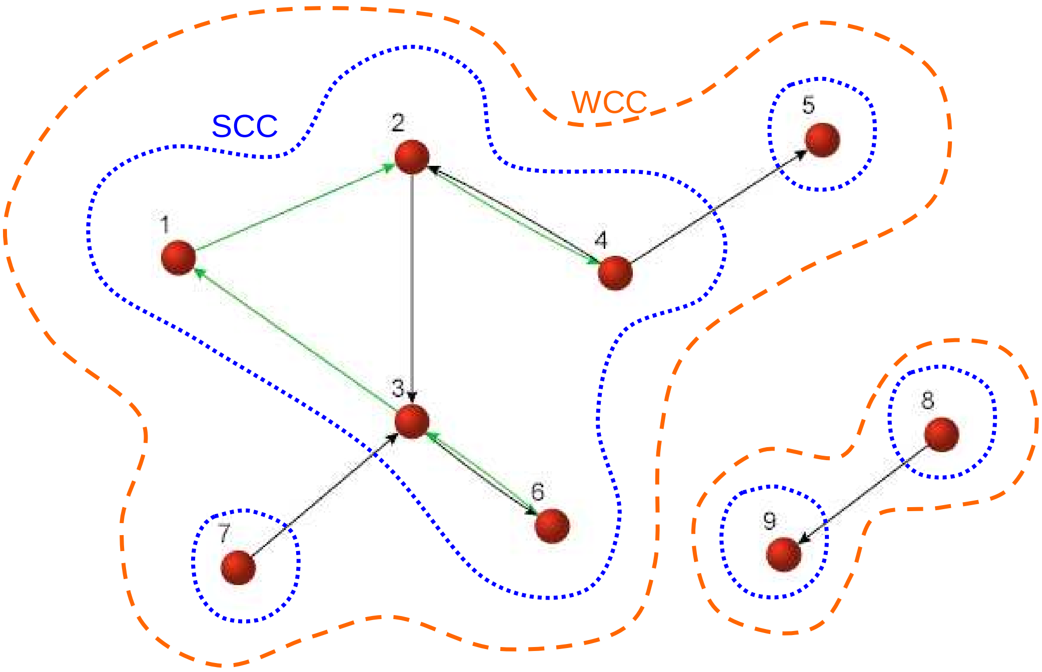
The average degree of a network is equal to the average degree of its vertices, denoted by $k(G)$. The vertices with highest degree are termed *hubs*. If we think of the degree of a vertex as a realization of a random variable K, the *degree distribution* is then the probability distribution of K,

[10] For the sake of simplicity, in the reminder of the text we generally omit the superscripts of *k*, and we often refer to total-degree simply as degree.

i.e. the probability that a vertex has degree exactly equal to k, and it is indicated by $p(k)=\Pr(K=k)$[11]. In the text we also refer to the *complementary cumulative degree distribution* (CCDD), denoted by $P(k)$, and defined to be $P(k)=\Pr(K\geq k)$.

We say there is a *path* from vertex i to vertex j, either if $l_{ij}=1$, or if there is a set of distinct intermediate vertices $j_1, j_2, ..., j_n$ such that $l_{ij_1}=l_{j_1j_2}=...=l_{j_nj}=1$. A network *component* is a set of vertices which are all reachable through paths, either mutually reachable, obtaining a *strongly connected component*, or just one-way reachable, obtaining a *weakly connected component*. A network may consist of several components, which can be ordered according to size, i.e. the number of vertices they comprise. We say a network exhibits a *giant component*, when the largest weakly connected component covers at least 50% of vertices ($n_{wcc} \geq n/2$), the largest strongly connected component covers at least 25% of vertices ($n_{scc} \geq n/4$), and the other components are small (typically of order $\ln(n)$). In the text, we refer to giant weakly/strongly connected components with the acronyms WCC and SCC, respectively. Path and components are exemplified in Figure 2.2.

Figure 2.2 – Strong components (blue, dotted), weak components (orange, dashed), and shortest path from vertex 6 to vertex 4 (green links)



[11] In directed networks there exist three different degree distributions: the in-degree, out-degree, and total-degree.

The length of a path from i to j is equal to the number of links we have to run along to reach j starting from i. In general, a pair of vertices can be connected by several different paths; we call *geodesic* the shortest path from i to j, and we denote its length by d_{ij} [12]. We then define *average path length* (APL) of a network the average length of the geodesics between all possible pairs of vertices in SCC, denoted by $d(G)$, yielding[13]

$$d(G) = \frac{\sum_{i \in SCC} \sum_{j \in SCC} d_{ij}}{n_{SCC}(n_{SCC} - 1)} \ . \tag{2}$$

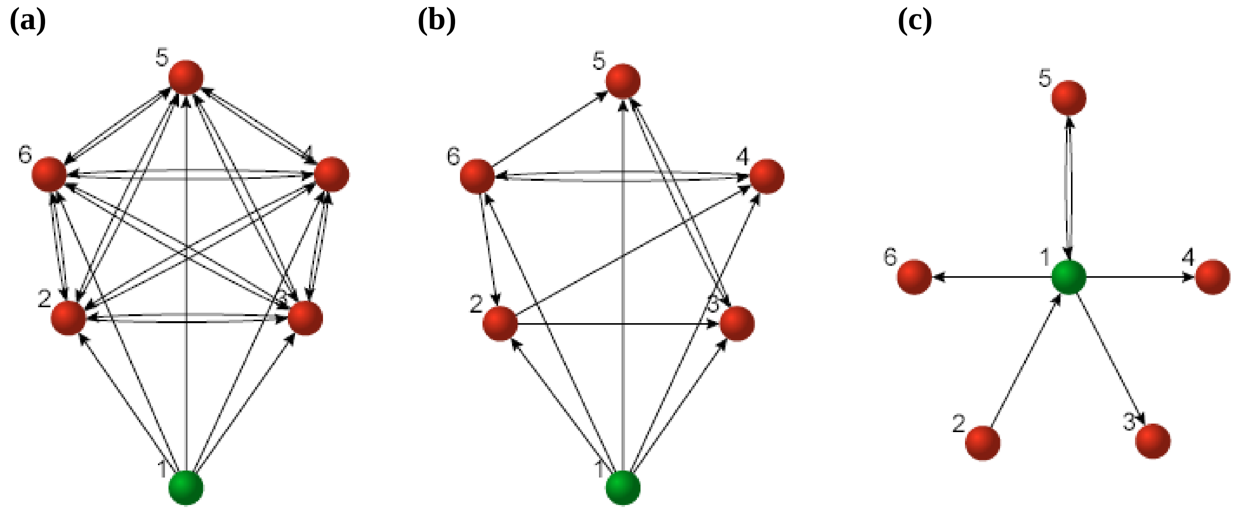
The set of firms with which firm i directly exchanges workers, both on entry and exit, is called (*nearest*) *neighborhood* of i, and it is defined as $N_i = \{ j \in V : l_{ij} = 1 \vee l_{ji} = 1 \}$; the number of neighbor vertices of i is thus $\eta_i = |N_i|$. This notion leads to the definition of a metric called *clustering coefficient*. The clustering coefficient of vertex i, denoted by C_i, measures the extent to which the neighbor vertices of i are linked together, forming a densely connected group. Following Watts and Strogatz (1998), we define the clustering coefficient of vertex i as the ratio between the actual number of links between its neighbors, and the maximum possible number of such links. Denoting by u and v two generic neighbors of i, we obtain the next definition

$$C_i = \frac{\sum_{u \in N_i} \sum_{v \in N_i} l_{uv}}{\eta_i(\eta_i - 1)} \ , \tag{3}$$

which takes values in the interval [0,1]. Vertices with $\eta_i = 1$ are assigned $C_i = 0$. The average clustering coefficient of a network is indicated by $C(G)$, and in the text we refer to it with the acronym ACC. When C_i is high, compared to $C(G)$, i is said to be part of a *local* structure (equivalently, i has local connections), as the average distance between its neighbors is smaller than expected; when C_i is less than average, i is said to be part of a *global* structure (equivalently, i has global connections), as its neighbors tend to be part of distinct, local groups. In Figure 2.3 different graphical examples of clustering for the green vertex are given.

[12] Notice that in directed networks usually $d_{ij} \neq d_{ji}$.
[13] See Boccaletti *et al*. (2006).

Figure 2.3 – Clustering coefficient: vertex 1 has max (a), intermediate (b), no clustering (c)



$C_1 = 1$ $C_1 = 0.4$ $C_1 = 0$

A further, essential network-theoretic concept is that of vertex *betweenness*. Such quantity offers an indication of the relevance of a vertex in a given network, measured as its capacity of controlling communication between other vertices. According to the original formulation given by Freeman (1977), a vertex is considered relevant to the extent that it falls on the geodesics between other vertices. The betweenness index of vertex i, denoted by b_i, is then defined as follows

$$b_i = \sum_{h,j \in V, h \neq j} \left[\frac{g_{h,j}(i)}{g_{h,j}} \right], \tag{4}$$

where $g_{h,j}$ is the total number of geodesics connecting the generic vertices h and j, in both directions, and $g_{h,j}(i)$ is the number of geodesics connecting h and j, passing through vertex i.

2.4 Data and network construction

The basis for our empirical evaluations is the VWH panel, a matched employer-employee dataset derived from administrative records of the Italian Social Security Institute, referring to the entire population of private sector workers and employers in Veneto, during the period 1975-2001.

Veneto is a dynamic, "manucentric" region, whose labor market, starting from the middle 80s, has been characterized by nearly full employment, and by a positive rate of job creation in almost every sector of the economy. The industrial system is characterized by a large population of small and medium firms, frequently organized in districts, whose specializations are garments, textiles, leather and shoes, goldsmiths, mechanical products, furniture, and plastics. Within this territory, VWH covers each single worker employed in the private sector (except only for self-employed, farm workers, and people receiving no salary), and each single establishment with at least one dependent worker. The information available is extremely rich and allows to build a monthly history of the working life of each employee, who has been hired for at least one day by an establishment based in Veneto, during the period of observation, regardless of the worker's place of residence.

Firms can be distinguished by their univocal Tax Identification Number, "codice fiscale", while workers are marked by an anonymous individual code. In the source archives, the firm code changes each time legal ownership of the firm changes, even if there is no stop in the underlying operations, nor appreciable change in the nature of the activity. Whenever such situation has been recognized, the business is said to be continuous, and the old employer (incorporated) is assigned the code of the new employer (incorporating)[14].

Another type of problem stems from the fact that employer codes actually identify *insurance positions*, not firms. Although in most cases each firm has only one security position, it is possible for firms to register their employees under different positions[15]. Anytime the Social Security archives provide an explicit indication of which positions are dependent on a parent one, all the data are consolidated into only one unit, retaining only the parent's identification code. Of course, we can only partially account for complex, and hence more elusive, business structures, as for instance informal groups. Nevertheless, according to scholars (Tattara and Valentini, 2003, 2004; Occari and Pitingaro, 1997), the adopted procedure leads to a satisfactory approximation of the real boundaries

[14] Formally, legal employer A is considered incorporated into legal employer B anytime more than 50% of its employees are taken over by B. This procedure is used by Tattara and Valentini (2003, 2004), and it is employed to construct the current version of the VWH dataset. For a detailed explanation of the method, see Occari and Pitingaro (1997).

[15] For instance, there may be distinct positions for blue and white collars, or for different plants.

of most enterprises. In the text, with the word firm or, alternately, employer, we always refer to the consolidated insurance position.

As for individual employment spells, if there are short breaks in working experience, as long as the worker continues at the old employer (as defined above), the spell is considered uninterrupted.

Three are the steps we make to built the network. First, we single out relevant reallocation episodes; then, we list all the ordered pairs of firms involved in such occurrences, so as to obtain the link set *L*; and, finally, we isolate from *L* the firms belonging to the network, getting the vertex set *V*. An important implication of such approach is that businesses not involved in labor reallocations do not enter the network; hence there are not isolated vertices in the graph.

We restrict our focus on the reallocations of workers of both sexes, aged between 15 and 65 years, whose separation occurred within the period 01/01/1991-12/31/2000, and where at most 12 months elapsed between the separation and the following engagement[16]. We also keep track of the reallocations cutting across the administrative boundaries of Veneto, so that firms located outside the region can enter the network sample, to the extent that they transfer/receive workers to/from firms located in Veneto. No restrictions are imposed on the duration of job spells, nor on types of occupation, whether blue or white collar, apprentice, or manager. We exclude reallocations in the same firm[17].

2.5 Small-world connectivity

According to the criteria defined in the previous Section, we are able to record 2,375,008 employer switches, and to map them onto a network of 379,391 vertices and 1,899,898 directed links. Network statistics are listed in Table 2.1. We observe that 54% of vertices represents firms located inside Veneto, and 68% of links corresponds to reallocations between firms both located inside the region. About 72% of employer switches goes along links which carry just one worker, the remaining run through links carrying 3.5 workers on average. The network density is equal to 1.32e-5, revealing a quite sparse topology. Such result clearly reveals how, at firm-level resolution, worker mobility appear to be made of a myriad of distinct trickles, substantiating the image of labor market as a sponge, through which workers percolate as water drops.

[16] Periods of apparent inactivity which are longer than one year are very likely to hide voluntary exits from the labor market, or temporary transitions to public- or self-employment; in these cases we cannot speak of simple job changes.
[17] This type of mobility typically concerns seasonal jobs, since temporary lay-offs are not permitted by Italian legislation.

Table 2.1 – Network statistics

metric	value
n. of vertices	379,391
n. of links	1,899,898
average degree (std. dev.)	10.02 (56.35)
density	1.32e-05
size of WCC (as percentage)	373,998 (98.6)
size of second largest weakly connected component	6
size of SCC (as percentage)	175,436 (46.2)
size of second largest strongly connected component	4
APL of SCC	4.41
ACC of actual network	3.48e-02
ACC of random network based on actual in-degree distribution	3.53e-04
ACC of random network (Erdős–Rényi)	5.49e-05

The very first way for appraising the level of network interconnection is through the analysis of its components. Bearing in mind the definitions provided in Section 2.3, we notice from Table 2.1 that the network exhibits a giant weakly connected component, comprising 98.6% of firms, which in turn has a *core* formed by a giant strongly connected component, covering 46.2% of firms. These findings reveal a surprisingly interconnected configuration with a centre of gravity in SCC.

The investigation can be pushed further, in order to uncover more subtle aspects of the relationship between the core, and the vertices belonging to WCC, but not to SCC. Namely, we perform a *bow-tie* type of analysis, grouping the vertices connected to SCC into four categories: IN component, consisting of vertices that can only reach the core; OUT component, consisting of vertices that can only be reached from the core; TENDRILS, comprised of vertices that cannot reach the core, nor can be reached from it; and, finally, TUBES, comprised of vertices that can reach OUT, while can be reached from IN (Broder *et al*., 2000). In the actual network, IN and OUT components cover most of the firms which are not directly part of SCC, respectively 107,336 and 86,398, corresponding to 28.3% and 22.8% of the totality; whereas TENDRILS and TUBES play a negligible role (few tens of vertices). Interestingly, 76% of the firms belonging to IN and OUT has total degree equal to just one. Therefore, the topology of the network may be sketched as a huge *flower eye* of strongly interconnected firms, surrounded by a *corolla* of vertices, each of which have a single link, either pointing to, or coming from the eye. Such an outline brings to light an extremely integrated labor market structure, made up of a single continent practicable along nearly all possible directions, as opposed to an archipelago of segregated islands.

The sparse topology and the existence of giant components are two necessary conditions, in order for the network to be classified as a *small world*, a well-known model of network, which fits a variety of real world phenomena[18]. Formally, a directed graph is said to be a small world if the following properties hold:

1) the network is integrated, i.e. it exhibits giant components;
2) the network is sparse;
3) average path length in the giant strongly connected component is small compared to the size of the component (typically of order $\ln(n_{\mathrm{scc}})$ [19]);
4) average clustering coefficient is high.

A small world can be described as an interconnected system, essentially dominated by local clustering, with a relatively few long-range links that act as shortcuts, connecting different bunches of vertices which otherwise would be much farther away from each other. The crucial functional significance of a small world is to guarantee high accessibility of network locations, i.e. to make it easy to reach a relatively large fraction of vertices from any given network position. In a small-world network, SCC guarantees the existence of paths between all possible locations comprised within its boundaries, while low APL indicates such locations can be reached with little effort; besides, high ACC, i.e. redundancy of links at local level, promotes robustness to disconnection and, through multiple independent pathways, reliable accessibility as well (White and Houseman, 2002). These are all highly desirable characteristics for a labor mobility network, whose capacity of allocating labor and absorbing local shocks relies, in a natural way, on its level of integration, on the existence of many alternative career opportunities, and on easy access to such opportunities.

To verify whether our network behaves as a small world, we still have to verify whether the fundamental properties (3) and (4) hold.

---

[18] The first formal specification of the small-world model has been proposed by Watts and Strogatz (1998); for a comprehensive review of small-world models, see Newman (2000); for an empirical study of the small-world network of scientific collaborations in economics, see Goyal *et al.* (2006).
[19] This condition stems from the study of random networks, where APL varies only logarithmically with n, so that it is usually claimed that the average degree of separation is small, compared to the size of the network (Newman, 2000).

From Table 2.1, we notice that APL is equal to 4.41, meaning the whole SCC – hence almost half of the global network – can be traversed in less than five steps on average, an exceptionally small number compared to SCC size, and even smaller than the benchmark value $\ln(n_{\mathrm{scc}})$. Such a result leads us to conclude that the labor mobility network indeed shows the short distance pattern typical of a small world.

Table 2.1 reports ACC equal to 3.48e-02. In order to evaluate this value, we compare the actual network with two counterfactual random models; if the real network exhibits significantly higher clustering than such benchmarks, we can rightly claim that it is highly clustered. First of all, we build a network of the same size as the real one, but with links placed completely at random. Such network has ACC equal to 5.49e-05, that is three orders of magnitude smaller than the one observed in the real data. Secondly, we build a random network with the same in-degree distribution as the real one, yielding ACC equal to 3.53e-04, that is two orders of magnitude below the actual value. The real network therefore reveals itself to be strongly clustered, thus manifesting its unambiguous nature of small world.

The observed clusterization is likely to be, at least partly, a reflection of the geographical dimension embedded in the data, revealing the well-known fact that labor mobility in Veneto tends to remain mostly local in spatial terms, because of the cost of long-distance commuting. But high clusterization is likely to reflect also another prominent feature of Veneto economy. Namely, the phenomenon of industrial districts, that is bunches of firms whose productive activities are tightly interwoven along the value chain, and which are located in proximity to one another.

Districts are clusters of firms closely knit by means of a range of different types of relationships, among which the mobility of labor plays an important role, so that some scholars qualify districts as “self-contained labor markets” (Tattara and Volpe, 2001). Nevertheless, by no means districts should be thought as entities totally separated from the rest of the labor market. The work of Tattara *et al*. (2000) – based on an earlier version of the VWH dataset – shows that industrial districts indeed continuously exchange workers with the neighboring economic system, sketching out essentially the same framework that here we call small world.

Another special trait of Veneto is the presence of a plurality of middle-size urban centers, with weak hierarchical relationships, which may deepen the tendency of labor mobility to exhibit clustering, since each conurbation is expected to be a densely interconnected labor market.

In the next Sections we explore thoroughly the characteristics of the firms that populate our small world.

2.6 A close look at the degree distribution

Intuitively, at firm level, a larger workforce generates – holding all other conditions fixed – a higher worker turnover, that is likely to translate into a higher number of connections, both on entry and exit. Consequently, we could be induced to think that connectivity is by and large determined by employment size, and we might conclude it is the size distribution of firms that ultimately determines the distribution of connections in a labor mobility network. Hence, we might conclude it would be much worth focusing on analyzing the distribution of firm size.

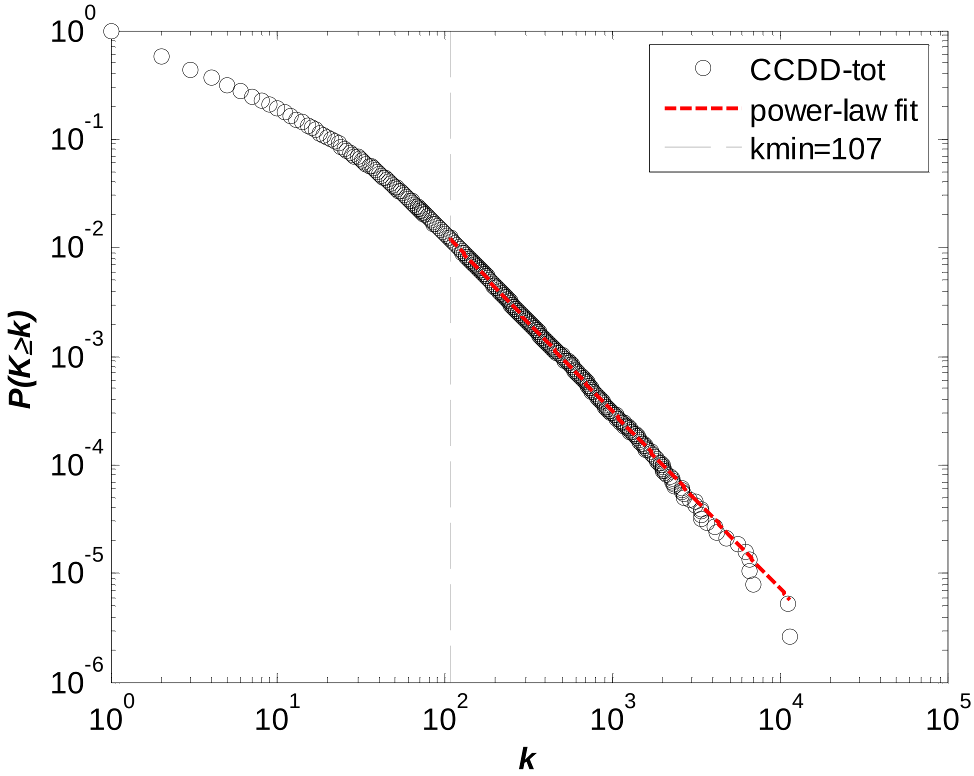
As for just the employers located inside Veneto – the only ones for which we observe the whole stock of employees – the correlation between degree and firm size is ρ=0.575, positive and moderately relevant in magnitude (ρ=0.596 and ρ=0.536 for in-degree and out-degree, respectively). The distribution of employment stocks alone hence appears to be inadequate, in order to explain the distribution of links. Several variables are likely to be at play in determining the activation of inter-firm connections, but we still have no effective priors about what such determinants actually are, and how they affect connectivity. Among the very first steps to be made, in order for truly advancing in our understanding of the reallocation phenomenon, it is worth autonomously assessing the properties of the degree distribution systematically.

The total-degree sequence of our network ranges from one to 11643, with average value $k(G)$ equal to 10, standard deviation of 56, and median of just two; 82.5% of vertices has $k<k(G)$, 41.2% has k=1, and 1.3% has k>100. Such a description points to a very unequal pattern, markedly right-skewed, and characterized by a heavy or fat tail. Similar considerations hold true for both the in-degree and the out-degree distributions. To grasp further details, in Figure 2.4 we plot, on a log-log scale, the complementary cumulative distribution, CCDD, for total-degree, in-degree, and out-degree[20]. At a glance we notice that each plot follows a clear-cut negative relation, that appears to be almost linear above some threshold, located at $k\approx100$ for Figure 2.4a and 2.4b, and at $k\approx50$ for Figure 2.4c. This pattern is characteristic of probability distributions belonging to the Paretian or Zipf's family, which have attracted a great deal of attention in network literature.

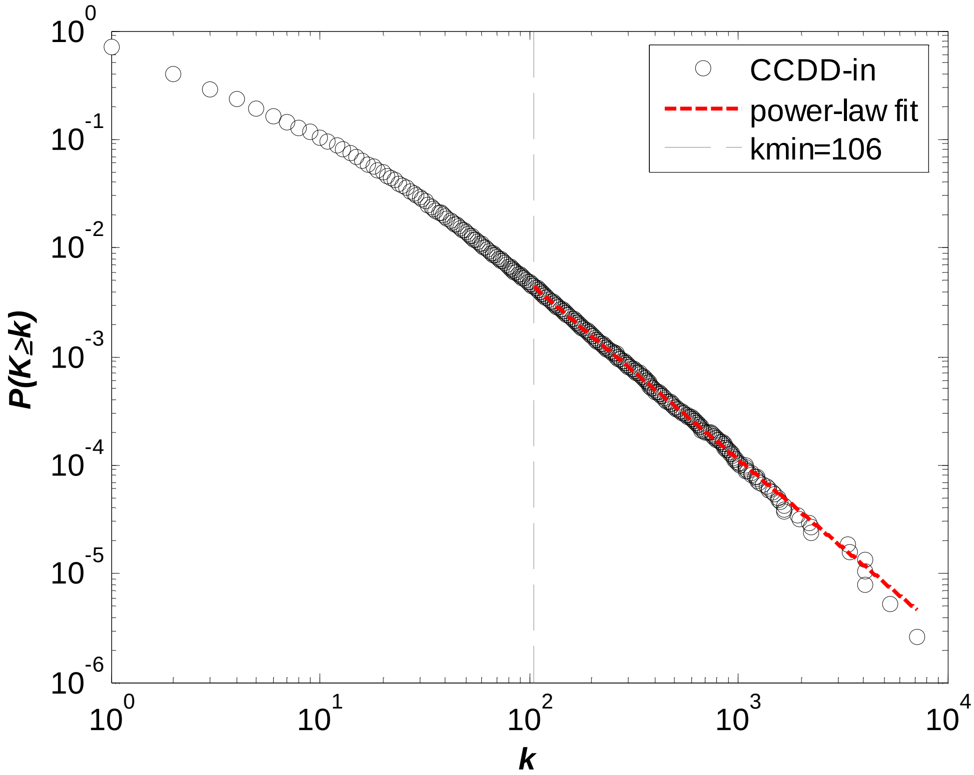
[20] The complementary cumulative distribution guarantees a better visual display than the basic frequency distribution, because it reduces possible fluctuations in the extreme right tail, due to the low number of observations in this region (Newman, 2005).

Figure 2.4 – Complementary cumulative degree distributions and power-law fits

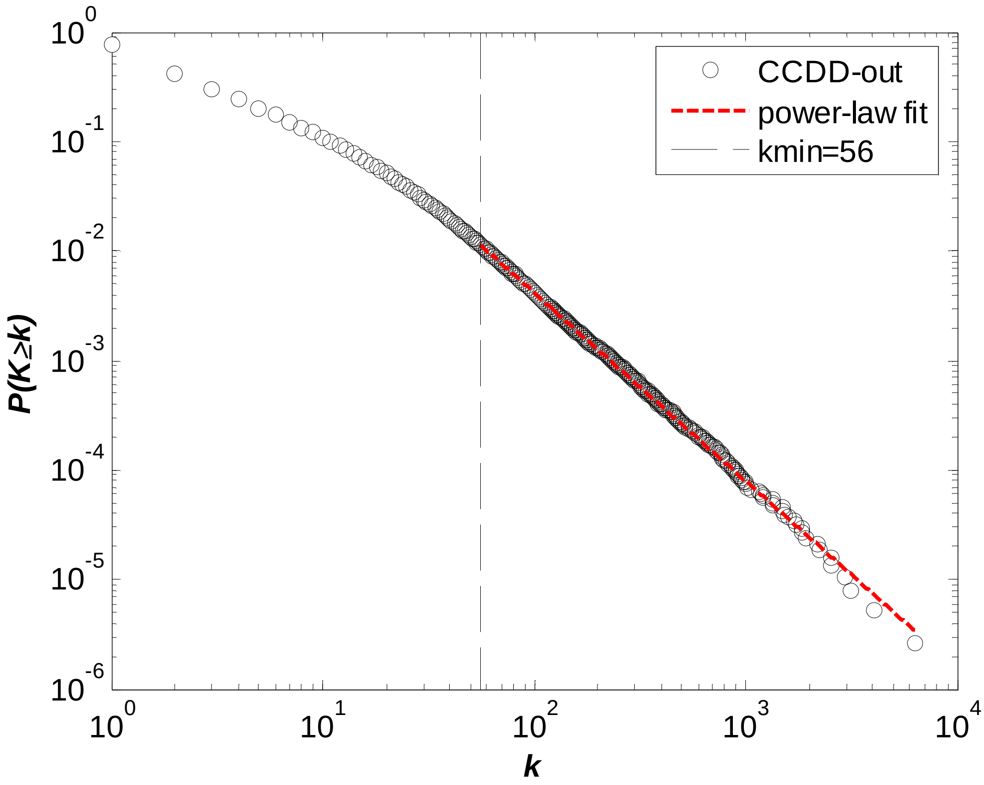
(a) total-degree



(b) in-degree



(c) out-degree



It has been claimed that, in many real world networks, the degree distribution obeys a power law, i.e. the probability of observing a vertex with degree equal to k is proportional to k raised to a constant exponent (Albert and Barabási, 1999). A power-law distribution is right-skewed and has a fat tail indicating that extremely large events are rare but much more likely than what we would expect in a standard Gaussian model. On a doubly logarithmic scale, a power-law distribution displays a straight line, revealing its perhaps most distinctive feature, namely, the property of *scale invariance*, meaning that, if we increase the scale or units by which we measure the quantity of interest k by a given factor, the shape of the distributions $p(k)$ and $P(k)$ remain unchanged, except for an overall multiplicative constant (Newman, 2005)[21]. For this reason, networks characterized by power-law degree distributions are usually referred to as *scale-free* networks.

In what follows, we attempt to assess rigorously whether the degree distributions characterizing our labor mobility network indeed behave as power laws. It is worth stressing that, in most practical cases, it is extremely difficult to know for certain whether a given quantity is drawn from a power-

[21] For instance, a Normal distribution curves sharply on a log-log plot, implying that the probability of a vertex having a degree greater than a certain cutoff value is effectively zero.

law distribution; what can be typically done is rather to verify that the data at hand are consistent with a model in which the given quantity is assumed to be drawn from a power-law distribution.

The probability distribution of a quantity k is said to be power law if it is drawn from a probability distribution of the form given by the following expression

$$p(k) \propto k^{-\alpha} \ , \tag{5}$$

where α represents the scaling exponent. Notice that such distribution diverges as k tends to zero, so, provided that α>1, the power-law behavior must set in only above a certain threshold $k_{\min}$>0. Moreover, when dealing with vertex degree, the quantity we are interested in can take only positive, integer values; hence, we are confronting a discrete distribution. Putting together these two observations, we obtain the following expression for $p(k)$

$$p(k) = \Pr(K = k) = \frac{k^{-\alpha}}{\zeta(\alpha, k_{\min})} \ , \tag{6}$$

where the function ζ is the generalized, or Hurwitz zeta function of the form

$$\zeta(\alpha, k_{\min}) = \sum_{n=0}^{\infty} (n + k_{\min})^{-\alpha} \ . \tag{7}$$

Then, the complementary cumulative distribution has the form

$$P(k) = \frac{\zeta(\alpha, k)}{\zeta(\alpha, k_{\min})} \ . \tag{8}$$

To verify whether the empirical distributions shown in Figure 2.4 have power-law tails, we resort to the procedure proposed by Clauset *et al.* (2009) [22]. In extreme synthesis the methodology runs as follows:

1) we fit a power law to the empirical data using maximum likelihood, simultaneously estimating the scaling parameter α and the lower bound of the scaling region $k_{\min}$;

[22] More technical details are given in Appendix 2.1.

2) we evaluate the goodness of the power-law fit by calculating an appropriate *p*-value;
3) if the power law is not ruled out by the previous test, we contrast it with plausible alternative distributions, all characterized by fat tails, by means of likelihood ratio tests.

Table 2.2 – Power-law fit to actual data

	total-degree	in-degree	out-degree
total n. of observations with $k>0$	379,391	272,875	292,371
scaling parameter α	2.633	2.625	2.710
cutoff point $k_{\min}$	107	106	56
p-value of the fit	0.137	0.660	0.393
n. of observations with $k \geq k_{min}$	4592	1661	4298

Table 2.2 shows the key results of the power-law fitting. Notice that, in this context, *p*-values are used to rule out the power-law hypothesis; hence, for the power law to be a plausible model for the data, the *p*-value has to be high, and vice versa; we make the relatively conservative choice of rejecting the power law if the *p*-value is less than 0.1. For in-degree and out-degree, we obtain scaling parameters equal to 2.625 and 2.710, respectively, and cutoff points k=106 and k=56; the *p*-values corresponding to such fits are 0.659 and 0.278, revealing that the power law is actually a plausible model in both cases. As for total-degree, we estimate a scaling parameter equal to 2.633, with a lower bound k=107, implying that the scaling behavior is limited to 4592 observations in the right tail of the distribution. The *p*-value corresponding to such fit is 0.137, indeed not an extremely high value, but sufficient to accept the power law as a reliable hypothesis.

We now compare the power law with a choice of alternative discrete distributions, all characterized by fat tails. In such comparisons, a small *p*-value and a positive likelihood ratio indicate that the power law is favored over the alternatives; when the *p*-value is large enough (*p*-value >0.1), the sign of the likelihood ratio is not reliable, and we should conclude that, according to the data at hand, the test does not favor one model over the other. Table 2.3 summarizes the results.

The exponential distribution, Poisson, and stretched exponential are firmly ruled out by the tests. The large *p*-values for the log-normal, Yule, and power law with exponential cutoff indicate that there is no sufficient information in the data, in order to distinguish between alternative hypotheses; from a statistical point of view, this means that either the pure power law, the log-normal, or the Yule distribution are equally good models for the data[23].

Following considerately the reasoning of Clauset and colleagues, we conclude that the tests offer a rather good support to the power-law model, and hence we can follow the main literature on networks, in order to understand the possible functional implications of such a finding.

Most importantly, in the literature, power-law degree distributions have been associated with models of network growth based on the rule of *preferential attachment*[24], meaning that new connections are assigned to vertices, with probability that is proportional to the number of connections vertices already have. This process gives rise to “rich get richer” phenomena, mirrored in empirical distributions evolving towards increasingly unequal patterns, since even small inequalities tend to deepen over time. Preferential attachment mechanisms are, in other words, self-reinforcing; therefore – most important for our analysis – in a world governed by preferential attachment, the position of well-connected vertices is usually difficult to overthrow[25].

In the world of labor reallocation, the position of best connected firms, hubs, cannot be easily taken by firms starting with just a few connections, either new comers or small players. Hubs are in a position of persistent dominance, that can only be threatened by their failure. Thus, hubs take up the fundamental role of points of reference of the system; and the system largely *self-organize* around hubs. The importance of hubs will be thoroughly discussed in Section 2.8.

Table 2.3 – Power law *vs*. alternative fat-tail distributions for discrete data

	total-degree		in-degree		out-degree	
	LR	*p*-value	LR	*p*-value	LR	*p*-value
power law with exponential cutoff	-0.887	0.183	-0.772	0.214	-0.284	0.451
exponential	9.051	0.000	6.187	0.000	8.908	0.000
log-normal	-0.558	0.577	-0.523	0.601	0.007	0.995
Poisson	8.449	0.000	6.360	0.000	8.112	0.000
stretched exponential	186.826	0.000	115.665	0.000	190.636	0.000
Yule	-0.834	0.404	-0.682	0.495	0.233	0.816

23 Notice that both log-normal and Yule are actually extremely similar to the power law, and hence they are very difficult to distinguish, even by the most fine statistical test (Clauset *et al*. 2009).
24 For a thorough discussion, see Albert and Barabási (1999), Watts (2004), and Newman (2005).
25 Implications of preferential attachment in the context of labor mobility are thoroughly discussed in Chapter 3.

2.7 Hierarchical structure

The coexistence of a high level of clustering, and a Paretian-tailed degree distribution results in a negative correlation between clustering and degree, known as *hierarchical clustering*, meaning that the network exhibits a hierarchy of vertices, with the most important hubs at the top, with the lowest clustering, and the less connected vertices at the bottom, organized into small, highly clustered communities. Ravasz and Barabási (2003) illustrate how hierarchical clustering can result from a modular network architecture, where small, highly integrated clusters of vertices are assembled into increasingly larger groups, progressively less integrated, but still clearly separated from each other.

In the actual network, we measure a statistically significant, negative correlation (ρ=-0.548) between degree and clustering, a sign of considerable hierarchical organization. So, as the number of connections increases, vertices are more likely to have neighbors which are not interconnected, i.e. neighbors belonging to distinct, local clusters; accordingly, hubs prove to be characterized, not only by a large number of connections, but also by a large number of long-range connections, spanning different communities.

We can push the analysis further, in order to possibly extract other interesting patterns from the data. To this aim, in Figure 2.5 we plot, on a log-log scale, the average clustering coefficient against degree. The display shows a clearly negative overall trend; moreover, we notice that for higher k, the plot becomes more dispersed, most likely due to the ever smaller number of observations available for high degrees. But the perhaps most interesting observation concerns the emergence of a clear discontinuity in the outline, approximately located between k=100 and k=200. Up to such region, the clustering scales down only slowly with k; above such region, it scales visibly much faster, although the relationship is considerably more noisy. All things considered, we advance the hypothesis that two different scaling regimes do exist: firms in the first regime – i.e. below the discontinuity – are embedded into interconnectivity structures which are essentially local, whereas firms in the second regime – i.e. above the discontinuity – belong to structures that span the network globally.

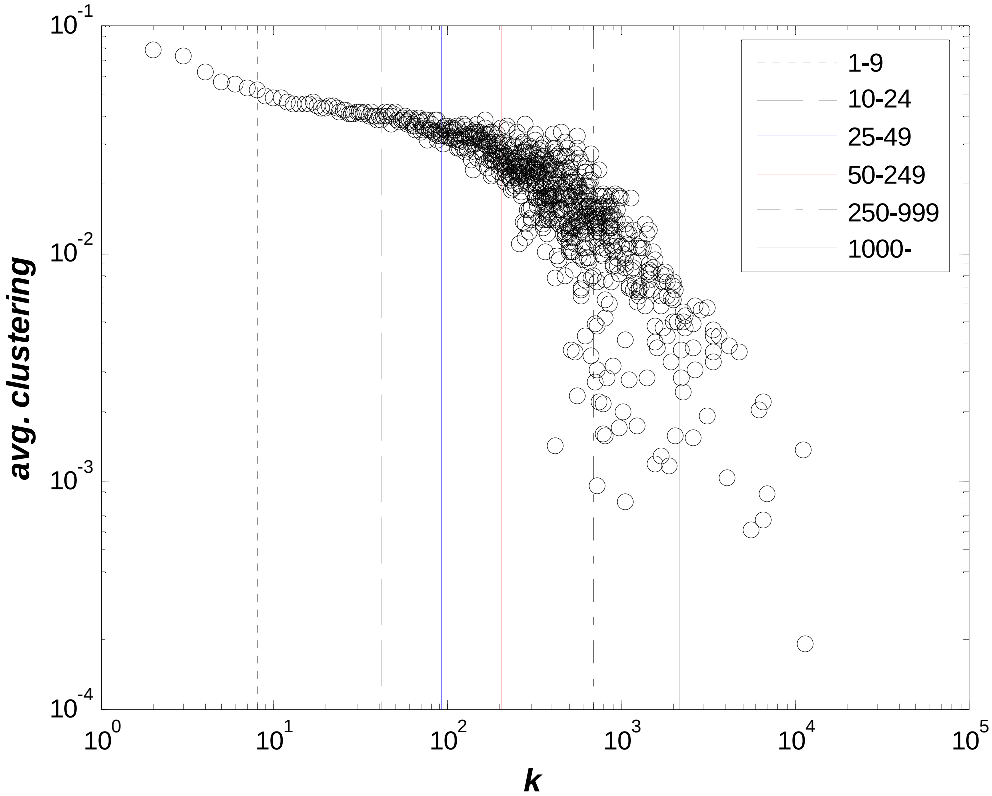
In order to substantiate better such a claim, we now focus on the employer side of the labor network, and recall the correlation between firm size and degree. In Figure 2.5 the position of the mean degree of relevant employment classes is highlighted; we especially focus on the category 25-49 employees (blue line), and 50-249 employees (red line), whose mean degrees are located at k≈91 and k≈205 respectively. Firms above 50 employees are usually considered mid-size, while below such threshold they are small; we thus notice that the switch between clustering regimes approximately corresponds to the transition between small- and mid-size firms. The same pattern holds also with respect to both in-degree and out-degree.

In Italy, and especially in Veneto, the size class 50-249 comprises a huge fraction of the most dynamic and innovative businesses, namely, those with comparatively greater capacity of adopting articulated schemes of division of labor, and most likely to occupy leading segments of the value chain (Caprio, 2001; Mediobanca-Unioncamere, 2008). Medium firms retain the control of several commercial brands spread worldwide, and rely on production activities localized in many countries, so as to be commonly labeled “pocket-multinationals”, (Censis, 2001).

The size class 25-49 identifies much smaller organizations, often artisan firms[26], which usually exhibit quite pervasive family control, partake to subordinate segments of the value chain, and overall show a less complex structure than medium firms. Such category may hence be viewed as the ultimate class of expansion for small, traditional manufacturing firms whose operations largely depend on the contribution of the work of the entrepreneur-founder.

Our analysis suggests that the interaction with distinct, far-distant areas of the labor market is a an emerging trait, distinguishing medium firms from smaller ones. Hence, medium firms appear to be bridges between the local and global dimension of the production process.

Figure 2.5 – Hierarchical clustering



[26] According to the current Italian legislation, in sectors as for instance the garment industry, firms can still be considered artisan up to 34 employees.

All these considerations yield to compelling policy implications. When designing measures aimed at especially favor the evolution of small firms into medium ones (a matter of never-ending debate in Italy), we should bear in mind that such transformation implies an increased capacity of covering distant locations within the labor market. But this in turn is not automatically granted to any organization, because of the costs and difficulties inherent in dealing with a wider and more heterogeneous neighborhood. Consequently, policy actions pushing dimensional growth which do not simultaneously supply firms with specific means, in order to expand their recruiting strategies far beyond the boundaries of local clusters, are most likely destined to be ineffective.

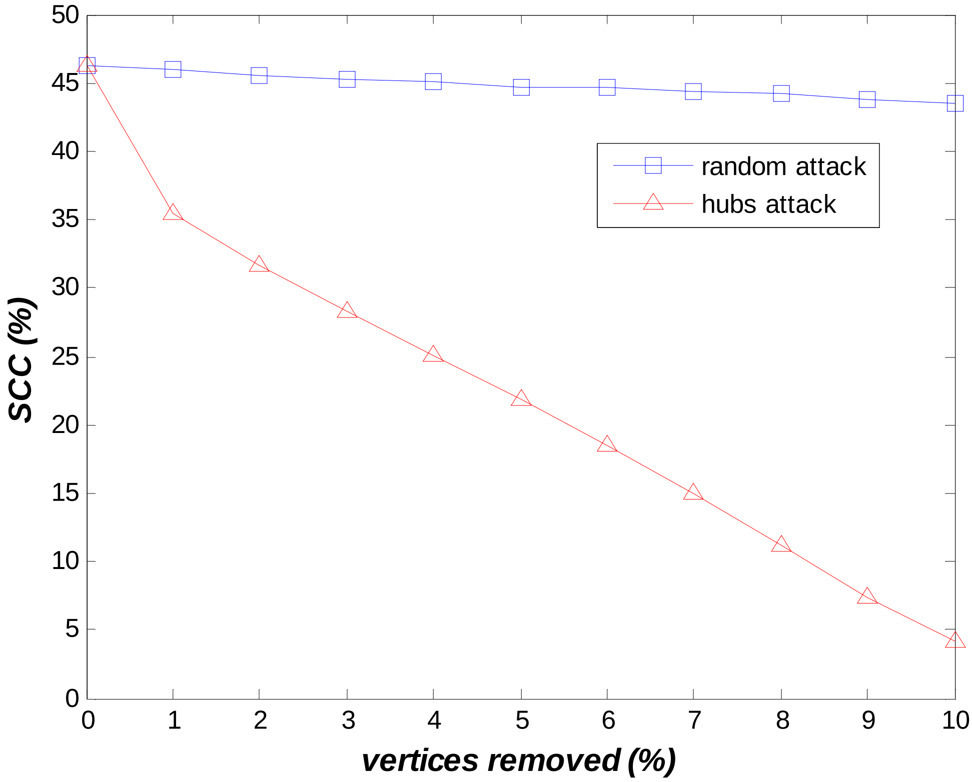
2.8 The importance of hubs

The hierarchical architecture discussed in the previous Section discloses the critical function hubs have within the reallocation topology: by means of long-range connections, hubs tie up many small communities into a single, integrated small-world network. The present Section is specifically devoted to appraise the hubs role in determining the connectivity properties of the network. First, we quantitatively assess to what extent hubs lie in between other vertices; then, we evaluate how hub failures affect the connectivity of SCC; and finally, we minutely describe the fields of activity and the organizational forms of major hub firms.

The index of betweenness measures how much a given vertex lies on the shortest paths between other vertices: low values denote somewhat isolated or peripheral positions, high values reveal positions in control of large numbers of pathways across the network. Vertices with high betweenness are commonly referred to as *bridges*, i.e. intermediaries between different areas of the labor market, and bear high responsibility in directing labor flows, connecting together many, distinct local communities. In the actual network, we find a positive and very strong correlation between degree and betweenness, ρ=0.861, meaning that good hubs tend to be also good bridges.

We next aim at verifying to what extent small-world connectivity relies on the presence and functioning of hubs. According to the procedure proposed by Albert *et al*. (2000), we assume a fraction of employers is hit by a crisis, pushing them to close down the firms, and we observe how the size of SCC varies in response to such failures. Two series of simulations are performed, one in which we delete increasing fractions of vertices chosen completely at random, the other in which we progressively remove the highest degree vertices. The results are shown in Figure 2.6.

Figure 2.6 – Impact of vertices removal on SCC coverage



Hub failures prove to have a disruptive impact on the coverage of SCC, and, consequently, also on small-world connectivity; whereas the closure of an equivalent number of firms chosen at random leads to only marginal changes in the size of the giant component. In particular, the removal of just 1% of hubs reduces SCC by 23%, pushing it from 46.2% to 35.5% of network coverage; on the contrary, the deletion of 1% of vertices chosen at random reduces SCC by less than 1%. The elimination of 5% of the highest degree vertices cuts SCC connectivity by more than a half, down to 22%; and a 10% removal leads to a complete cracking of the component, down to 4.2% of network extension. On the other hand, a 10% random removal of vertices reduces SCC connectivity by less than 6%, leaving almost intact the character of the main continent.

The explanation for such results is rooted in the Paretian nature of the degree distribution. Since most vertices have only a few connections, and therefore lie on a very few paths between other vertices, it is unlikely that their (random) removal affects connectivity substantially. But when the removal is deliberately targeted at hubs, each individual failure has disruptive effects, up to deprive the network of its small-world character, via the disintegration of the giant component. The hierarchical structure of the network makes hubs critical in keeping connected different parts of the system, and such feature is precisely mirrored in the high vulnerability of the system to hub closures.

Furthermore, in a small-world network, hubs have the important function of making the architecture, not only accessible, but effectively searchable, or navigable (White and Houseman, 2002). A little like if they were “observation towers” from which workers can easily sight around the system, and which can be seen from all around the system. Consequently, to the extent that labor market accessibility and searchability constitute priority objectives of policy action, we may want to preserve hubs.

Making use of additional information available in the VWH database, we classify the first 50 hubs according to sector of activity, and for each sectoral group we display the average workforce, together with the main, average network statistics. Results can be seen in Table 2.4. At a glance, we notice that hubs are mostly very large firms, by far larger than the overall average, which in Veneto is around 10 employees. Such result is not a surprise; we have pointed out already that, in our network, the correlation between firm size and degree is positive and significant.

Table 2.4 – The first 50 hubs by type of activity

activity	n. firms	workforce	degree	clustering	betweenness
hotel trade and tourism	2	1876	7115	0.0025	0.0129
temporary employment agencies	5	1013	6432	0.0023	0.0296
wholesale, supermarkets	10	1929	3326	0.0032	0.0070
porterage and cargo handling services	6	270	2966	0.0059	0.0083
personal and social services, leisure	5	724	2725	0.0055	0.0071
manufacturing	14	1663	2416	0.0048	0.0049
catering	6	576	2219	0.0038	0.0044
construction	1	388	1711	0.0013	0.0039
advertising (dissemination of)	1	165	1710	0.0081	0.0048

Examining the data thoroughly, three broad categories of businesses can be detected:

1) big and long-tradition manufacturing firms;
2) companies involved in services and commerce, typically organized into chains of stores, or performing services directly at the costumer's;
3) temporary employment agencies and cargo handling subcontractors.

As for the manufacturing group, it is easy to recognize several activities distinctive of Veneto economy. Four companies produce household and professional appliances, either as final makers or suppliers of dedicated parts; they belong to the so called "Inox Valley" district, located in the province of Treviso, and they all hold prominent positions in their respective market segments at international level. Two hubs are the undisputed, worldwide leaders of the eyeglass industry; they are the major players around which the eyewear district of the Belluno province is organized. Another company is a prominent, historical producer of wool fabrics, now mostly involved in the garment sector, which during various decades has fed a vast textile district in the province of Vicenza. Each of these firms is deeply rooted in a local, socio-economic context, and tightly nested into a cluster of firms among which the exchange of workers is particularly intense; at the same time, each player has connections spanning different, distant areas of the regional and also national economy[27].

Not very tightly embedded into a district framework, there are seven more manufacturing companies: three mechanical firms, dealing with production of motorcycles, gears, and energy plants; one furniture maker; three companies working in the food and beverages industry. Notably, all three food-processing firms are involved in productions subject to a great deal of seasonality, resulting in a high workforce turnover over the year, which in turn is, at least partly, responsible for the exceptionally large number of connections.

All manufacturing hubs are well-known, historical trade names whose popularity can attract applicant workers from afar. Moreover, production activities are in some cases carried out through multiple plants, facilitating the emergence of long-run connections, once the plant-level data are consolidated into one single company; even though in all the examined cases, the plants belonging to the same company tend to be located in a quite limited area.

Firms involved in the service sector – comprising hotel trade and tourism, personal and social services, commerce, and catering – share two major traits: they typically carry out business through

[27] Notice that, not all the major industrial districts of Veneto have a hub figuring among the largest ones. For instance, the goldsmith district of Vicenza, as well as the footwear district of Riviera del Brenta do not compare in our shortlist.

multiple local units, and they are inherently characterized by a high rate of workforce turnover. The ten department stores or supermarkets listed in Table 2.4 own chains of stores, or point of sales in different cities and towns all over Veneto. The organizations dealing with personal and social services or catering have a highly decentralized structure as well; in this case operations are performed, not only by means of distinct local units, but also through posting workers directly to costumer's place. As for high turnover, that is short average job spell, we acknowledge that a job in a supermarket, or a summer spent working in the tourist sector are often taken as temporary career steps, on hold to find other, better job opportunities. Service sector hubs often play the role of intermediate ports-of-stay for people who are waiting for better careers.

A completely different condition is that of temporary employment agencies and cargo handling subcontractors. For these firms, acting as hubs in the labor market is somewhat inborn in their economic activity. In Italy, porterage cooperatives represent a long-standing phenomenon, that has been intensifying over time, hand in hand with the increasing segmentation of production processes, and the rising importance of the logistics sector. In contrast, employment agencies offering temporary jobs in a range of different fields represent a true novelty.

The rapid settlement of a number of private employment companies – suddenly emerged in the role of hubs – is the result of the policies adopted in the second half of the 90s, aimed at rendering the labor market more flexible (labor market reform of 1997). Employment agencies – often local branches of companies operating worldwide – act in a natural way as transmission belts for labor reallocation. Moreover, they treat a variety of occupational profiles, and allocate skilled personnel; whereas, porterage cooperatives deal almost exclusively with low value-added services, to be performed by unqualified workers, often gathered within the weakest components of the workforce, as for instance immigrants. Importantly, employment services are almost always operated through a network of subsidiaries spread all over the territory, in order to intercept a larger portion of labor demand and supply.

Employment agencies play a role under many respects analogous to the one played by *system integrators* in the context of product value chains. The term system integrator was first introduced by Brusoni and Prencipe (2001), referring to companies responsible of design and assembly of complex products, whose realization requires the contribution of several, (mostly) independent producers of components. Modular product architectures, involving a large number of specialized organizations, represent a major phenomenon in contemporary markets (Baldwin and Clark, 2000), increasingly taking place across, rather than within countries (Feenstra, 1998; Gereffi *et al.*, 2005). A modular and decentralized production scheme allows for superior efficiency, stemming from specialization, but such an advantage is continuously contrasted by the risk of coordination failure, inherent in the interplay of a multiplicity of agents. Such a trade off is precisely resolved by system integrators, whose task is to coordinate individual operations along the value chain, supplying the key interfaces of communication between modular units. System integrators have a comprehensive sight of the production process, and they use it to effectively coordinate several actors, each of which is endowed with limited information, aiming at achieving superior outcomes for the system as a whole.

Employment agencies search both sides of the labor market, looking for parties available for matching, and then they recombine such options into effective matches; in so doing, they allow workers and firms to enlarge the horizon of choice significantly beyond the boundaries of their local neighborhood, possibly granting access to better matches. In this respect, employment agencies play the function of system integrators, since they coordinate agents by means of a superior knowledge of the market, allowing for possibly superior aggregated outcomes. This aspect is almost always overlooked in the Italian, current debate over labor market intermediaries, but it brings to light that, when addressing the issue of labor mobility, policy makers more and more should consider temporary employment agencies as important counterparts to interact with.

From the previous observations, it is clear that decentralized business structures have a crucial role in determining network connectivity. By construction, our network of inter-organization mobility does not consider the spatial articulation of individual firms. We can imagine decentralized structures as "networks in the network", which we cannot observe directly, but which can help traversing the actual network – somewhat as an underground transport network in a big city allows people to move more quickly and effectively, compared to surface transportation. Engaging into an organization that operates through several distinct units, in distinct locations, but whose units respond to a unique management, undoubtedly opens up major opportunities for mobility, first within the organization itself, and then possibly across the whole network, in directions and at distances that would otherwise be much less likely to occur.

2.9 Conclusions

This essay addresses the phenomenon of worker reallocation by way of a network-based approach, which is new to labor market studies. Using matched employer-employee data, referring to the whole dependent workers in the Italian region of Veneto, we construct a directed graph whose vertices represent employers, and whose links denote passages of workers from one employer to another, occurred throughout the 90s. We show the network is a small world, whose degree distribution is well approximated by a power law, and whose architecture is denoted by hierarchical clustering.

The simultaneous presence of a high level of interconnection, redundancy of paths through clusterization, and small distances between vertices reveals that workers can easily flow through almost the entire network in only a few steps, and they can access a variety of job opportunities with a limited effort.

The observed connectivity crucially depends on the presence of a small number of highly connected hubs, that span the network from side to side, bridging together distinct local clusters of firms, and also providing the system with effective navigability.

The network architecture exhibits a hierarchy of vertices with the most important hubs at the top, and the less connected vertices at the bottom. We show the hierarchical relationship is characterized by a discontinuity separating small firms, which are essentially embedded into local communities, and medium firms, which interact considerably more with different distant areas of the labor market. We hence conclude that, in order to favor the evolution of small firms into medium ones, policy makers should provide employers with specific tools aimed at expanding their recruiting strategies beyond the boundaries of local labor markets.

The failure of central hubs most likely results in the split of the labor market into different separated pieces; a more segregated labor market is in turn especially exposed to the harmful effects of asymmetric shocks, which cannot be effectively re-absorbed, and hence may cause persistent unemployment in the most isolated areas of the economy. In the light of these considerations, policy makers should pose a special attention in supporting precisely those firms that guarantee a major connectivity to the system. Hence, an effective reallocation policy hinges critically upon our ability to localize hubs and their connection patterns.

The most important hubs are large firms belonging to three distinct categories: agencies offering temporary jobs; long-tradition manufacturing firms; companies involved in personal services and commerce, typically organized on different local units or posting workers to the customers' place. In Italy, temporary job agencies represent a new, emergent phenomenon that has been promoted in the second half of the 90s, through legislative measures aimed at fostering labor market flexibility. Our study reveals that such provisions also strengthened labor market accessibility, via the establishment of new hubs, an effect almost always overlooked in the actual debate over flexibility and labor market intermediaries.

A major scope for policy intervention is represented by the safeguarding of big manufacturing hubs, nowadays particularly exposed to the competitive pressure stemming from low-wages countries. But a special attention has to be devoted also to firms operating in the service sector and commerce through a decentralized organization; such firms are particularly important for labor market connectivity because they can facilitate long-range reallocations, via posting workers to different locations of the same company.

Especially during a deep and widespread economic crisis, as the one we are facing in these days, the strategy for protecting hubs should be accurately tailored on the basis of the characteristics and conditions of the targeted subjects. Network analysis of labor mobility, of the type proposed in this essay, can offer a suitable tool, in order to achieve this goal. In our view, the identification and characterization of hubs may also offer a transparent criterion for assigning subsidies, as well as extraordinary funds aimed at supporting employment (in Italy for instance: CIGS, or Mobility Compensation), which are in the discretional disposal of the public administration.

Appendix 2.1

Estimating power-law parameters

Let us assume the discrete quantity x follows a power law for $x \geq x_{\min}$. The complementary cumulative distribution then has the form

$$P(x) = \frac{\zeta(\alpha, x)}{\zeta(\alpha, x_{\min})} , \tag{1a}$$

equivalent to equation (8) in the text, where the function ζ is the generalized, or Hurwitz zeta function of the form

$$\zeta(\alpha, x) = \sum_{n=0}^{\infty} (n + x)^{-\alpha} . \tag{2a}$$

The maximum likelihood estimator for the parameter α proposed by Clauset *et al*. (2009) is

$$\hat{\alpha} \cong 1 + n\left[\sum_{i=1}^{n} \ln \frac{x_i}{x_{\min} - \frac{1}{2}}\right]^{-1} . \tag{2a}$$

This estimator is proven to give good results provided $x_{\min} \geq 6$ and $n > 50$. Before calculating expression (2a), we need to know $x_{\min}$. The authors propose to choose the value $\hat{x}_{\min}$ that makes the probability distributions of the empirical data and of the best-fit power law as similar as possible above such threshold. In the case of non-normal data, evaluations over similarity between distributions are usually done by calculating the Kolmogorov-Smirnov (KS) statistic, which is defined to be the maximum distance between the distributions of the actual data and of the fitted model

$$D = \max_{x \geq x_{\min}} \left| S(x) - P(x) \right| . \tag{3a}$$

where $S(x)$ is the complementary cumulative distribution of the actual data for the observations with value equal to or above $x_{\min}$, and $P(x)$ is the complementary cumulative distribution for the power-law model that best fits the data for the observations with value above $x_{\min}$. The calculation of such difference returns a single number that is smaller for hypothesized distributions that better fit the data. The estimate $\hat{x}_{\min}$ is then the value of $x_{\min}$ that minimizes D. Equations (2a) and (3a) together hence yield the estimated values of both the scaling parameter of the power-law distribution, and related lower bound.

Goodness-of-fit test for the power-law model

Clauset and colleagues suggest evaluating the goodness of the power-law fit, obtained with the previous method, again by means of using a KS test. In synthesis, the idea is to build a test that generates a *p*-value quantifying the plausibility of the hypothesized distributional model. The test is based on the distance between the distributions of the empirical data and of the hypothesized model; such distance is then compared with distance measurements for synthetic datasets generated according to the same hypothesized model, and of the same size of the actual dataset.

The *p*-value is defined as the fraction of synthetic samples for which the distance measurement is larger than that obtained for the actual data. If the *p*-value is much lower than one, we can conclude that the data are unlikely to be drawn from a power law; if it is close to one, then the data may indeed be drawn from a power law. Notice that the goodness-of-fit test is a tool aimed only at ruling out models, that is to say, the test can only tell us when the hypothesized model is probably wrong, while it cannot tell us when it is right.

More specifically, the procedure runs as follows:

1) fit the power law to the data using the method above;
2) calculate the KS statistic for the best-fit power law to the data;
3) generate a large number of synthetic datasets of the same size of the actual sample, and with same parameters of the estimated fit, then fit each sample according to the methods at point (1), and calculate the KS statistic for each fit;
4) calculate the *p*-value as the fraction of the KS statistics for the synthetic datasets whose value exceeds the KS statistic for the actual data; if the *p*-value is sufficiently small the power-law distribution can be ruled out[28].

[28] Keep in mind that the statistical variation of the KS statistic becomes smaller as n becomes large. This means that the *p*-value becomes a more reliable test as n becomes large, but for small n it is possible to get quite high *p*-values even when the power law is the wrong model for the data. This is not a deficiency of the method; it reflects the fact that it is genuinely hard to rule out the power law if we have only a few observations. For this reason, the *p*-value should be treated with caution when n is small, namely when $n \leq 50$.

Goodness-of-fit tests for competing distributions

Even if the power-law model is proven to be a god fit for our data, there may exist other types of distributions that match the data equally well, or even better. In order to make our judgment over the plausibility of the power law, in case it is not ruled out by the goodness-of-fit test defined above, we have to contrast it with alternative, competing distributions. To this aim, we have to solve two problems: first, defining how to identify which of two hypothesized models, the power law or a competing candidate, better fits the data; second, selecting a suitable choice of alternative distributions for comparison

In order to compare alternative fittings, Clauset and colleagues suggest to use a likelihood ratio test (LR). Such test consists of computing the likelihood of the empirical data under two different distributions, and then calculating the logarithm of the ratio R of the two likelihoods. A positive (negative) value of R then indicates the winning (losing) distribution.

Notice that the log LR is subject to statistical fluctuation. If its true value is close to zero, then the fluctuations can easily change the sign of the ratio, and hence the test cannot be trusted. To make a quantitative judgment about whether the sign of the log LR is sufficiently reliable, we hence need to know the size of the expected fluctuations, i.e. we need to know the standard deviation of R, that can be estimated from our data through the method proposed by Vuong (1989).

Let us denote our two candidate distributions by $p_1(x)$ and $p_2(x)$. Then the log LR is

$$R = \sum_{i=1}^{n} \left[\ln p_1(x_i) - \ln p_2(x_i) \right] = \sum_{i=1}^{n} \left[\ell_i^{(1)} - \ell_i^{(2)} \right] . \qquad (4a)$$

It can be demonstrated that R becomes normally distributed as n becomes large, with expected variance $n\sigma^2$, where σ^2 is the expected variance of a single term, that can be approximated by the variance of the data

$$\sigma^2 = \frac{1}{n} \sum_{i=1}^{n} \left[\left(\ell_i^{(1)} - \ell_i^{(2)} \right) - \left(\overline{\ell}^{(1)} - \overline{\ell}^{(2)} \right) \right]^2 . \qquad (5a)$$

Then the probability that the measured R has a magnitude as large or larger than the observed value $|R|$ is

$$p = \frac{1}{\sqrt{2\pi n\sigma^2}} \left[\int_{-\infty}^{-|R|} e^{-t^2/2n\sigma^2} \mathrm{d}t + \int_{|R|}^{+\infty} e^{-t^2/2n\sigma^2} \mathrm{d}t \right] = \left| \operatorname{erfc}\left(R / \sqrt{2n}\sigma \right) \right| , \qquad (6a)$$

where σ is derived from (5a), and erfc(·) is the Gaussian error function. The probability expressed by (6a) is another example of p-value. If p is small, then the sign of R can probably be trusted as an indicator of which model is the better fit to the data. If p is large, then the LR test is inadequate to discriminate between the given distributions[29].

Next step is to choose which distributions compare with the power law. We follow Clauset *et al.* (2009), and choose a few well-known distributions which are all right-skewed, with a fat tail: the power law with exponential cutoff, exponential, log-normal, Poisson, stretched exponential or Weibull, and the Yule distribution. In Table A.2.1.1 the normalized functional forms are reported.

Tab. A.2.1.1 – Distributions

Name	$p(x)$
power law with exponential cutoff*	$\frac{\lambda^{1-\alpha}}{\Gamma(1-\alpha,\lambda x_{\min})} \cdot x^{1-\alpha} e^{-\lambda\alpha}$
exponential	$(1-e^{-\lambda})e^{\lambda x_{\min}} \cdot e^{-\lambda x}$
log-normal*	$\frac{1}{2}\sqrt{\frac{2}{\pi\sigma^2}}\left[erfc\left(\frac{\ln x_{\min}-\mu}{\sqrt{2\sigma}}\right)\right]^{-1} \cdot \exp\left[-\frac{(\ln x-\mu)^2}{2\sigma^2}\right]$
Poisson	$\left[e^{\mu} - \sum_{k=0}^{x_{\min}} \frac{\mu^k}{k!}\right]^{-1} \cdot \mu^x / x!$
stretched exponential*	$\beta\lambda\left(x^{\beta-1}e^{-\lambda^{\beta}}\right) \cdot e^{\lambda x_{\min}^{\beta}}$
Yule	$(\alpha-1)\frac{\Gamma(x_{\min}+\alpha-1)}{\Gamma(x_{\min})} \cdot \frac{\Gamma(x)}{\Gamma(x+\alpha)}$

*approximated by continuous distributions

Notice that, since the power law with exponential cutoff is a superset of the pure power law, it can never be a worse fit than the latter model. However, if the corresponding p-value shows that the LR is not significant, then there is no statistical reason to prefer the cutoff form over the pure one, which gives a more parsimonious representation of the data, through a functional specifications that employs less parameters.

[29] A slightly different test, based on Chi-squared, is required for comparing nested distributions. For a more detailed discussion of this special case, see Vuong (1989).

3 Temporary employment agencies make the world smaller. Evidence from labor mobility networks

3.0 Abstract

This Chapter investigates how temporary employment agencies (TEAs) affect the shape and functioning of the network of inter-firm worker mobility in a highly industrialized region of Italy, Veneto.

Drawing upon a matched employer-employee dataset that covers the universe of private dependent workers, individual job changes are mapped onto a directed graph, where vertices indicate firms, and links denote transfers of workers between firms. A sequence of year networks is computed, in order to appreciate the effects of TEAs after their establishment occurred in 1997.

We explore two related issues: (1) how, and to what extent intermediaries affect accessibility of jobs for people who reallocate within the market, where accessibility is measured by the small-world characteristics of the network; (2) how the market power of intermediaries in controlling worker reallocation flows evolves over time.

TEAs are found to considerably improve job accessibility, both reducing the average network distance between firms, and increasing clustering.

A few TEAs rapidly become the most connected vertices of the system, being in control of progressively higher shares of reallocation channels, and causing a significant concentration of the market. We interpret such empirical evidence in the light of a model of network formation, according to which intermediaries affect attachment (engagement) decisions by reducing search/transaction costs workers incur in order to find a job.

Our study provides an original representation of the transition from a system in which matching between workers and firms is completely decentralized, to a system in which matching is brokered and, hence, centralized. The trade off, inherently associated to intermediation, between increased accessibility of matching opportunities, through information centralization, and monopolistic and/or monopsonistic power, descending from increased concentration of the market, is neatly captured by our methodology. Important indications are finally disclosed to policy makers, who may want to keep the market monitored, and to possibly hamper the system from becoming excessively polarized, through properly limiting the market power of TEAs.

3.1 Introduction

This Chapter aims at offering an original grasp of how employment intermediaries impact on labor market functioning. We use employer-employee matched data from Veneto, a region of Italy, to investigate two related issues: (1) how, and to what extent intermediaries affect *accessibility* of jobs for people who reallocate within the market; (2) how the market power of intermediaries in controlling worker reallocation flows evolves over time, and which are the fundamental dynamics of such process. We focus on a special category of intermediaries, temporary employment agencies (TEAs), and exploit the labor market reform of 1997, that allowed such intermediaries to be the first operating in Italy, in order to appreciate the effects of labor intermediation in the very first years after its introduction (1997-2001). During the period specifically chosen for this study, TEAs are the only intermediaries in the market, and our data keep track of all worker reallocations involving TEAs as origin or destination, hence we are able to capture the whole labor mobility actually related to intermediaries, offering a quite unprecedented picture of intermediated labor markets. Our main object of analysis is a directed graph, whose vertices indicate employers (firms or TEAs), and whose links denote transfers of workers between employers.

We are interested in a particular notion of job accessibility, intuitively defined as the possibility, for workers who reallocate within the market, to locate and reach new employers[1]. Accessibility, in this sense, is of crucial importance for labor market operation: only an accessible market does allow the mixing and matching process – through which demand and supply continuously recombine (re-match) into new arrangements – to unfold all its potential benefits, ultimately generating productivity gains. In order to obtain a workable definition of job accessibility, we think of the reallocation network empirically mapped as if it were an existing infrastructure, specifically designed for guiding worker flows. Hence, we say the network is accessible if it exhibits the typical properties of a *small world*. Next, we quantify the impact of TEAs on the small-world architecture, interpreting the tendency of the world of worker mobility to become smaller as the signal of increased job accessibility.

We next center our attention on the position of TEAs in the reallocation market, and, more specifically, we focus on the TEAs power of controlling hiring channels, as revealed by the number of incoming links TEAs exhibit in the labor mobility network. To this purpose, we consider the process of network formation as it can be inferred from the statistical distribution of connections

[1] Labor reallocation is a two-sided process, and hence a notion of accessibility of market opportunities can be formulated for either parties involved in the matching process, workers and firms. In the present work, we choose to take the worker perspective, and we preferentially interpret inter-firm labor mobility as a worker reallocation process over given locations (employers). In the text, we use the term job to refer to a working position offered by a specific employer, so that to change job always means to change employer.

over vertices. We first track the evolution of the distribution, and point out how labor flows globally adjust to the presence of labor market intermediaries; then, we introduce a toy-model of network formation that fits the empirical data, and helps us casting some light on the mechanisms governing TEAs activity. In this way, we are able to devise policy warnings intended to address possible excess of power of TEAs in controlling engagement channels.

The Chapter is organized as follows: Section 3.2 provides a brief overview of the theoretical foundation of labor market intermediations, with a specific focus on TEAs; Section 3.3 describes the role of TEAs in Italy in the period under study; Section 3.4 introduces the network analytical framework; Section 3.5 describes the data; Section 3.6 is devoted to appraise TEAs effect on job accessibility; Section 3.7 investigates how TEAs control worker flows; finally, Section 3.8 concludes.

3.2 Outline of labor market intermediation

The conceptual foundation of labor intermediation is rooted in the existence of labor market imperfections that hamper an efficient (competitive) matching between demand and supply of labor. One major feature of real, imperfect labor markets is the difficulty, for both individuals and firms, to locate partners for matches, and/or to effectively negotiate over the terms of a possible matching agreement. In the real world, indeed, match opportunities are not generally guaranteed nor costless, and the outcomes of the matching process can be very often improved upon by identifying and eliminating existing obstacles to labor market navigation, and to negotiation over contractual terms. Hence, some third parties – the intermediaries – may come into play, in order to exploit such a situation, and to realize profits by selling ad hoc matching services to workers and firms, that in turn will benefit from better matching.

In the introduction to a recently published collection of essays on labor market intermediation, probably the most authoritative and comprehensive treatment of the subject now available, Autor offers the following definition of labor market intermediaries: "Labor market intermediaries (LMIs) are entities or institutions that interpose themselves between workers and firms to facilitate, inform, or regulate how workers are matched to firms, how work is accomplished, and how conflicts are resolved" (Autor, 2009, p. 1). Two are the main categories of market imperfections which can be addressed and exploited by LMIs, and which ultimately allow for the existence of intermediaries:

1) costly information;
2) asymmetric information, resulting into adverse selection.

Workers looking for jobs are not generally informed about all existing vacancies in the market, and firms looking for new workers are not generally informed about all people available for work. Both workers and firms have to actively look for potential matching counterparts, and they incur a cost for this activity. Workers bear the direct cost of exploring the employers side of the market, applying for job, and sitting in interviews, and the indirect cost of foregone work or leisure. Employers bear the direct cost of vacancy advertising and applicants screening, and the indirect cost of foregone output, up to when vacancies are filled.

LMIs reduce search costs by way of collecting information about players on one side of the market, and then selling them to players on the other side of the market, at a price lower than the cost the latter players would incur if searching by themselves. Types of services offered by LMIs are for example: contacting pools of candidates with specific characteristics, accepting and filtering curricula, tracking applications, and providing access to databases of candidates or vacancies.

Noticeably, when information are costly, very often they are also asymmetric. Whenever it is too costly to collect complete information about prospect matches, the more informed actors have some incentive to exploit such advantage to the detriment of less informed ones. Workers might hide or blur some information in their curricula or credentials, in order to appear more attractive to potential employers. Similarly, firms might exploit asymmetric information to the detriment of workers, for instance by underpromoting deserving workers, in order not to pay higher wages (Garcia-Perez and Muñoz-Bullón, 2005), or by omitting or misrepresenting real job conditions, in order to attract aspirant workers (Lee, 2009).

LMIs can mitigate the problem of adverse selection due to asymmetric information by way of performing accurate prescreening of both job seekers and employers, and by assuming direct responsibility for selection, through special contractual provisions. The actual scope for LMIs is ultimately determined by the incidence of the information asymmetry LMIs are intended to solve.

The literature also points to a third element of informational asymmetry that is specific to intermediation activity, namely, the asymmetry between the LMI itself and its clients, either firms and workers. Indeed, LMIs which are in the business of selling information are inherently better informed about the information they sell, than are their customers. Therefore, the informational advantage of LMIs over each single participant in a labor market transaction represents a potentially strong incentive for the intermediary to use its information in order to extract a rent from the intermediation services. The analyses of Lee (2009) and Kleiner and Todd (2009) exactly illustrate how intermediaries can actually use their advantage to the detriment of customers.

The potentially harmful consequences of this kind of informational asymmetry bring to light the compelling trade off – inborn in any process of information brokerage/concentration – between the benefits of increased accessibility of information (in our case represented by availability of huge blocks of information at a reasonably low price), and the detriments resulting from the monopolistic and/or monopsonistic position of mass information provider (in our case represented by high markups charged by LMIs for intermediation services, or by promotion of best-markup matches, rather than matches that are optimal for the parties).

Assuming that the amount of information available to the parties through a broker positively depends on the broker actual market share, then the benefits of information brokerage for costumers increase with the market share, giving rise to a self-reinforcing incentive mechanism that prompts further growth of the intermediary market power. Big brokers tend to attract more clients because they can deliver potentially higher benefits, so becoming ever bigger. But also the informational advantage of the intermediary over its clients, and the resulting monopolistic/monopsonistic behavior do increase with the market share, up to possibly neutralizing the benefits of information brokerage, and producing net damages, when the market reaches a deep level of concentration.

In order to prevent such pernicious outcomes in the labor market, it is of crucial importance to keep under control the market power of LMIs. According to standard arguments, competition between private LMIs, and/or between private LMIs and public employment agencies, can significantly favor workers and firms, by keeping low (competitive) the price of intermediation services, while guaranteeing matching quality. As a general rule, we would like LMIs to play freely in the market, improving the matching between demand and supply of labor, but at the same time we do not want any LMI to be in substantial dominant position in the market. In this respect, the role played by policy makers in shaping market structure, and in regulating market functioning, is of fundamental importance for a good performance of intermediated labor markets.

The present work focuses on a particular category of LMIs, that is temporary employment agencies, perhaps the most widespread and popular intermediaries based on voluntary participation on both sides of the market. TEAs are formally intended for supplying firms with extra-employment during periods of exceptional activity, by means of special contracts whose duration is strictly limited in time. However, TEA action may de facto go – and indeed it goes – beyond the letter of regulatory provisions.

People apply to TEAs for accessing short-term employment with negligible investment in job search, but very often, they also resort to TEA contracts as an entry stage to more stable occupations, in the hope of transforming temporary appointments into permanent ones (Autor, 2001; Autor and Houseman, 2002).

Firms rely on TEAs so as to reduce the fixed costs of labor search, while they can count on a pool of workers from which to single out the most suitable candidates for temporary jobs in time of peak activity, or in exceptional, unforeseen situations. But it is also documented that employers often outsource to TEAs the staffing of critical categories of workers, or even the selection of the whole workforce. In this case, people who want to get a job in such firms simply must start working through a TEA (Houseman, 2001; Ichino *et al*., 2004).

Garcia-Perez and Muñoz-Bullón advance the even stronger argument that TEAs "in fact offer a unique screening device that matches the individual with the most appropriate skill-level to the job in question" (Garcia-Perez and Muñoz-Bullón, 2005, p. 1). The same authors highlight that hiring TEA workers, in order to screen them, and then to offer permanent positions only to the most suitable ones, has become a common strategy for firms. Along the same lines, Autor shows that, in several sectors of the economy, TEA services represent the most important channel for recruiting new, permanent workers (Autor, 2001).

In Italy, throughout the period considered in this study, TEAs are the only type of intermediaries allowed to operate in the labor market. Hence, hiring through TEAs is the unique means available to firms and workers, in order to access external searching and screening services. At the same time, contracts with fixed term, even of short duration, can be signed by the parties without the necessary intervention of an intermediary. Such a particular context extends the scope of TEAs to the whole range of LMIs typical functions, that is well beyond the mere channeling of short-term workers. Indeed, as thoroughly discussed in the next Section, there is far strong evidence that Italian TEAs do search and select people aimed at eventually filling permanent positions, very often appointing skilled workers, technicians, and professionals.

3.3 Temporary employment agencies in Italy (1997-2001)

Private temporary employment agencies constitute a relatively new phenomenon in the Italian labor market. They were allowed to operate by Legge (Law) n. 196 of 1997[2], the so called Treu reform of the labor market, and the first companies were established between 1997 and 1998. The reform provided for the end of the public monopoly of employment services, and introduced a new type of employment contract, called "interinale", that is a provisional contract in which an agency hires

[2] The precise normative references is Legge 196/1997 (artt. 1-11), integrated by Decreto Ministero del Lavoro 381/97 and 382/97, Circolare esplicativa Ministero del Lavoro 141/97, Decreto Ministero del Lavoro 31/05/1999 and 29/11/1999, and modified by Legge 488/1999 and 388/2000. See also CCNL "Imprese fornitrici di lavoro temporaneo" (National Labor Contract for the temporary employment sector) of 1998.

people for the purpose of placing them at the disposal of a client firm for a period of fixed duration. Up to the year 2003, the only type of contract intermediaries can deal with is the interinale[3].

Since the approval of the Italian Civil Code in 1942, the standard form of employment agreement has always been the open-ended contract, although fixed-term contracts, especially targeted to seasonal jobs in agriculture, food industry, and tourist trade sector, were also allowed[4]. The scope for fixed-term contracts was significantly enlarged in 1987 by Legge n. 56, and there is evidence that the use of such arrangements has massively increased during the 90s, up to represent 42% of total engagements in the private sector in Veneto during the year 2001 (that is the final year relevant for our analysis), corresponding to 6.2% of employment in terms of days worked (Veneto Lavoro, 2008a and 2008b). Interinale contracts exhibit a rapid diffusion immediately after their introduction, generating 58,500 engagements in 2001 in Veneto, corresponding to 11% of total engagements in the private sector, and 0.8% of employment in terms of days worked. Notwithstanding all this, in 2001 the share of days worked with open-ended contracts is still more than 84%, indicating that the labor market is still dominated by arrangements characterized by high firing costs and tight regulatory restrictions[5].

Until 1997, Italian legislation strictly prohibited the intermediation of subordinate labor, even when such activity was freely given, and it inflicted heavy penalties for failures to comply with this rule[6]. Before Treu reform, employment services were a public monopoly operated through a network of provincial agencies, which were usually very inefficient, and in most cases were of no help at all to unemployed people (Barbieri *et al*. 2001). TEAs thus represent the very first example of private employment intermediary in contemporary Italy.

Treu reform, and the related National Labor Contract for temporary employment sector, signed by the representatives of workers and employers in 1998, officially provide for three cases in which firms can resort to provisional contracts:

- during peak activity;
- when there is temporary need for specific expertises;
- in case of temporary replacement of workers on sick, or on maternity leave.

[3] The relevant normative was modified in 2003 by D.lgs. 276/03, the so called Biagi reform, enlarging the scope for labor market intermediaries.

[4] Fixed-term contract were also regulated by Legge 230/1962.

[5] During the period considered in the present study, the Italian labor market maintained a very strict employment protection legislation, as far as standard employment is concerned. In 1999, the OECD still ranked Italy 23rd over 27 countries in terms of “overall strictness of protection against dismissals”, where lower ranking indicates stricter regulation (OECD, 1999). Noticeably, according to Brandt *et al*. (2005), Italy has been the country with the largest drop in the OECD Employment Protection Legislation sub-index for temporary employment since the mid-90s.

[6] The normative reference are: codice civile (Civil Code) art. 2127; Legge 264/49, and Legge 1369/60.

Nevertheless, as pointed out by the Italian Department of Labor in 2001, the use of provisional contracts in practice responds to a variety of reasons, which go far beyond the letter of the regulatory measures. In addition to the cases provided for by law, Italian employers resort to provisional employment agreements also to select candidates to fill posts, pending permanent appointments (Ministero del Lavoro e delle Politiche Sociali, 2001).

This choice is partially motivated by the short probationary periods provided for by National Labor Contracts in case of standard employment. A probationary period is an initial period in which the employment relationship may be terminated at the initiative of either parties, without previous notice and further obligations. After the conclusion of the probationary period, the employment relationship becomes permanent, and dismissal is possible only in the cases strictly regulated by law, and, specifically, individual dismissals are in practice extremely costly[7]. According to most Italian Labor Contracts, the probationary period cannot exceed six months, and it is typically just one or two months for low-skill contractual positions[8]. On the contrary, provisional contracts de facto allow for a much longer trial period, given that they can be stipulated for up to more than 24 months[9,10], while being subject on the whole to less regulatory restrictions, than other fixed-term contracts.

Most importantly, by resorting to provisional contracts – differently from what happens with other forms of fixed-term contracts – firms can access the searching and screening services provided by TEAs, in order to identify the professional and individual profiles which are most suitable for the specific vacancies they have to fill.

As for the initial years of TEA activity, the importance of the screening motivation is well illustrated by the high rate of transformation of temporary positions into permanent ones. A survey conducted by the Italian Department of Labor shows that, in both 2000 and 2001, roughly one fourth of provisional contracts were subsequently transformed into permanent positions (Ministero del Lavoro e delle Politiche Sociali, 2001). But in terms of head count such percentage is actually much higher, since the same individual can sign a series of distinct provisional contracts with the same employer.

---

[7] See the discussion in Ichino *et al*. (2003), and in Kugler and Pica (2008).

[8] The current National Labor Contract for the mechanical sector, which is widely recognized to be the leading employment agreement in Italy, in the case of open-ended contract, provides for a probationary period of 4-6 weeks for low-skilled workers, 12 weeks for medium-skilled, and 24 weeks for high-skilled; these figures are reduced to 3-4, 8, and 12 weeks respectively, for workers who have already completed the apprenticeship in another firm, or have attained two years of working experience in another firm, doing the same job.

[9] Legge n. 196 of 1997, and the related National Labor Contract for the temporary employment sector of 1998 did not specify the maximum duration of provisional contracts. The official provisions only established that there could be up to four extensions of the initial appointment, for a cumulative period of the extensions not greater than 24 months. D.lgs. n. 386 of 2001 introduced a maximum term of 36 months overall.

[10] According to the Italian Department of Labor, in 2001 in Italy, the average duration of appointments is around five months, with a markedly right-skewed distribution of durations (Ministero del Lavoro e delle Politiche Sociali, 2001).

Furthermore, the role of TEAs in terms of searching and screening is revealed by the fact that firms very often ask agencies for workers who meet strict requirements, and/or who have high-skill profiles, as highlighted by Iacus and Porro (2002). Indeed, in Veneto in the years immediately after Treu reform, low-skilled workers occupied only 50% of provisional jobs, with a marked tendency to decrease over time (Veneto Lavoro, 2008b). More in general, Italian TEAs are proved to have a truly multivocal capacity of treating a variety of professional profiles; they do not just deal with the traditional figure of young, male, low-skilled worker, but they also treat more mature, manual workers with specialized skills, as well as young men and women with medium-high educational attainment, who typically work in the service sector (Porro *et al*., 2004).

As for workers, several may be the reasons to apply for provisional jobs: a favorable attitude towards flexibility, the possibility to identify firms with suitable vacancies, the opportunity to signal individual skills to firms, the advantage of receiving specific training from TEAs, or simply the lack of valid alternatives. It is in general an empirical question whether such form of employment is a *trap* that inexorably leads to precariousness, or constitutes a *bridge* to permanent jobs (Buechtemann and Quack, 1989).

In this regard, Ichino *et al*. (2004) – using data on the entire population of provisional workers during the first six months of 2001 in two regions of Italy, Tuscany and Sicily – show that the probability of finding a permanent job is substantially higher for people having an interinale contract, than for people unemployed. Specifically, the authors consider the outcome "finding a permanent job after 18 months", and they estimate the average effect of the treatment "being engaged in a provisional job" on treated workers. They find a positive and large effect of TEA employment, accounting for 50-60% of the baseline outcome probability of the treated group. Such a study demonstrates that provisional employment "has not been a 'trap' of endless precariousness in Italy, but has been an effective springboard toward permanent employment" (Ichino *et al*., 2004, p. 31), also thanks to the intermediation services provided by TEAs. Yet, a word of caution is in order, since such evidence might not extend to more recent periods.

3.4 Data: the Veneto Worker History panel

The empirical ground for investigation is the VWH panel, a matched employer-employee dataset derived from administrative records of the Italian Social Security Institute, covering the entire population of workers and employers in Veneto, during the period 1975-2001.

Veneto is a dynamic, "manucentric" region, whose labor market, starting from the middle 80s, has been characterized by nearly full employment, and by a positive rate of job creation in almost every sector of the economy. The industrial system is characterized by a large population of small and medium firms, frequently organized in districts, whose specializations are garments, textiles, leather and shoes, goldsmiths, mechanical products, furniture, and plastics. VWH covers each single worker employed in the private sector (except only for self employed, farm workers, and people receiving no salary), and each single establishment with at least one employee. The information available are extremely rich, and allow to build a monthly history of the working life of each employee, who has been hired for at least one day by an establishment based in Veneto, regardless of the worker's place of residence.

Firms can be distinguished by their univocal Tax Identification Number, "codice fiscale", while workers are marked by an anonymous individual code. In the source archives, the firm code changes each time the legal ownership of the firm changes, even if there is no actual stop in the underlying operations, nor appreciable change in the nature of the activity performed. Whenever such situation is recognized, the business is said to be continuous, and the old employer (incorporated) is assigned the code of the new employer (incorporating)[11].

Another problem is that employer codes formally identify *insurance positions*, not firms. Although in most cases each firm has only one security position, it is possible for employers to register different categories of employees under different positions[12]. Anytime the Social Security archives provide an explicit indication of which positions are dependent on a parent one – and hence pertain to the same firm – all the data are consolidated, retaining only the parent's identification code. Of course, we can only partially account for complex, more elusive business structures, as for instance informal groups. Nevertheless, the adopted procedure, in our view, leads to a satisfactory approximation of the real boundaries of most enterprises. In the text, with the word firm or, alternately, employer, we always refer to the consolidated insurance position.

Given the triangular structure of provisional contracts, we observe TEAs as formal employers of temporary workers. We do not know which are the client firms temporary employees actually work for, while engaged through TEAs, but we can track all reallocations having TEAs as either origin or destination. Hence we can include TEAs in the network as vertices, exactly in the same way we include other firms involved in episodes of worker reallocation. Importantly, we can keep track in our network of mobility episodes related to people – especially young people – who first enter the labor market through a TEA, and then find a job as direct employees of some private firm.

[11] Formally, legal employer A is considered incorporated into legal employer B anytime more than 50% of its employees are taken over by B. This procedure is used by Tattara and Valentini (2003, 2004), and it is employed to construct the current version of the VWH dataset.

[12] For instance, there may be distinct positions for blue and white collars, or for different plants.

In order to build our labor mobility network, we select from the VWH database all worker reallocations responding to a set of defined criteria, and we map them onto a directed graph, whose vertices represent firms and TEAs, and whose links denote passages of workers from one firm to another, or between firms and TEAs[13]. An important implication of such approach is that businesses not involved in labor reallocations do not enter the network; hence, there are not isolated vertices in the graph.

We construct 11 year networks for the period 1991-2001; we restrict our focus on the reallocations of workers of both sexes, aged between 15 and 65 years, whose engagement – following a separation – occurred within the 1st of January and the 31st of December of each year, and where at most 6 months elapsed between the separation and the subsequent engagement[14]. We also keep track of the reallocations cutting across the administrative boundaries of Veneto, so that firms located outside the region can enter the network sample as well, as long as they transfer/receive workers to/from firms located in Veneto. No restrictions are imposed on the duration of job spells, nor on the type of occupation, whether blue or white collar, apprentice, or manager. We exclude reallocations in the same firm[15].

3.5 Network setup and empirical strategy

An ideal setting for appreciating network properties, such as accessibility, is when there is an observable network infrastructure – that is a given configuration of channels (links), through which different locations (vertices) communicate with each other – upon which some dynamical phenomenon, usually represented by flows – for instance traffic flows, information flows, or disease diffusion – takes place. The ultimate goal of investigation is to understand something about the phenomenon running along the infrastructure, e.g. appreciating how the process actually takes place, to what extent, and with which consequences; and in order to do so we need to know some characteristics of the infrastructure, since it is the particular arrangement of available channels that decisively determines the process dynamics[16].

In our specific case, however, it is not possible to distinguish in advance between the network infrastructure, and the process taking place on it. We only observe the process – i.e. workers

[13] For a precise formalization and explanation of the graph-theoretic concepts we use throughout the present study, especially those highlighted in the text by means of italic letters, see Section 2.3.
[14] Long periods of apparent inactivity could possibly hide voluntary exits from the labor force, hence, we make the relatively conservative choice of not including in our analysis people whose inactivity spells exceeds 6 months.
[15] This type of mobility typically concerns seasonal jobs, since temporary lay-offs are not permitted by Italian legislation.
[16] Comprehensive reviews of network analysis and its applications can be found in Albert and Barabasi (2002) and Newman (2003); the issue of processes taking place on networks is specifically addressed in Section VIII of Newman's.

reallocating between firms – as it progressively comes to pass, while we are not aware of the channels potentially available to each worker at the time of the engagement decision. We thus carry out our analysis relying only on actually accomplished worker transfers; we map the arrangement of such moves, and treat the resulting network as if it were a real, practicable infrastructure specifically intended for guiding worker flows. Then, we ask how the shape of the infrastructure would affect a reallocation process possibly taking place on it.

When analyzing a networked system, a key concept is that of *path*, that is an uninterrupted chain of links connecting several vertices in sequence. Based upon the existence of paths, and on their characteristics, we evaluate the extent to which different locations are reachable from a given position in the network. In the case of inter-firm worker reallocation, paths are given by the combination of distinct mobility episodes into longer routes, cutting across the system. Of course, the recognition of a path does not necessarily mean that single individuals do cover the whole path length through subsequent reallocations. Indeed, workers usually move just one, or a few steps at a time, so that, at firm-level resolution, the flowing of labor through the system looks more like a gradual process of percolation through a porous material, than like a process of massive, long-distance migrations. Hence, just as the microscopic architecture of pores determines the permeability of a sponge, the layout of firm-to-firm pathways determines how our mobility network can be traversed[17].

Considering the network of labor mobility as an actually practicable infrastructure, we can think of job accessibility as the possibility of reaching the largest possible fraction of employers, by means of the fewest job changes to be carried along existing paths, regardless of the initial position in the network. Noticeably, the theory of complex networks closely relates this notion of accessibility to a specific model of network known as small world (Watts and Strogatz, 1998; Newman, 2000; Goyal *et al.*, 2006), whose crucial functional significance is precisely that of making locations easily reachable one from another, employing a parsimonious assembly of links. The smaller the world, the more accessible locations are. We hence make the original choice of using the small-world properties of the inter-firm network as a proxy indicator of job accessibility.

[17] The role of network paths is strongly supported by empirical evidence about vacancy-chain-driven reallocations, a widespread phenomenon in the tight labor market characterizing Veneto during the 80s and the 90s. Based on an earlier version of the VWH dataset, and limited to the manufacturing sector in the Veneto provinces of Treviso and Vicenza, during the period 1991-1996, Tattara and Valentini (2004) show that the share of employer-to-employer transitions accomplished within 4 months accounted for by vacancy-chain processes is on average 88%. Given the only slightly broader definition of reallocation we adopt, and taking into account the further tightening of Veneto labor market throughout the second half of the 90s, we believe in our setting the share of employer-to-employer transitions explained by vacancy chains is unlikely to be much lower than the one calculated by Tattara and Valentini.

According to the literature, a network is said to be a small world when the following four conditions simultaneously apply:

1) a large number of locations is reachable from whatever position in the network, i.e. there exist paths connecting a relevant fraction of possible pairs of vertices;
2) locations are reachable with little effort, i.e. interconnected vertices are on average only a few steps away from each other (where to go along a link is assumed to be costly);
3) the system is overall parsimonious, i.e. the actual number of links is much smaller than the maximum possible number, obtained when a link is placed between every possible pair of vertices (where to provide a link is assumed to be costly);
4) vertices form cohesive groups, i.e. vertex neighbors tend to be interconnected among each others, meaning that it is easier for a given vertex to establish, maintain, or reproduce a connection with another vertex, if the latter is already connected to most its neighbors.

The combination of such principles confers on the notion of accessibility an immediate economic meaning: the system is accessible if, whatever initial location we are in, both the number of opportunities potentially available for future moves is high (condition 1), and the cost of actually accessing such opportunities is, on average, low (conditions 2, 3, and 4). In many real-world situations, there is a striking trade off between the number and variety of alternative opportunities, which are in principle reachable from a given initial position or status, and the cost of actually reaching such opportunities. The small world reveals itself to be an extremely effective configuration in order to resolve such a trade off, because it guarantees maximum reachability, while minimizing the costs both for the system designer – i.e. the cost of constructing the infrastructure – and for the system user – i.e. the cost of using the infrastructure in order to reach a given target.

The four defining properties of the small-world model can be re-framed in exact graph-theoretic terms in a directed network, resulting in the following propositions respectively:

1) the network exhibits a *giant weakly connected component* (WCC) and a *giant strongly connected component* (SCC);
2) *average path length* (APL) in SCC is appreciably small;
3) *density* of links is low;
4) *average clustering coefficient* (ACC) is appreciably high.

A small world thus comes into view as an integrated system, essentially dominated by local clustering, with a relatively few long-range links that act as shortcuts, connecting different bunches of vertices which otherwise would be much farther away from each other. The giant strongly connected component guarantees the existence of paths between all possible locations comprised within its boundaries, while short distances indicate that locations can be reached with little effort; besides, clustering – meaning redundancy of links at local level – promotes robustness to link disconnection and, through multiple independent pathways, reliable accessibility as well (White and Houseman, 2002).

In order to quantitatively appraise the small-world properties, the thumb rules we follow are:

1) SCC and WCC cover at least 25% and 50% of vertices respectively, and the other components are small (typically of order $\ln(n)$, where n is the total number of vertices);
2) APL in SCC is of the same or lower order as $\ln(n_{\mathrm{SCC}})$;
3) the link density is several orders of magnitude lower than its maximum possible value;
4) ACC is at least two orders of magnitude lower than ACC of a random network of the same size as and with the same *in-degree distribution* of the actual network.

The combination of these criteria identifies a range of parameters values for which a network shows small-world characteristics. The evolution of the small-world parameters over time can then indicate whether the world is getting smaller or bigger, or whether it is possible to recognize a transition from a large to a small world, or vice versa.

In order for a small-world architecture to be accessible in practice, there is still one other property to be satisfied, namely, the possibility for agents to effectively uncover short paths using only local information – a property known as *navigability* after the work of Kleinberg (2000). Indeed, the mere existence of short paths connecting possible pairs of vertices is not enough, in order to guarantee that agents with little knowledge of how the system is globally structured can easily locate such paths. Therefore, effective navigability has to be provided by other network characteristics.

In heterogeneous networks – i.e. networks different from regular lattices – some vertices tend to fall significantly more than others on short paths, an effect known as “funnelling” (Newman, 2001). Vertices falling on many shortest paths are said to have high *betweenness*; they constitute particularly advantageous positions, in order to pinpoint network locations, and to easily traverse the system, playing as gateways to a large fraction of vertices. This in turn means that, if agents can reach locations with very high betweenness, then it is easier for them to find a short way towards given target sites. Holding fixed other network characteristics, the vertices with many connections, that is with high *degree*, on average tend to have also high betweenness, simply because the larger the number of links a vertex has, the higher the chance that many of the existing shortest paths pass through it, while the chance of many shortest paths passing trough a low-degree vertex is much smaller (Holme and Kim, 2002; Bienenstock and Bonacich, 2003)[18].

Such observations lead us to conclude that, whenever actors do not possess perfect knowledge of the network structure, one possibility to render a small world navigable is to allow for the presence of *hubs*, that is vertices with many more connections than average, and whose connections span far distant sites. By virtue of their size and centrality, hubs can be easily located from almost every position within the system, being close to most sites. Agents can thus effectively navigate the network by first locating a hub, and then being redirected toward their objective. This explanation appears to be particularly convincing in the context of inter-firm labor mobility, where network locations (firms) are crowded with agents (workers) which interact among each other, exchanging information about the conditions and the structure of the labor market. Hub firms are crossing points where people can find the richest mass of information, in order to extend their own knowledge of the labor market, and consequently direct their future explorations.

To guarantee that a small-world network is truly accessible, or navigable, hubs must thus be present. The literature on complex network shows that the presence of a hub "backbone" is signaled by a very right-skewed degree distribution, characterized by a fat tail: a few, very big hubs occupy the tail, while the bulk of vertices has much less connections than average.

Verifying the existence of a hub architecture naturally leads to our second block of research questions, namely, to what extent TEAs control worker flows, and how TEAs market shares of hiring channels evolve over time. We tackle these issues by looking at the functional form of the degree distribution, which is widely acknowledged to be a key indicator of the mechanisms at play in network formation (Newman, 2003). We thus abandon the view of the network as an infrastructure, denoted by certain arrangement of links, and focus on the process responsible for the accumulation of links over vertices in time.

In this respect, the literature on complex networks shows that the degree distribution of a network with a hub backbone is very often well approximated in the tail by a Paretian distribution, more specifically, by a negative power law (Albert and Barabasi, 1999, 2002; Newman, 2003). This behavior can be in turn explained by precise mechanisms of link formation based essentially on preferential attachment. In Chapter 2, we have already demonstrated that the degree distribution of

[18] The actual strength of the correlation between degree and betweenness is an empirical matter, and it may vary considerably across networks; but in general, and most relevant for our analysis, vertices with many more connections than average tend to have also betweenness much higher than average.

the labor mobility network in Veneto indeed has a Paretian tail. In the present work, we focus on the evolution of the degree distribution over time, with special emphasis on where TEAs are exactly positioned, and how they affect the shape of the distribution.

Overall, our empirical strategy consists of two stages. In the first stage, we calculate the main topological properties of the year networks. We evaluate the small-world characteristics, devoting particular attention to detecting discontinuities emerging around the year 1997 – that is when Treu reform was passed – by means of comparing the actual network with expressly designed counterfactuals, so as to prove to what extent TEAs really affect the system (Section 3.6.1). Next, we verify the presence of a hub backbone, with focus on the position of TEAs (Section 3.6.2). In the second stage, we first introduce and discuss a model of network formation, whose simple theoretical assumptions are compatible with the reality of labor mobility (Section 3.7.1). Subsequently, for each year network, we calculate the degree distribution, evaluating whether the obtained results match the predictions of the theoretical model, and also discussing policy implications (Section 3.7.2).

3.6 TEAs effect on job accessibility

3.6.1 Small-world analysis

For each year network we compute the following properties: number of vertices and links, density, size of WCC and SCC, APL, and ACC. Moreover, we compare the structural properties of the actual year networks in the period 1997-2001, with the respective properties of two different series of counterfactual networks, constructed according to the following rules:

- counterfactual (1): we take the actual network and remove all TEA vertices, together with incident links (both incoming and outgoing), obtaining a new network with the same architecture of the actual one, but without reallocations involving TEAs;
- counterfactual (2): we take the actual network and for each TEA vertex j, we remove the non-TEA vertex i that satisfies $k_i = \min(k)$ subject to the condition $k \geq k_j$, where k is the *total-degree*; i.e. we leave TEAs and related mobility in the network, but we remove the non-TEA firms most equivalent to TEAs in terms of number of connections, together with incident links.

The difference between the actual network structure and that of counterfactual (1) provides us with an estimate of TEAs impact, which assumes TEA mobility – i.e. labor mobility involving TEAs either as origin or destination of reallocation – has no substitute in the labor market, and hence representing an upper-bound to the real TEAs effect. The difference between the actual network structure and that of counterfactual (2) is meant to proxy for the substitution of TEAs by other firms, selected from those which in the actual network are most similar to TEAs in terms of number of connections. Accordingly, the comparison between the structure of counterfactual (1) and that of counterfactual (2) yields a prudential approximation of TEAs effect, which can be thought of as lower-bound estimate. In extreme synthesis, for TEAs to have a substantial role in shaping the network architecture, we want counterfactual (1) to be sizably different from the actual network, and counterfactual (2) to be as similar as possible to it.

Before entering the core of the analysis, it is important to stress that labor reallocation networks tend to be affected by the business cycle. It is indeed a well established empirical fact that labor mobility is strongly correlated with the cyclic fluctuations of the economy, with worker turnover being markedly procyclical, and reallocations constituting the most dynamical component of such trend[19]. Hence, the business cycle affects the size and, most likely, the density of the reallocation network, with consequences that extend also to the arrangement of links, and, in particular, to the existence and size of giant connected components, whose emergence in random graphs is proven to be related to the density of connections[20]. When the cycle is exceptionally low – as it was in Italy during the recession of 1992-93 – the network will appear comparatively much sparser and less interconnected, while in periods of high cycle – such as in 1994-95 – it will be much more dense and interconnected.

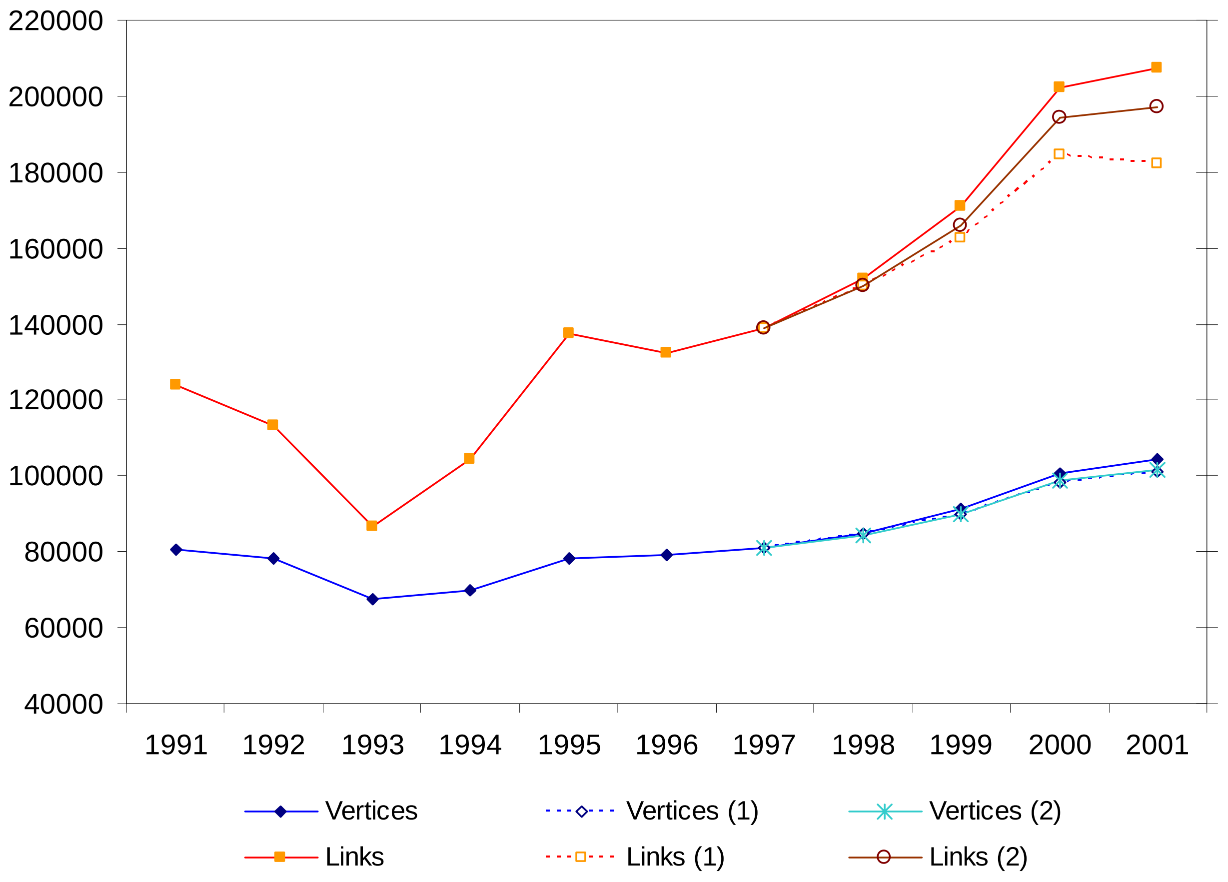
Figure 3.1 shows the evolution of network size. The system exhibits a minimum extension in 1993, with 67,578 vertices and 86,602 links, and a maximum in 2001, with 104,439 vertices and 207,504 links. Throughout the period, the link density is very low, around 2.0e-05, with a minimum of 1.84e-05 in 1992, and a maximum of 2.23e-05 in 1995. The network is extremely sparse, as required by the small-world model.

A procyclical pattern is evident during the time span 1991-1997. There is a pronounced downward spike in correspondence of the 1992-93 recession (-25% links), followed by a rapid growth in 1994-95 (+47% links), as the economy recovers in consequence of a Lira devaluation that boosts export competitiveness, which in turn especially favors the largely export-oriented economy of Veneto. After 1997, the business cycle impact appears to be much weaker; the network exhibits

[19] For the US labor market, see for example Davis *et al.* (1996); Fallick and Fleischman (2004). For the Italian labor market, see Tattara and Valentini (2004); Leombruni and Quaranta (2005).
[20] The first exhaustive treatment of the emergence of giant components in random graphs is in Bollobás (1985).

an intense, sustained increase in vertices and links all over the period 1997-2001 (+49% links, +29% vertices), with a partial slow down in 2001, again in correspondence of a downturn, induced by the burst of the new-economy bubble, and by increasing uncertainty in the international geopolitical scenario.

Figure 3.1 – Vertices & links



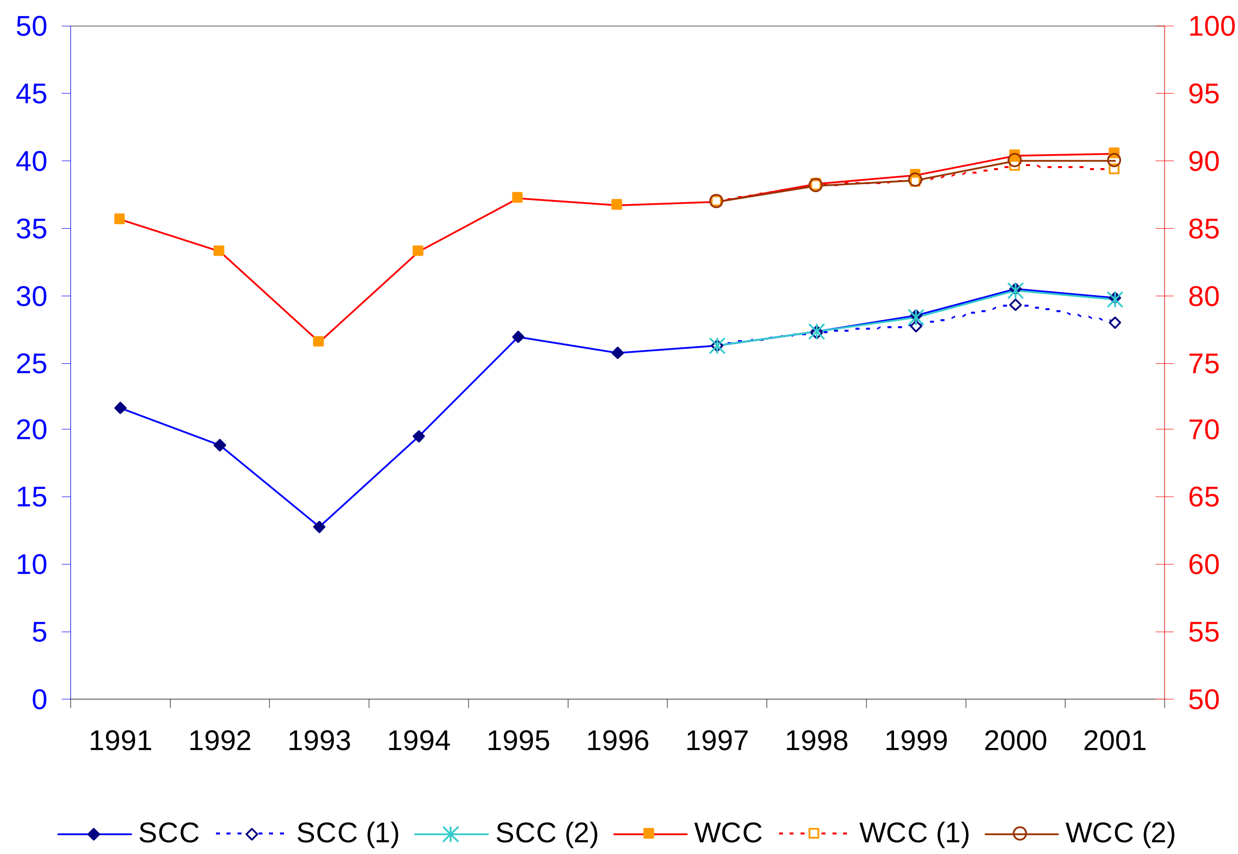
Comparing the actual trend with counterfactual (1), we notice that TEA links considerably contribute to explain the observed growth of connections, augmenting the counterfactual base by 1% in 1998, 5% in 1999, 10% in 2000, and 14% in 2001[21]. Noticeably, counterfactual (1) exhibits a decrease of links in 2001, compared to the year 2000, so that, in the last year of observation, the action of labor market intermediaries turns out to be the sole factor driving the increase in the actual

[21] Most of the increase in links between 1997 and 2001 is anyway independent on TEA direct action, and corresponds to a general growth of labor mobility involving the whole Italian labor market, which started in the mid 90s and went on during the first decade of the present century (Leombruni and Quaranta, 2005).

number of active channels of communication between firms. In 2001 counterfactual (2) has 8% more links than counterfactual (1); this figure represents our prudential estimate of TEAs impact, revealing that, Treu reform, through the establishment of private intermediaries, indeed appears to be able to effectively unlock new reallocation paths, disclosing unprecedented mobility opportunities.

Figure 3.2 shows the extent of the largest strongly/weakly connected components, in terms of percentage of vertices covered, allowing us to cast a first look at the inter-connectivity architecture. A procyclical pattern is again neatly recognizable. SCC shows a minimum in 1993 at 13%, and a maximum in 2000 at 30%, for WCC such figures are 77% and 90% respectively. From the year 1995, SCC keeps on permanently above 25%, and WCC remains above 85%; in the same period, the second largest strongly connected component never covers more than 6 vertices, while the second largest weakly connected component does not extend beyond 14 vertices. The system, hence, clearly exhibits the inter-connectivity structure distinctive of a small world, that is a single, large "continent", surrounded by several, very small "islands".

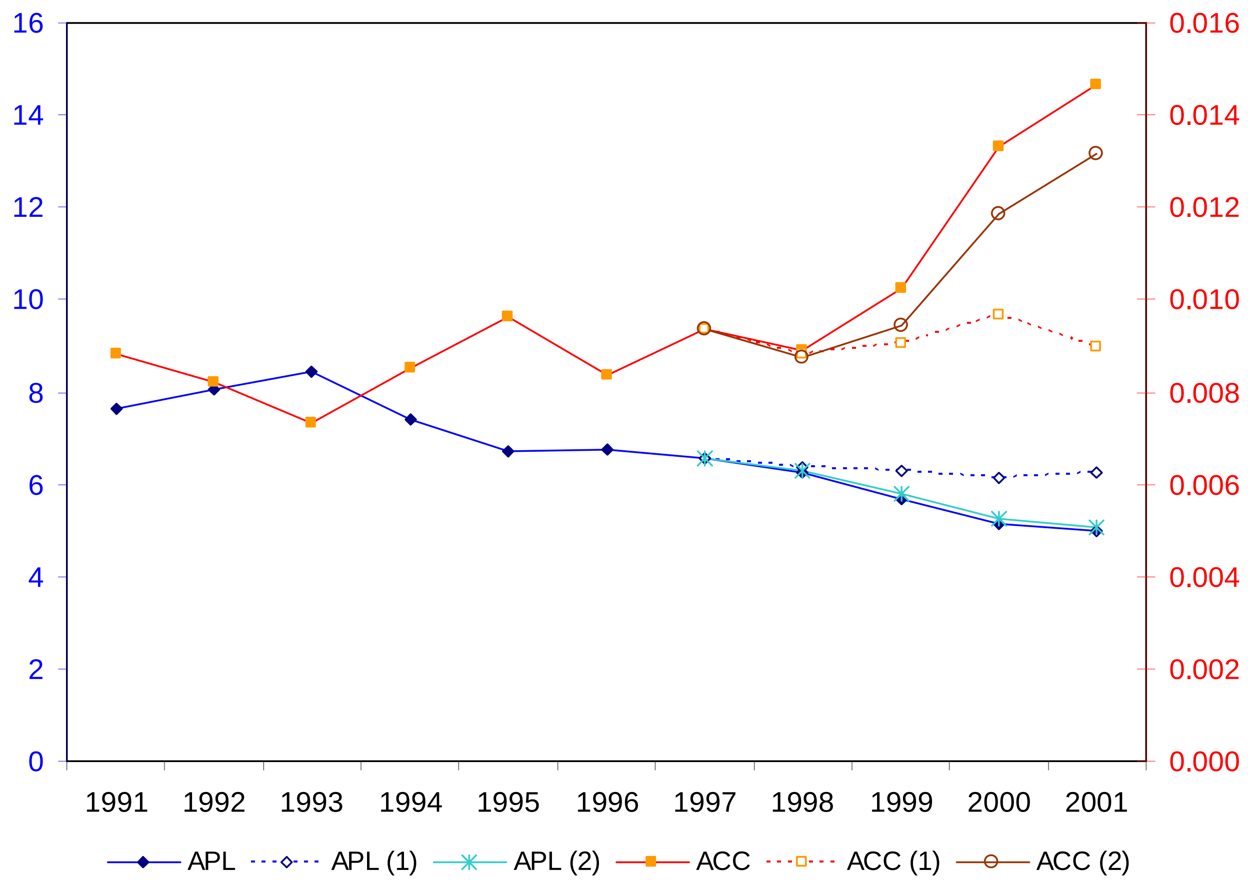
Figure 3.2 – Largest components (% coverage of the entire network)



In 1997, the giant continents enter a steady growth path, leading to a cumulative increase of 13% for SCC, and 4% for WCC, over the period 1997-2001. In 2001, SCC of counterfactual (2) substantially superimposes the actual SCC, and both are 6% larger than SCC of counterfactual (1), revealing how the extent of mutual connectivity is in fact positively affected by TEAs, while it is insensitive to the exclusion of non-TEA firms. A strong evidence that TEAs appreciably favors the integration of the system.

Figure 3.3 shows APL and ACC, the former expressed in number of links between locations (left axis), the latter expressed as an index number that varies between 0 and 1 (right axis). All over the period, ACC is at least two orders of magnitude higher than ACC of a network of the same size of, and with the same in-degree distribution as the actual one, but with links placed at random; the clustering pattern typical of a small world is thus clearly into sight. Up to the year 1998, ACC fluctuates between 0.007 and 0.010, with only a very slight tendency to increase over time; from 1999 to 2001, the indicator goes through a phase of extremely intense growth, scoring 0.015 at the end of the period, 57% above the level of 1997.

Figure 3.3 – APL & ACC



ACC of counterfactual (1) remains substantially flat at the pre-reform level, while ACC of counterfactual (2) closely follows the actual path. In 2001, the actual network exhibits ACC 63% higher than counterfactual (1); while ACC of counterfactual (2) lays 46% above counterfactual (1), thus revealing a strong, positive effect of TEAs on clustering.

APL exhibits a maximum in 1993 at 8.5, a minimum in 2001 at 5, and all through the period it is strictly lower than $\ln(n_{scc})$, as required in order for the network to be a small world. After Treu reform, mutually interconnected vertices become significantly closer to each other: between 1997 and 2001, the average distance is reduced by as much as 24%. Counterfactual (1) has an almost flat behavior, while counterfactual (2) lays just 1 percentage point above actual APL. In the last year of observation, APL is 20% less than APL of counterfactual (1). There is sharp evidence that TEAs provided shortcuts to network locations, substantially reducing average distances.

There is another important observation, emerging from comparing the charts in Figure 3.1 and 3.3. Looking at counterfactual (1), we notice that links considerably increase over time, but such expansion has an almost neutral effect on the internal arrangement of links, as measured by ACC and APL. On the contrary, the increase in network size directly due to labor market intermediation does modify the structure, in the direction of higher cohesion and lower distances. This is a further proof that, ultimately, it is the special action of TEAs that makes the small world of labor mobility smaller, and therefore more accessible.

In order to have a grasp of the dynamics underlying the observed increase in clustering (Figure 3.3), in Figure 3.4 we plot the actual ACC in function of degree, grouping vertices into 7 degree classes and showing ACC values for each class[22].

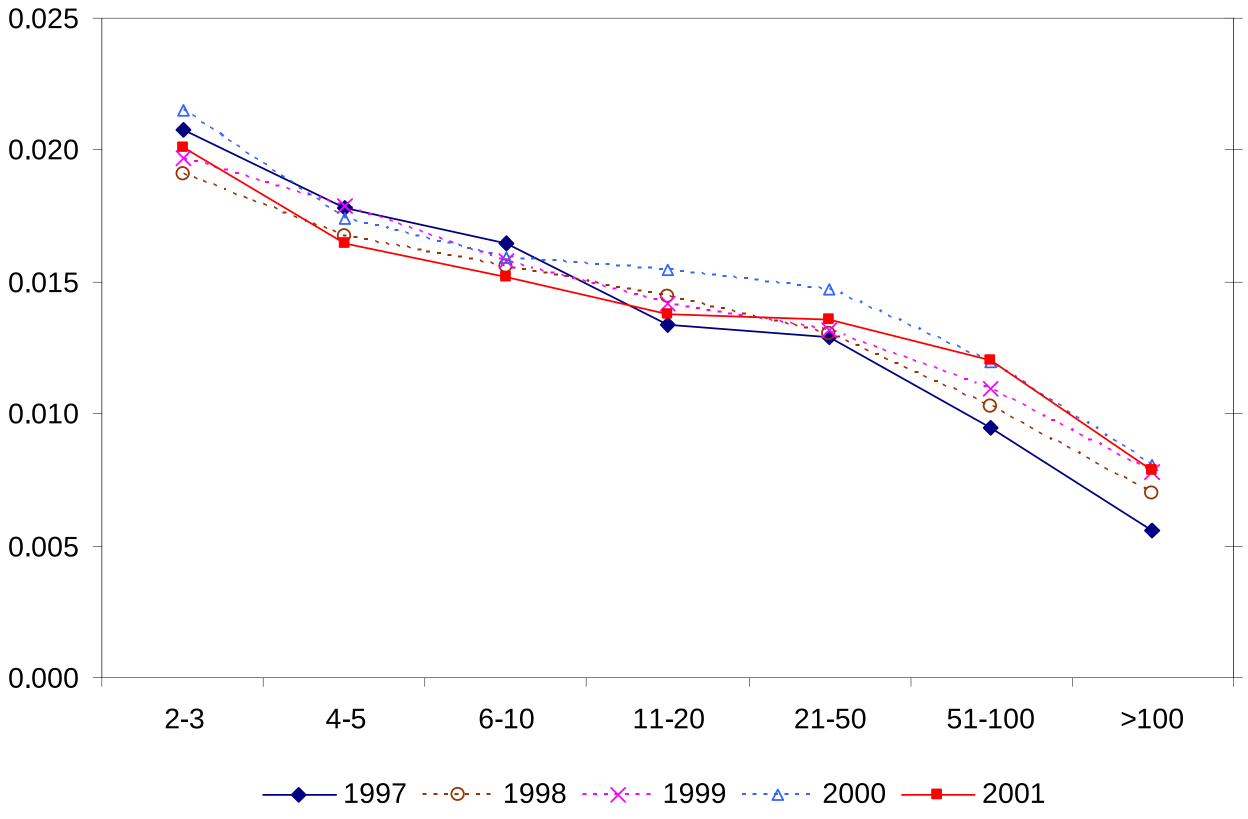
As made clear by the chart, ACC of best connected vertices, namely those with $k>10$, increases significantly over time, while ACC of vertices with just a few connections falls remarkably. This suggests that TEAs simultaneously reduce the embeddedness of firms with a handful of connections, which generally tend to be part of fairly cohesive local communities, and increase the embeddedness of companies with many connections (often big companies), which tend to be little clustered, because they are more likely to operate on several distinct labor markets, interacting with firms that are not directly linked together[23]. Thus, intermediaries, not only enhance overall cohesiveness, but also transfer cohesion from local to more global scale.

The clustering reduction for little-connected firms suggests that TEAs offer to small employers, and to their employees, recruitment sources and reallocation opportunities that are different from those offered by their strictly local communities. The clustering increase for well-connected firms

[22] Of course, clustering is not defined for vertices with degree equal to one (no interconnected neighbors).
[23] On the positive correlation between degree and firm size, see Chapter 2.

indicates that several employers, which interact with a same hub firm, but not much among each others, become closer, by means of applying to common TEAs.

Figure 3.4 – ACC (Y) *vs*. degree classes (X)



On the whole, the small-world analysis, together with the counterfactual comparisons, reveals how labor intermediaries indeed make the labor market significantly smaller, through the establishment of shortcut paths that span the economy from side to side, knitting together distant vertices into more cohesive communities, and reducing average distances. This is partially a consequence of the TEAs capacity to operate across a large variety of economic sectors, professions, and geographical locations. Such transversal nature makes TEAs hubs for heterogeneous workers and firms, reflecting into a widespread and far-reaching connectivity.

3.6.2 Hub structure

We begin the hub analysis by considering the total-degree sequence of each year network. In Table 3.1 a few summary statistics are reported: number of vertices (n), average degree (k_G), median degree (k_{50}), degree of the 99th percentile (k_{99}), maximum degree (k_{max}).

From the very beginning, the total-degree sequence exhibits a quite broad range of values, that tends to widen over time. Despite the relatively high maxima (315 in 1992, rising up to 6,524 in 2001), the average degree is always very low, ranging from 2.6 in 1993 to four in 2000 and 2001. This is due to the extreme concentration of the distribution around the minimum degree, as revealed by the median, which takes the value one up to 1994, and two thereafter. Two striking features are thus revealed: the by far largest fraction of vertices has degree less than average, with the bulk of vertices exhibiting just the minimum degree; a small fraction of vertices has degree many times larger than average, as shown by the scores of the 99th percentile, which is 6 to 9 times greater than average.

Table 3.1 – Total-degree distributions: main descriptive statistics

year	n	k_G	k_{50}	k_{99}	k_{max}
1991	80,680	3.1	1	23	429
1992	78,300	2.9	1	21	315
1993	67,578	2.6	1	17	507
1994	69,816	3.0	1	22	527
1995	78,450	3.5	2	28	467
1996	78,966	3.4	2	27	358
1997	80,820	3.4	2	29	480
1998	84,823	3.6	2	30	731
1999	91,136	3.8	2	32	2,100
2000	100,671	4.0	2	35	4,635
2001	104,439	4.0	2	33	6,524

All through the period, the total-degree sequence shows an extremely unequal pattern, markedly right-skewed, with a heavy or fat tail. The same is true for both the in-degree and the out-degree distributions. Such features identify a particular network configuration in which a few hub vertices largely dominate the system, by means of widespread connectivity. Hubs do not constitute a defining element of small-world networks, but their presence enhances the navigability of the system, so crucially determining the extent to which a small world is actually accessible by agents with little knowledge of the overall infrastructure. The analysis shows that the small world of labor mobility hinges upon a clear-cut hub backbone, thus being maximally qualified to guarantee effective accessibility[24]. Moreover, the maximum degree shows a steep increase just after the year 1997, with an average annual growth of about 100%, suggesting that Treu reform favors the formation of large hubs.

Table 3.2 – Ranking of the 10 biggest TEAs, according to total-degree

	overall ranking (1= highest total-degree)				
first 10 TEAs	1997	1998	1999	2000	2001
a	40,455	4	1	1	1
b	40,456	16	2	2	2
c	-	37	3	3	3
d	-	56	4	4	4
e	-	103	7	6	6
f	-	301	22	8	7
g	-	321	27	10	9
h	-	331	30	13	11
i	-	514	36	22	13
l	-	689	56	23	14

In Table 3.2 the overall ranking of the 10 biggest TEAs in terms of total-degree is reported. In 1997, only two TEAs are operating, with a very limited activity, as revealed by their low ranking. Already in 1998, one TEA reaches the extreme tail of the connectivity distribution, ranking fourth overall, while other four TEAs are positioned within the first hundred vertices, and all the first 10 TEAs are within the 99th percentile of the distribution. In 1999, TEAs definitively take over the degree distribution, with four intermediaries firmly occupying the first four positions. Soon after their appearance in the system, TEAs show high attractiveness and strong capacity to capture labor

[24] On the same topic, see also the discussion in Section 2.8.

mobility flows, becoming the far most important hubs. Labor market intermediaries prove themselves to be very effective in seizing and routing worker reallocations, making the network easily navigable, and hence truly accessible.

This last piece of evidence completes our empirical appraisal of TEAs effects on job accessibility, and allows us to finally organize the results in terms of the following stylized facts:

- the network is a small world;
- TEAs make the system appreciably smaller, shortening distances between firms;
- the network exhibits a hub architecture suitable to guarantee effective navigability;
- TEAs promptly emerge as major network hubs.

The combination of such elements provides a decisive evidence that TEAs enhance labor market accessibility in a remarkable way. The system on the whole tends to assume the character of a large cohesive community, taking upon itself some of the characteristics typical of much smaller communities. Moreover, many crucial shortcut paths between firms are firmly under control of TEAs, and therefore they are particularly easy to locate from workers with limited information about the market.

These facts certainly embed a positive element of judgment in terms of economic policy. An efficient reallocation of labor is essential, in order for the economy to be productive, to allocate the available resources in the most effective way, and to absorb local and transitory shocks that hit sectors, and industries. Furthermore, an easy and smooth reallocation process is fundamental in guaranteeing workers more rapid and less costly job market transitions, with immediate and long-lasting benefits on individual income profiles. Accessibility, as defined in the present context, is undoubtedly one of the factors at the very root of a good functioning of labor markets.

Nevertheless, after Treu reform, the system turns out to be strongly dependent on TEAs, in particular on a handful of them. Such a situation is especially critical, because the collapse, or malfunction of even a small number of hubs can compromise connectivity at a great extent (Albert *et al.*, 2000). Moreover, not only we might fear the failure of the biggest TEAs, and the consequent “hole” produced in the network, that would hamper reallocation, but – as thoroughly discussed in Section 3.2 – we are concerned about the growing monopolistic/monopsonistic power a few TEAs can exert on the reallocation market.

3.7 Control over reallocation channels, and evolution of TEAs market power

3.7.1 Models of network formation

In the last decade, the literature on complex network has concentrated much on connectivity distributions, producing a mass of theoretical and empirical work. In particular, very skewed distributions with heavy tails, such as those we observe in the labor mobility network, have been associated to link formation mechanisms based on *preferential attachment*, where the probability that a new vertex connects to a given one is assumed to be proportional to the degree of the existing vertex. According to such a process, vertices with many links are more likely to attract new links, so that a highly unequal configuration is gradually generated.

Perhaps the most widely acknowledged model of network that exploits a preferential attachment rule is the one proposed by Albert and Barabasi (1999). The authors develop an algorithm of network formation that gives rise to degree distributions denoted by power-law tails. In its original formulation, the model is based solely on the arrival of new vertices in time, and on linear preferential attachment. After this model, many degree distributions from empirical networks have been claimed – and in several cases demonstrated – to be power-law distributed, so that preferential attachment is now generally accepted to be the mechanism at work behind these results (Newman, 2003; Clauset *et al*., 2009).

Scholars have also attempted to build models that account for the upper truncation, or cutoff, to the power-law behavior that is often observed in empirical degree distributions. The presence of a cutoff is explained by the existence of a constraint to the preferential attachment mechanism, limiting the addition of new links to vertices. Interestingly, Mossa *et al*. (2000) model such constraint as an information cost. The intuition behind this approach is that agents/vertices bear a cost in order to gather and analyze information concerning other vertices. Therefore, especially when the system is large, agents are assumed not to know the state of the entire network. In large networks, the authors argue, it is very unlikely that a new coming actor knows the degree of all existing vertices. The decision about which vertex to connect with, hence has to be taken based only on information about a subset of possible locations (either a fraction or a fixed number of vertices). Then, preferential attachment comes into play within such a subset. On the whole, the link distribution resulting from these rules turns out to be power law with an upper, exponential cutoff, whose strength depends on the incidence of information costs.

We now want to verify whether the key assumptions underlying network models based on preferential attachment are plausible in the context of labor mobility, so that such theoretical indications can be used as a base for modelling the distribution of hiring channels – i.e. the in-degree distribution – in the reallocation market. Three are the points we have to validate[25,26]:

1) network growth, i.e. addition or activation of new vertices in time;
2) attractiveness of highly connected vertices;
3) possible presence of information/transaction costs.

As for the first point, network growth, the explanation is quite straightforward in our case. In Veneto there has been a positive, strong rate of creation of new ventures throughout the 90s. Hence, the potential number of sources, or destinations of worker reallocations increases in time, because a progressively larger number of firms operates in the market, so the actual number of vertices in the labor mobility network can also increase in time[27].

In order to explain why agents are willing to transfer to well-connected firms, we propose two related arguments. First, people may seek to join employers with many incoming connections, because they interpret this evidence as a signal of firms prosperity. In most cases, firms that grow and hire people from different sources can be certainly thought to be a good destination for successful reallocation. Second, people might simply adopt a herd behavior, addressing those firms which have been already addressed by many workers from different origins.

Besides, whenever the network structure is such that in-degree and out-degree are strongly correlated, people may seek to join employers with high in-degree because such locations tend to be overall more central in the system, hence being likely to offer easier access to further reallocation opportunities. That is to say, people perceive the importance of hubs in providing accessibility, and actively seek for them, since hub locations embed a positive option value in terms of future career[28]. Given a minimum knowledge of the network – e.g. the possibility of directly observing, or proxying for firm degrees – it is therefore convenient to reallocate towards more central locations.

The assumption about the existence of information/transaction costs reasonably holds true as well. It is indeed unlikely that workers are able to costlessly evaluate the characteristics of all firms and jobs present in the system, especially when the system is formed of several thousands firms,

[25] We empirically focus on the in-degree distribution, because it captures exactly how agents choose their reallocation targets, and how firms can control the reallocation market.

[26] The analysis is mainly focused on the worker side of the market, hence the emphasis on the factors governing attachment decisions. Vacancies are simply assumed to exist, and to always be available to reallocating workers.

[27] For a generative model of network that accounts for both contraction and re-growth and that produces networks with topological features similar to preferential-attachment networks, see Saavedra *et al*. (2008).

[28] In our specific case, the observed correlation between in-degree and out-degree is high (ρ=0.8 on average over the years), indicating that employers with high in-degree tend to have high out-degree as well, so representing good locations from which to access many other locations in the market.

and even more jobs, as it is the case in our reallocation network. Workers, indeed, usually have limited resources to invest in the process of job search, employer screening, and bargaining over contractual conditions.

Building on the evidence of power-law-like degree distributions, and hinging upon the fundamental assumptions discussed so far, some recent studies propose a paradigm of network formation in which preferential attachment is not directly assumed, but arises naturally from the simultaneous optimization of multiple competing objectives. This approach is of particular interest from an economic perspective, because it explicitly models the trade off between costs and benefits – represented by distinct network metrics – agents typically face when taking decisions in a context of scarce resources (as it is typically the case of job search).

The fundamental outline of this sort of models is described and discussed in Fabrikant *et al*. (2002), and further developed in D'Souza *et al*. (2007). A brief description of the basic framework may be the following. Network vertices – representing agents – are thought to arrive uniformly at random in a given space. Upon arrival, each vertex must link with another vertex that is already present in the system. Newcomer vertices are immediately aware of the position – both in the space and in the network – of other vertices, and in order to establish a connection with them, they have to bear an attachment cost, which is assumed to be proportional to the Euclidean distance between the current location and the target one. Newcomer vertices are assumed to benefit from linking with vertices that are centrally located in the system, that is vertices with high degree; accordingly, when deciding about linkage, they choose targets which are simultaneously:

1) close to their actual position in the space;
2) centrally located in the network.

The former objective captures the attachment cost due in order to establish a successful relationship with a vertex far away in the space. The latter objective represents the option value associated to very well connected locations. In other words, networking activity is assumed to yield a trade off between (immediate) costs, represented by distance, and (future) benefits, represented by centrality.

We may think of the attachment cost as the cost related to gathering from target vertices information about some specific aspects of the attachment relationship, analyzing such information, and then negotiating about relevant aspects. The farther the target in the space, the more difficult and costly is to obtain accurate, fundamental indications about attachment conditions, and to evaluate such information. In the context of labor mobility, such costly effort may easily be thought to concern specific features of jobs, contractual conditions, tasks to be performed, working environment, just to mention a few characteristics.

More formally, the model can be framed as follows. Vertices arrive uniformly at random in a defined space (e.g. the unit square, or the unit line). The set of vertices at time t is denoted by V_t . The system at t=0 has a single root vertex and no connections; at each time step a new vertex i arrives and selects an existing vertex $j \in V_{t-1}$ with which to establish a link. Let s_{ij} be the Euclidean distance between i and j, reflecting the cost of effort for i to reach j; let $q_{j,t-1}$ be some measure of network centrality of vertex j, e.g. degree, evaluated at time t-1, assumed to be proportional to the benefit offered by location j. The terms regulating the attachment decision of i to j are captured by a simple objective function $F(q, s)$, whose argument is the weighted sum of factors q and s, as described by the expression

$$F_{i,t}(q,s) = q_{j,t-1} - \alpha \cdot s_{ij} \ , \tag{1}$$

where the parameter α reflects the relative weighting between the two objectives, with $\alpha \geq 0$. Vertex i then chooses j so as to maximize F; the agent's optimization problem can be written

$$\max F = \max_{j \in V_{t-1}} \left(q_{j,t-1} - \alpha \cdot s_{ij} \right) \ . \tag{2}$$

The choice of j, and the consequent behavior of the model, depends crucially on α. When α is above a particular threshold $r(n)$, expressed as a function of n whose exact shape depends on the characteristics of the space considered, the trade off between Euclidean distances and centrality holds, and the resulting connectivity distribution turns out to be a power law, characterized by an emerging, upper, exponential cutoff, whose intensity grows with α. Almost pure power-law-distributed networks are obtained when α is very close to the threshold. As α goes below the threshold, Euclidean distances s_{ij} progressively loose importance in the optimization process, and the resulting connectivity distributions assume highly polarized shapes, with a few, very large hubs being the targets of most connections. For very small values of α, the network would collapse to a *star*, i.e. the most polarized possible structure, with a single vertex as center, and all other vertices just pointing to the center (Fabrikant *et al*., 2002).

Such optimization-based model (OPT model henceforth) reveals itself to be very flexible, being able to account for a wide range of distributional behaviors in function of just a single parameter. Moreover, the simple assumptions of the model have straightforward interpretation in the context of labor mobility, capturing in a very simple way the trade off that workers willing to reallocate have to face between search/transaction costs and benefits of job search. We hence take the OPT framework as reference model for labor reallocation[29].

In a complex system of interactions between entities, characterized by a power-law connectivity distribution with upper cutoff, a well-defined hierarchy is manifest, but the influence each entity has – i.e. the portion of the system a single entity can control through direct connections – is limited, possibly constrained by the same forces that govern the network formation. So that on the whole, the system maintains a noteworthy level of decentralization. On the contrary, a star network is the ultimate stage in degree concentration, corresponding to a fully integrated system, in which hierarchy is manifest at its utmost level: all the power is in just one's hands. Both such organizational patterns are common in nature. As reported by Clauset *et al*. (2009), several network data, ranging from social relationships to physical quantities, exhibit power laws with exponential cutoffs; on the other side, integrated systems composed by multiple elements each of which individually responds to a central "authority" are very frequently observed in institutions, firms, up to biological beings.

3.7.2 Empirical degree distributions

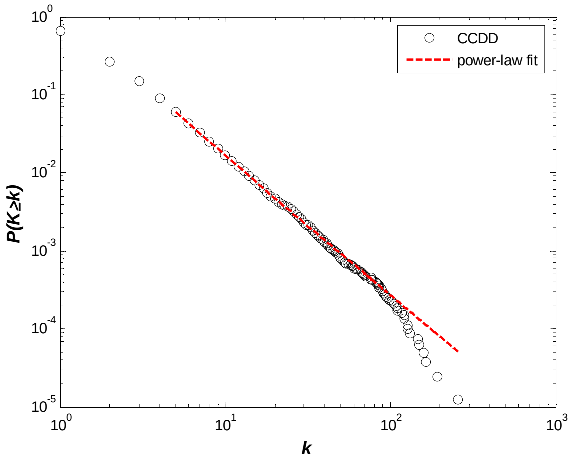
In Figure 3.5 we plot on a log-log scale the complementary cumulative in-degree distributions, CCDDs, together with the corresponding power-law fits. At a glance, we notice that each year plot follows a clearly negative, and almost linear trend. In the extreme tail of the distribution, a downward departure from the power-law fit is evident in the years 1991, 1992, 1995, 1996, 1997, and 1998, while it is much less pronounced in 1993, and 1994. In 1999 the empirical data overlap almost exactly the straight line, whereas in 2000 and 2001 the distribution tail drifts progressively more upward, concentrating greater weight than predicted by a pure power law.

This brief, visual inspection yields several considerations. First, the straight-line plots visibly match the power law hypothesis. Second, the fast decay of the extreme tail observed up to the year 1998 is in all effect a truncation, and it means that extremely massive events are actually less likely to occur than in a pure power law. Third, after 1998, in coincidence with the materialization of TEAs effects on the connectivity structure, the in-degree distribution shows a transition from an upper truncated pattern to a much more unequal one, in which the tail becomes much heavier.

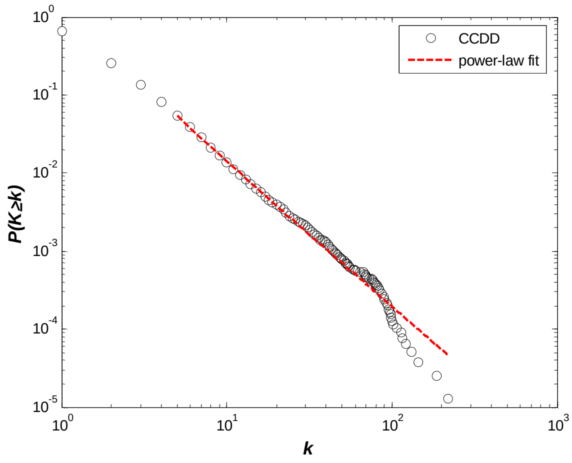
[29] Of course, we do not claim such model offers an accurate, true description of the way the inter-firm labor mobility network develops. We just aim at drawing attention on the fact that a generative model built on these simple and highly stylized lines can still yield remarkable results, as it will be made clear in the following sub-Section.

Figure 3.5 – In-degree distributions, power-law fits

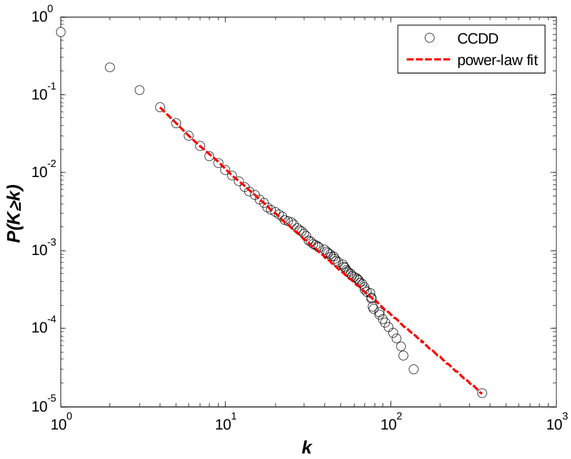
1991



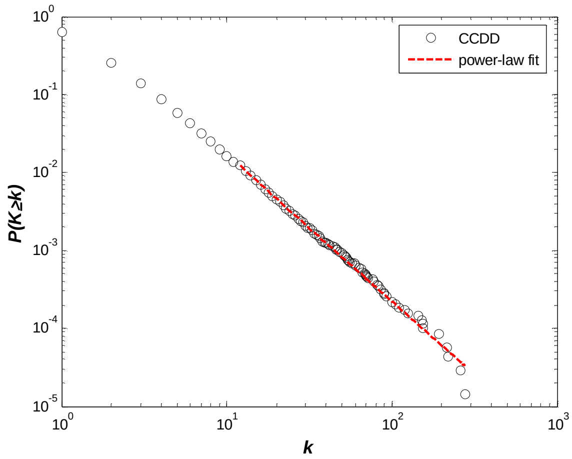
1992



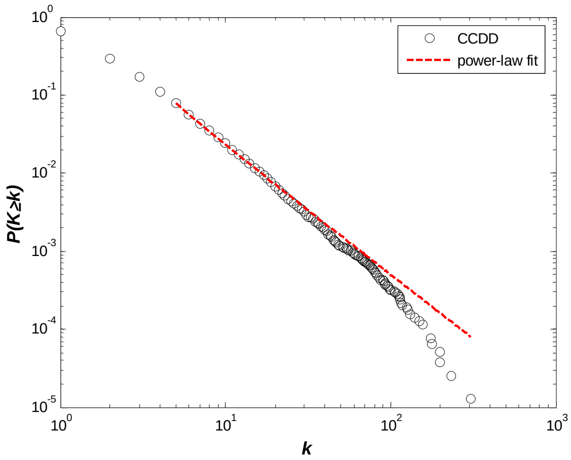
1993



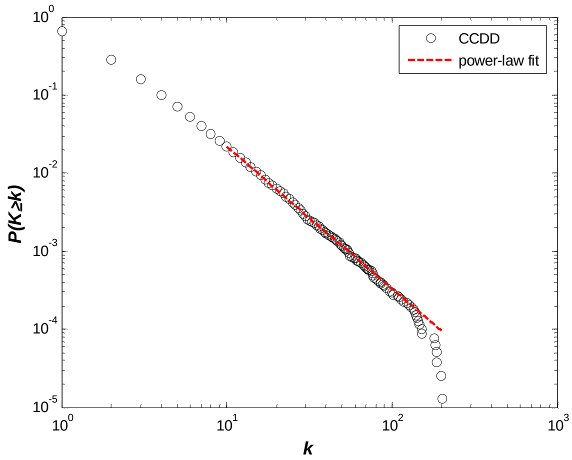
1994



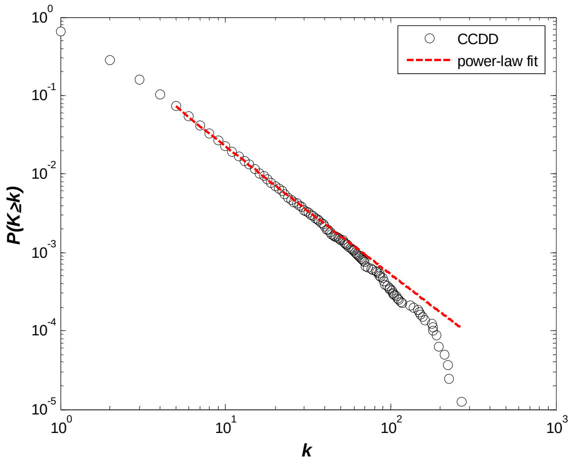
1995



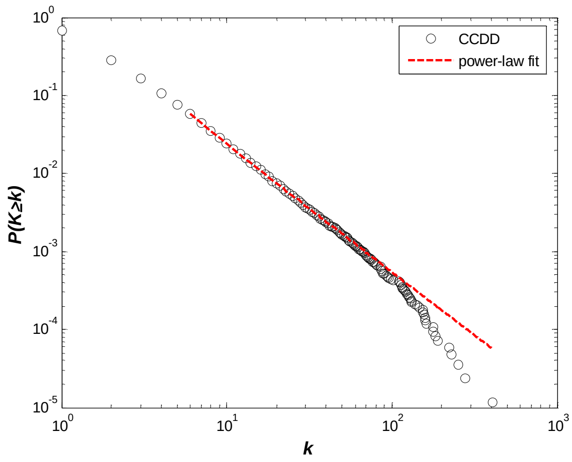
1996



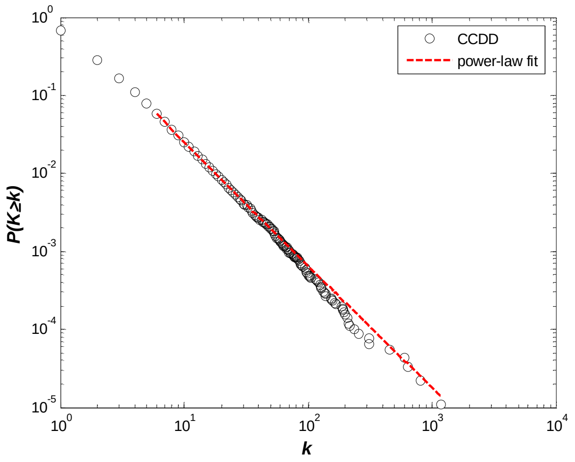
1997



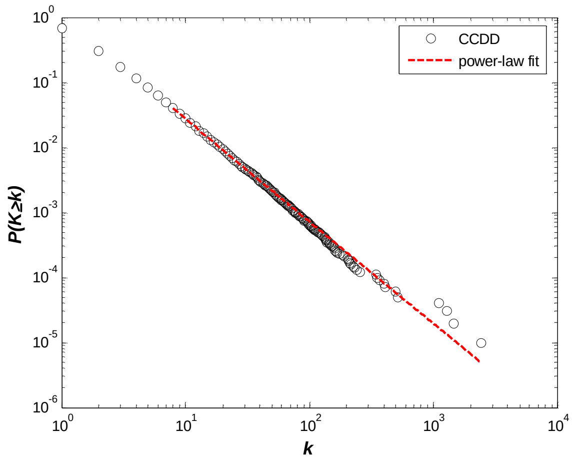
1998



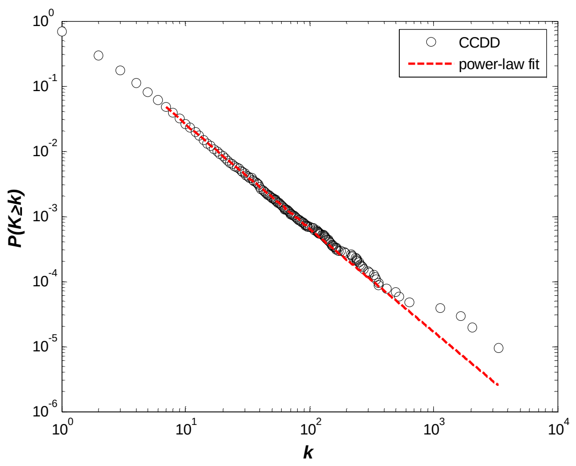
1999



2000



2001



From the analysis performed in Section 3.6.2, we know that in the years 1999, 2000, and 2001 the four biggest hubs are TEAs, and several other TEAs occupy the very last percentiles of the distribution. It straightforwardly follows that the biggest TEAs are capturing unprecedented shares of hiring channels, which are moreover increasing in time. And in so doing, intermediaries produce a sharp polarization of the degree distribution, that deviates consistently from both the simple, and the cutoff version of the power law distribution.

Following the OPT model, we frame the statistical investigation in order to verify whether a power law is indeed a suitable distribution for in-degree, and then we assess whether and when a power law with exponential cutoff is preferred to a pure power law. We devote special attention to identifying possible pattern transitions induced by TEAs.

In general terms, the probability distribution of a quantity k is said to be power law if it is of the form given by the following expression[30]

$$p(k) \propto k^{-a} \ , \tag{3}$$

where a represents the scaling exponent. Notice that such a distribution diverges as k tends to zero, so, provided that a>1, the power-law behavior must set in only above a certain threshold $k_{\min}$>0. When dealing with degree distributions, the quantity we are interested in can take only positive, integer values; hence, we are confronting a discrete distribution. Putting together these two observations, we obtain the following expression for $p(k)$

$$p(k) = \Pr(K = k) = \frac{k^{-a}}{\zeta(a, k_{\min})} \ , \tag{4}$$

where the function ζ is the generalized, or Hurwitz zeta function of the form

$$\zeta(a, k_{\min}) = \sum_{n=0}^{\infty} (n + k_{\min})^{-a} \ . \tag{5}$$

When empirically fitting power-law-like distributions, it is generally appropriate to use the complementary cumulative distribution, instead of the simple probability distribution of the form (4); the cumulative representation indeed reduces possible fluctuations in the extreme right tail, due

[30] The passages henceforth closely follow Clauset *et al*. (2009).

to the low number of observations in this region, and it ultimately allows for better estimates and better visualization (Newman, 2005). The complementary cumulative distribution associated to expression (4) has the form

$$P(K \geq k) = \frac{\zeta(a, k)}{\zeta(a, k_{\min})} \ , \qquad (6)$$

and it is again power-law distributed, appearing as a straight line on a doubly logarithmic scale.

The mere appearance of a straight line nonetheless represents only a necessary, but not sufficient condition for a distribution to be power law. Hence, to rigorously assess the plausibility of the power-law model, we implement the test method proposed by Clauset *et al.* (2009). In extreme synthesis the procedure runs as follows:

1) fit a power law to the empirical data using maximum likelihood, simultaneously estimating the scaling parameter a and the lower bound of the scaling region $k_{\min}$;
2) evaluate the goodness of the power-law fit by calculating an appropriate p-value;
3) then contrast the pure power law with the power law with exponential cutoff by means of a likelihood-ratio test[31].

In Table 3.3 the key parameters of the fitted power laws, together with the p-values of the related goodness-of-fit tests, are shown; in the last two columns the likelihood-ratio tests of the comparison between the pure power law and the power law with exponential cutoff, together with the related p-values, are reported. In the goodness of fit test for the pure power law, p-values are used to rule out the power-law hypothesis, hence for the power law to be a plausible model, p-values must be high, and vice versa (we make the standard choice of rejecting the power law for p-values less than 0.05). Whereas, in the likelihood-ratio test a small p-value and a positive (negative) likelihood ratio indicate that the power law wins (loses) over the alternative; on the contrary, when the p-value is large enough (>0.05), the test does not favor one model over the other.

[31] The power law and the power law with exponential cutoff are nested distribution, meaning that one family of distributions, the power law, is a subset of the other, the power law with cutoff. As highlighted in Clauset *et al.* (2009), it is always the case that the larger family of distributions provides a fit at least as good as the smaller family, since every member of the smaller family is also member of the larger one. The p-value associated to the likelihood-ratio test is precisely meant to indicate whether the fitting improvement of the power law over the pure power law with cutoff is substantial or not.

Table 3.3 – Distribution fitting

	Power-law fits			Comparison with power law with cutoff	
year	a	$k_{\min}$	p-value	LR test	p-value
1991	2.752	5	0.520	-2.354	0.030
1992	2.822	5	0.000	-0.552	0.293
1993	2.827	4	0.060	-0.262	0.469
1994	2.857	12	0.780	-0.268	0.464
1995	2.630	5	0.000	-11.176	0.000
1996	2.787	10	0.140	-2.749	0.019
1997	2.595	5	0.080	-7.779	0.000
1998	2.609	6	0.500	-4.958	0.002
1999	2.554	6	0.540	-1.604	0.073
2000	2.556	8	0.560	-0.065	0.716
2001	2.576	7	0.880	0.000	1.000

In all years, except for 1992 and 1995 (remember the particular turbulences the Veneto labor market underwent in the period 1992-1995), the power-law model provides good fits, with excellent performance in 1991, 1994, and all over the period 1998-2001; in 1993, 1996, and 1997 there is only a moderate evidence in favor of the model, but overall, the power law performs quite well, hence revealing itself to be a reasonable theoretical benchmark for our data.

The power law with exponential cutoff is strictly preferred over the pure power law in 1991, 1996, 1997, and 1998. While in 1999, 2000 and even more so in 2001, the two models are not statistically different according to the likelihood-ratio test[32], but from the plotting in Figure 3.5 the cutoff distribution appears to be unquestionably unfavored, compared to the standard power law.

From the analysis performed so far, we can pinpoint the following, compelling stylized facts:

- up to the year 1998 the data are well fitted by a power law with upper truncation;
- in 1999, as TEAs reach the tail of the distribution, a pure power-law sets in;

[32] We do not have a model that can specifically account for the observed rise in the extreme tail of the distribution, we can just say in the years 2000-2001 the truncated distribution does not provide a better fit than the simple power law.

- in 2000-2001 the tail of the distribution, lead by the biggest TEAs, drifts upward away from the power law prediction, pushing the system towards an increasingly polarized configuration, in which the few biggest TEA hubs control a massive share of reallocation channels.

The behaviour of the data can be consistently explained by the OPT model in a very effective and parsimonious way. Progressively reducing the parameter α in the OPT model can produce a rise in the extreme tail of the degree distribution similar to the one manifesting in the data just after the appearance of TEAs in the market, and amplifying as TEAs increase their connectivity. As already mentioned, in the OPT framework α represents the incidence of information costs, relative to benefits of attaining central locations; a reduction in the parameter α means a reduction in the information/transaction costs agents bear in order to explore the system and to establish successful links. In the actual network, TEAs can hence be viewed as the vehicles of such a drop. In particular, from 1999 on, a small bunch of TEAs overtake the power law, hinting to a strong polarization of the system, that might deepen even more, eventually triggering a collapse of the network to a star configuration.

Of course, the fact that the evolution empirically observed closely matches the predictions of a simplified network model of the kind invoked in the previous sub-Section, does not mean such a model is an exhaustive representation of the real phenomenon of worker reallocation in intermediated labor markets. Rather, the proposed parallel is aimed to show that TEAs affect the process of network formation very much *as if* there were a drop in information/transaction costs, as provided for in the OPT framework.

Indeed, a major role of intermediaries – as highlighted in Section 3.2 – is “sinking the searching and matching costs workers would otherwise fully face individually, by means of centralized collection and use of information that is then made available to workers and firms” (Autor, 2009; p. 17). Noticeably, the triangular form of provisional contracts offered by TEAs also provides a way of concentrating the negotiation process over employment conditions, entirely devolving it to TEAs, so further curbing transaction costs. These are the rationales, identified by the economic theory, for the existence and action of labor market intermediaries; we have just demonstrated that there exist a convincing and consistent set of empirical results supporting, and quantitatively illustrating such arguments.

Most relevant for policy is the tendency towards ever-increasing polarization of the system, with TEAs in control of overriding market shares of new engagements. The OPT model suggests that the action of TEAs considerably shifts the trade off between cost of search and benefits of central locations, in favor of the latter factor. This in turn reflects into reallocation decisions that increasingly aim at TEA targets. Such process is self sustaining – according to the attachment rule in the OPT model, and also in agreement with the arguments discussed in Section 2, i.e. increasing attractiveness of bigger brokers – and could eventually produce a strong, or even complete concentration of the market in the hands of some TEAs.

Although we can rely just on four years of observations as for appreciating TEA activity, given the trend observed, we might be concerned that – in a market such as the one we study, where intermediation activity is not subject to quantitative constraints at the level of single TEA – TEAs become so much attractive for the parties (because of self-reinforcing incentives inherent in information brokerage) so as to determine an excessive concentration of the labor mobility network. This would mean that the market of hiring services de facto becomes a monopoly/monopsony, controlled by a few TEAs, which, once gained dominant positions, can exploit this advantage to the detriment of their customers. Such a scenario would be harmful, both because of the high rent TEAs could extract from their activity, and because of the bad matching services firms and workers receive in a non-competitive intermediation market. Indeed, either parties, workers and firms, and the economic system as a whole, would incur the direct cost of high TEA prices, and the indirect cost of mismatch.

Whenever the first tangible signs of market concentration are in sight, prudent policy makers may want to intervene, so as to monitor the market trends, and then deciding whether to possibly restrain the action of intermediaries, by means of passing appropriate regulative measures, or fostering competition in the intermediation sector, through establishing efficient public intermediaries.

The call for well-timed intervention of the public authority is even more compelling given the fact that, as self-sustaining mechanisms of cumulative advantage – such as those which seem to drive TEAs attachment – progressively set in, it becomes more and more costly and difficult to intervene, in order to modify the individual-level incentive structure underlying the functioning of such mechanisms. In these cases it is hence better to uncover market trends in the very bud, and, where appropriate, rectify them while they are not yet widespread. Essential to such good practice is market monitoring.

The analysis carried out in this Chapter, and in the present Section in particular, provides transparent and well-defined policy tools in order for monitoring labor markets, and for detecting market-concentration processes. The set of techniques we have presented nevertheless calls for further development, and we still need more sophisticated analyses, which can yield additional indications about market evolution. In the light of our first, promising results, we believe policy authorities should promote labor market studies that use network-based methodologies, which may result to be particularly effective in uncovering and predicting a variety of phenomena.

3.8 Conclusions

This study originally combines two different strands of research: the empirical analysis of labor mobility, based on linked worker-firm data from administrative archives, and the investigation of social networks, making use of graph theoretic concepts. We specifically address the role of temporary employment agencies in shaping the network of inter-firm worker reallocation, trying to answer two major questions: (1) how TEAs affect job accessibility for people reallocating within the market; (2) how TEAs capacity of controlling worker flows evolves over time, and with which consequences. In this work, the focus is on the impact of TEAs on worker flows direction and arrangement, while the effects of intermediation on individual job market outcomes, as for instance wages and employment duration, constitute a topic for future research.

Using employer-employee matched data from Veneto, a region of Italy, we construct a directed graph, where vertices indicate firms, and links denote passages of workers between firms.

We first consider the actual arrangement of worker transfers between firms, as if it were an infrastructure aimed at supporting and directing labor flows, and we assume the small-world properties of such infrastructure as an indicator of job accessibility.

The network shows a remarkable small world character all during the period 1995-2001, i.e. after the recession of 1992-1993; and the key small-world traits visibly deepen just after the arrival of TEAs, that were first allowed to operate in 1997 by Treu reform of the labor market. In order to better identify the impact of labor market intermediaries, we perform a counterfactual analysis aimed at providing reliable measures of such effect. We find that, in 2001, TEAs generate an increase in clustering between 46% and 63%, compared to a counterfactual situation with no TEAs, and a corresponding reduction in average network distances of around 20%. TEA mobility also increases the level of network interconnectivity. Besides, TEAs provide the small world of labor mobility with improved navigability, suddenly becoming the most important hubs of the network, to the point that, already in 1999, four TEAs firmly dominate the connectivity distribution.

Such evidence urges us to conclude that Treu reform, through the establishment of TEAs, enhances labor market accessibility in a significant way. The labor network as a whole assumes the character of a large cohesive community, which can be easily traversed from side to side. Moreover, most shortcut paths between firms are firmly under control of TEAs, and therefore they turn out to be particularly easy to locate from workers with limited information about the market.

We then shift our attention to TEAs position in the market, and focus on the mechanisms of network formation. By looking at the time evolution of the link distribution, we notice that the market share of engagements controlled by TEAs increases considerably. This evidence reveals that TEAs greatly increase their market power over reallocation services; and this is very likely to exacerbate the negative effects of the information asymmetries between labor market intermediaries and clients, workers and firms, thus representing a risk for good labor market functioning.

We make a step further, and interpret the impact of TEAs on the link distribution in the light of a simple model of network formation, based on straightforward assumptions, and offering good grasp of the fundamental trade off workers have to face when reallocating. The underlying idea is that target vertices for reallocation are chosen by optimizing a function in two arguments: initial attachment cost of entering in touch with a potential employer (distance factor), and benefits deriving from centrality of the employer in the network (centrality factor). The centrality factor attract new links according to a logic of cumulative advantage, i.e. people prefer to attach to the most connected vertices; the distance factor continuously mitigates such attachment mechanism.

When the trade off holds, different link distributions can emerge, all characterized by Paretian tails with upper truncation, guaranteeing that there is a limit to the employers capacity to corner the market. That is to say, the trade off represents a strong obstacle in order for single employers to be able to control major shares of reallocation channels, so as to become dominant actors. This is exactly the situation we observe in the data up to 1997.

After Treu reform, the action of new players – the intermediaries – ease the trade off in favor of network centrality, diminishing the incidence of attachment cost. Hence, workers find it more advantageous to link to the most central vertex, and the cumulative advantage mechanism takes over the scene. As a result, the link distribution evolves towards a more unequal pattern, increasingly polarized around a few TEAs, that emerge as monopolist/monopsonist, controlling unprecedentedly high market shares – much bigger than those controlled by any other employer. This is what we observe during the years 1999-2001.

The theoretical model we use as benchmark predicts the network could eventually collapse to a star, with a single center, a TEA, that captures all reallocations, progressively pushing out of the market other competitors. Although such a result represents a purely abstract, speculative scenario, nonetheless, given the good correspondence between the model predictions and the empirical evidence collected, it entails an immediate warning to policy makers.

On the one side, TEAs prove themselves to be very effective in fostering job accessibility for workers; on the other side, the biggest TEAs appear to increasingly corner the market for reallocations, potentially exerting disproportionate power. A policy intervention might hence be needed, so as to guarantee competition in the intermediation sector, or some regulative mechanisms should be devised, in order to prevent the system from becoming excessively polarized. The techniques we employ represent a set of tools that is useful for monitoring the market, and providing quick identification of emerging trends, according to which designing well-timed interventions.

References

Acemoglu D. (2009), ‘The Crisis of 2008: Structural Lessons for and from Economics’, CEPR Policy Insight n. 28.

Aghion P. and P. Howitt (1992), ‘A Model of Growth Through Creative Destruction’, *Econometrica*, 60(2): 323-351.

Albert R., and A.-L. Barabási (1999), ‘Emerging of Scaling in Random Networks’, *Science*, 286: 509-512.

Albert R., and A.-L. Barabasi (2002), ‘Statistical mechanics of complex networks’, *Review of Modern Physics*, 74: 47-97.

Albert R., H. Jeong, and A.-L. Barabási (2000), ‘Error and attack tolerance in complex networks’, *Nature*, 406: 378-382.

Arranz J.M., M.A. Davia, and C. Garcia-Serrano (2005), ‘Labor market transitions and wage dynamics in Europe’, IZA Working paper 2005-17.

Arulampalam W. (2001), ‘Is Unemployment Really Scarring? Effects of Unemployment Experiences on Wages’, *The Economic Journal*, 111(475): 585-606.

Autor D.H. (2001), ‘Why Do Temporary Help Firms Provide Free General Skills Training?’, *Quarterly Journal of Economics*, 116 (4): 1409-1448.

Autor D.H. (2009), ‘The economics of labor market intermediation: an analytical framework’, in Autor D.H. (ed.), *Studies of Labor Market Intermediation*, Chicago, IL: University of Chicago Press.

Autor D., and S.N. Houseman (2002), ‘The Role of Temporary Employment Agencies in Welfare to Work: Part of the Problem or Part of the Solution?’, *Focus*, 22(1): 63-70.

Baily M.N, C. Hulten, and D. Campbell (1992), ‘Productivity Dynamics in Manufacturing Plants’, *Brookings Papers on Economic Activity: Microeconomics*, 1992: 187-249.

Baldwin C.Y., and K.B. Clark (2000), *Design Rules. Volume 1: The Power of Modularity*, Cambridge, MA: The MIT Press.

Barbieri G., P. Gennari, and P. Sestito (2001), **‘**Do Public Employment Services Help People in Finding a Job? An Evaluation of the Italian Case’, *Rivista di statistica ufficiale*, 3.

Bartelsman E.J. and P.J. Dhrymes (1998), ‘Productivity Dynamics: U.S. Manufacturing Plants, 1972-1986’, *Journal of Productivity Analysis*, 9: 5-34.

Bienenstock E.J., and P. Bonacich (2003), ‘Balancing efficiency and vulnerability in social networks’, in National Reasearch Council (eds.), *Dynamic Social Network Modeling and Analysis: Workshop Summary and Papers*, Washington, DC: The National Academic Press.

Boccaletti S., V. Latora, Y. Moreno, M. Chavez, and D.U. Hwang (2006), ‘Complex networks: Structure and dynamics’, *Physics Reports*, 424: 175 – 308.

Bollobas B. (1985), *Random Graphs*, Orlando, FL: Academic Press.

Brandt N., J.-M. Burniaux, and R. Duval (2005), ‘Assessing the OECD Jobs Strategy: Past Developments and Reforms’, OECD Economics Department Working Papers, No. 429.

Broder A., R. Kumar, F. Maghoul, P. Raghavan, S. Rajagopalan, R. Stata, A. Tomkins, and J. Wiener (2000), ‘Graph structure in the Web’, *Computer Networks*, 33(1-6): 309-320.

Brusoni S., and A. Prencipe (2001), ‘Unpackaging the Black Box of Modularity: Technologies, Products, and Organizations’, *Industrial and Corporate Change*, 10(1): 179-205.

Buechtemann C.F., and S. Quack (1989), 'Bridges or traps'?: Non-standard forms of employment in the Federal Republik of Germany; The case of part-time and temporary work', WZB Discussion Paper FSI 89-6.

Buldyrev S.V., J. Growiec, F. Pammolli, M. Riccaboni, and H.E. Stanley (2007), 'The Growth of Business Firms: Facts and Theory', *Journal of the European Economic Association*, 5(2-3): 574-584.

Burdett K. (1978), 'A Theory of Employee Job Search and Quit Rates', *The American Economic Review*, 68(1): 212-220.

Caballero R.J. and M.L. Hammour (1996), 'On the Timing and Efficiency of Creative Destruction', *Quarterly Journal of Economics*, 111(3): 805-851.

Caprio L. (2001), 'Diffusione e alcune caratteristiche dei gruppi di medie imprese industriali del Nord Est', in Mediobanca Unioncamere (eds.), *Le Medie Imprese industriali italiane (1996-2001)*, Milano-Roma, Italy.

CENSIS (2001), *XXXV Rapporto sulla situazione sociale del paese*, Milano, Italy: Franco Angeli.

Clauset A., C.R. Shalizi, and M.E.J. Newman (2009), 'Power-law distributions in empirical data', *SIAM Review*, 51: 661-703.

Cooper R., J. Haltiwanger, and J.L. Willis (2007), 'Search frictions: Matching aggregate and establishment observations', *Journal of Monetary Economics*, 54(1): 56-78.

Contini B., M. Filippi, and C. Malpede (2000), 'Safari nella giungla dei salari. Nel Mezzogiorno si lavora di meno?', Laboratorio R. Revelli Working paper n.3.

Contini B., C. Malpede, and C. Villosio (1996), 'Wage Dynamics and Labor Mobility in Italy', University of Turin WP n. 6.

Contini B., and M. Morini (2007), 'Testing bounded rationality against full rationality in job changing behaviour', Laboratorio R. Revelli Working paper n. 55.

Contini B., and L. Pacelli (2005), 'Mobilità dei lavoratori e dei posti di lavoro: problemi di misura e questioni aperte', in Contini B., and U. Trivellato (eds.), *Eppur si muove. Dinamiche e persistenze nel mercato del lavoro italiano*, Bologna, Italy: Il Mulino.

Contini B., and R. Revelli (1997), 'Gross flows vs. net flows in the labor market: What is there to be learned?', *Labour Economics*, 4(3): 245-263.

Curarrini S., and F. Feri (2006), 'Reti di trasferimenti di lavoratori', in Regione Autonoma Friuli Venezia Giulia (ed.), *Il mercato del lavoro in Friuli Venezia Giulia – Rapporto 2006*, Trieste, Italy.

D'Souza R.M., N. Berger, C. Borgs, J.T. Chayes, and R.D. Kleinberg, (2007), 'Emergence of tempered preferential attachment from optimization', *PNAS*, 104(15): 6112-6117.

Davis S.J. (1987), 'Allocative Disturbances and Specific Capital in Real Business Cycle Theories', *The American Economic Review*, 77(2): 326-332.

Davis S.J., R.J. Faberman, and J. Haltiwanger (2006), 'The Flow Approach to Labor Markets: New Data Sources and Micro–Macro Links', *Journal of Economic Perspectives*, 20(3): 3-26.

Davis S.J., R.J. Faberman, and J. Haltiwanger (2009), 'The Establishment-Level Behavior of Vacancies and Hiring', mimeo.

Davis S.J. and J.C. Haltiwanger (1990), 'Gross Job Creation and Destruction: Microeconomic Evidence and Macroeconomic Implications' *NBER Macroeconomics Annual*, 5: 123-168.

Davis S.J. and J.C. Haltiwanger (1992), 'Gross Job Creation, Gross Job Destruction and Employment Reallocation', *Quarterly Journal of Economics*, 107(3): 819-863.

Davis S.J. and J.C. Haltiwanger (1999), 'Gross Job Flows' in O. Ashenfelter and D. Card (eds.), *Handbook of Labor Economics Vol. 3B*, Amsterdam: The Netherlands: North Holland.

Davis S.J., J.C. Haltiwanger, and S. Schuh (1996), *Job Creation and Destruction*, Cambridge, Massachusetts: The MIT Press.

De Vos M. (2009), 'European Flexsecurity and Globalization: A Critical Perspective', *The International Journal of Comparative Labour Law and Industrial Relations*, 25(3): 209-236.

Dustmann C., and C. Meghir (2005), 'Wages, Experience and Seniority', *The Review of Economic Studies*, 72: 77-108.

Elliott R.J.R., and J. Lindley (2001), 'Intra-Sectoral Labor Mobility and Adjustment Costs', Leverhulme Centre Research Paper n. 38.

Fabrikant A., E. Koutsoupias, and C.H. Papadimitriou (2002), 'Heuristically Optimized Trade-offs: A New Paradigm for Power Laws in the Internet', *Proceedings of the 29th International Colloquium on Automata, Languages, and Programming, Lecture Notes in Computer Science*, 2380: 110-122.

Fallick B., and C.A. Fleischman (2004), 'Employer to Employer Flows in the U.S. Labor Market: The Complete Picture of Gross Worker Flows', FEDS Working Paper No. 2004-34.

Farber H.S. (1999), 'Mobility and Stability: The Dynamics of Job Change in Labor Markets', in Ashenfelter O.C., and D. Card (eds.), *Handbook of Labor Economics Vol. 3*, Amsterdam, The Netherlands: North Holland.

Feenstra R.C. (1998), 'Integration of Trade and Disintegration of Production in the Global Economy', *Journal of Economic Perspectives*, 12(4): 31-50.

Foster L., J.C. Haltiwanger, and C.J. Krizan (2001), 'Aggregate Productivity Growth: Lessons from Microeconomic Evidence' in E. Dean, M. Harper, and C. Hulten (eds.), *New Developments in Productivity Analysis*, University of Chicago Press, Chicago: 303-372, 2001.

Freeman L.C. (1977), 'A Set of Measures of Centrality Based on Betweenness', *Sociometry*, 40(1): 35-41.

Garcia-Pérez J.I., and F. Muñoz-Bullón (2005), 'Temporary Help Agencies and Occupational Mobility', *Oxford Bulletin of Economics and Statistics*, 67(2): 163-180.

Garcia-Perez J.I., and Y. Rebollo-Sanz (2005), 'Wage changes through job mobility in Europe: A multinomial endogenous switching approach', *Labor Economics*, 12(4): 531-555.

Gereffi G. J. Humphrey, and T. Sturgeon (2005), 'The governance of global value chains', *Review of International Political Economy*, 12(1): 78-104.

Golan L., J. Lane, and E. McEntarfer (2007), 'The Dynamics of Worker Reallocation within and across Industries', *Economica*, 74(293): 1-20.

Gould W.W., J. Pitblado, and W.M. Sribney (2006), *Maximum Likelihood Estimation with Stata 3rd edition*, College Station, TX: Stata Press.

Goyal S., M.J. van der Leij, and J.L. Moraga-Gonzales (2006), 'Economics: An Emerging Small World', *Journal of Political Economy*, 114(2): 403-412.

Greenaway D., R. Upward, and P. Wright (2000), 'Sectoral Transformation and Labor-Market Flows', *Oxford Review of Economic Policy*, 16(3):57-75.

Gregory M., and R. Jukes (2001), 'Unemployment and Subsequent Earnings: Estimating Scarring Among British Men 1984–94', *The Economic Journal*, 111(475): 607-625.

Haynes M., R. Upward, and P. Wright (2000), ‘Smooth and Sticky Adjustment: a Comparative Analysis of the US and UK’, *Review of International Economics*, 8: 517-32.

Holme P., and B.J. Kim, (2002), ‘Attack vulnerability of complex networks’, *Physical Review E*, 65, 056109.

Houseman S.N. (2001), ‘Why Employers Use Flexible Staffing Arrangements: Evidence from an Establishment Survey’, *Industrial and Labor Relations Review*, 55(1): 149-170.

Iacus S.M., and G. Porro (2002), ‘Il lavoro interinale in Italia: uno sguardo all’offerta’, Università di Milano, WP n. 26.2002.

Ichino P. (2009), ‘Progetto per la transizione a un regime di flexsecurity’, *ItalianiEuropei*, Quaderno n. 3/2009.

Ichino A., F. Mealli, and T. Nannicini (2004), ‘Temporary Work Agencies in Italy: A Springboard Toward Permanent Employment?’, *Giornale degli Economisti e Annali di Economia*, 64(1): 1-27.

Ichino A., M. Polo, and E. Rettore (2003), ‘Are judges biased by labor market conditions?’, *European Economic Review*, 47: 913-944.

Johnson W.R. (1978), ‘A Theory of Job Shopping’, *The Quarterly Journal of Economics*, 92(2): 261-278.

Jovanovic B. (1979a), ‘Job Matching and the Theory of Turnover’, *The Journal of Political Economy*, 87(5): 972-990.

Jovanovic B. (1979b), ‘Firm-specific Capital and Turnover’, *The Journal of Political Economy*, 87(6): 1246-1260.

Jovanovic B. (1984), ‘Matching, Turnover, and Unemployment’, *The Journal of Political Economy*, 92(1): 108-122.

Jovanovic B., and R. Moffit (1990), ‘An Estimate of a Sectoral Model of Labor Mobility’, *The Journal of Political Economy*, 98(4):827-852.

Kambourov G., and I. Manovskii (2008), ‘Rising Occupational and Industry Mobility in the United States: 1968-1997’, *International Economic Review*, 49(1): 41-79.

Kleinberg J.M. (2000), ‘Navigation in a small world’, *Nature*, 406: 845.

Kleiner M.M., and R.M. Todd (2009), ‘Mortgage Broker Regulations That Matter: Analyzing Earnings, Employment, and Outcomes for Consumers**’,** in Autor D.H. (ed.), *Studies of Labor Market Intermediation*, Chicago, IL: University of Chicago Press.

Kugler A., and G. Pica (2008), ‘Effects of employment protection on worker and job flows: Evidence from the 1990 Italian reform’, *Labour Economics*, 15(1): 78-95.

Lamo A., J. Messina, and E. Wasmer (2006), ‘Are specific skills an obstacle to labor market adjustment? Theory and an application to the E.U. enlargement’, ECB Working Paper Series n. 585.

Langot F. (1997), ‘Sectoral Shocks and Employment Reallocation in a Two-Sector Dynamic General Equilibrium Model’, mimeo, University of Le Mans.

Lee W. (2009), ‘Private Deception and the Rise of Public Employment Offices in the United States, 1890-1930’, in Autor D.H. (ed.), *Studies of Labor Market Intermediation*, Chicago, IL: University of Chicago Press.

Leicht E.A., and M.E.J. Newman (2008), ‘Community structure in directed networks’, *Physical Review Letters*, 100: 118703.

Leombruni R., and R. Quaranta (2002), ‘Unemployment route to versatility’, Laboratorio R. revelli Working paper n.16.

Leombruni R., and R. Quaranta (2005), ‘Eppure si muoveva già: una breve storia della mobilità dei lavoratori in Italia’, in Contini B., and U. Trivellato (eds.), *Eppur si muove. Dinamiche e persistenze nel mercato del lavoro italiano*, Bologna, Italy: Il Mulino.

Lilien D.M. (1982), ‘Sectoral Shifts and Cyclical Unemployment’, *The Journal of Political Economy*, 90(4): 777-793.

Lucas R.E., and E.C. Prescott (1974), ‘Equilibrium Search and Unemployment’, *Journal of Economic Theory*, (7)2:188-209.

Luttmer E.G.J. (2007), ‘Selection, Growth, and the Size Distribution of Firms’, *The Quarterly Journal of Economics*, 122(3): 1103-1144.

McCulloch R., and P.E. Rossi (1994), ‘An exact likelihood analysis of the multinomial probit model’, *Journal of Econometrics*, 64(1-2): 207-240.

Mediobanca-Unioncamere (eds.) (2008), *Le medie imprese industriali italiane (1996-2005)*, Milan-Rome, Italy.

Melitz M.J. (2003), ‘The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity’, *Econometrica*, 71(6): 1695-1725.

Ministero del Lavoro e delle Politiche Sociali (2001), *Rapporto di Monitoraggio sulle politiche occupazionali e del lavoro*, Roma, Italy.

Mortensen D.T. (1978), ‘Specific Capital and Labor Turnover’, *The Bell Journal of Economics*, 9(2): 572-586.

Mortensen D.T., and C.A. Pissarides (1994), ‘Job Creation and Job Destruction in the Theory of Unemployment’, *The Review of Economic Studies*, 61(3): 397-415.

Moscarini G. (2001), ‘Excess Worker Reallocation’, *The Review of Economic Studies*, 68(3): 593-612.

Moscarini G. (2005), ‘Job Matching and the Wage Distribution’, *Econometrica*, 73(2): 481–516

Moscarini G., and K. Thomsson (2007), ‘Occupational Mobility and the Business Cycle’, *Scandinavian Journal of Economics*, 109(4): 807-836.

Moscarini G., and F. Vella (2000), ‘Worker Mobility and Aggregate Labor Reallocation: Evidence from the NLSY79’, mimeo, Yale University and NYU.

Moscarini G., and F. Vella (2008), ‘Occupational Mobility and the Business Cycle’, IZA D.P. n. 3369.

Mossa S., M. Barthélémy, H.E. Stanley, and L.A. Nunes Amaral (2000), ‘Truncation of Power Law Behavior in “Scale-Free” Network Models due to Information Filtering’, *Physical Review Letters*, 88(13), 138701.

Newman M.E.J. (2000), ‘Models of the small world’, *Journal of Statistical Physics*, 101: 819-841.

Newman M.E.J. (2001), ‘Scientific collaboration networks. II. Shortest paths, weighted networks, and centrality’, *Physical Review E*, 64, 016132.

Newman M.E.J. (2003), ‘The structure and function of complex networks’, *SIAM Review*, 45: 167-256.

Newman M.E.J. (2005), ‘Power laws, Pareto distributions and Zipf’s law’, *Contemporary Physics*, 46: 323-351.

Newman M.E.J. (2006a), ‘Modularity and Community Structure in Networks’, *PNAS*, 103: 8577-8582.

Newman M.E.J. (2006b), ‘Finding Community Structure in Networks Using the eigenvector of matrices’, *Physical Review E*, 74, 036104.

Newman M.E.J., and M. Girvan (2004), ‘Finding and evaluating community structure in networks’, *Physical Review E*, 69: 026113.

Newman M.E.J., and E.A. Leicht (2008), ‘Community structure in directed networks’, *Physical Review Letters*, 100, 118703.

Neal D. (1995), ‘Industry specific human capital: evidence from displaced workers’, *Journal of Labor Economics* 13(4): 653– 677.

Neal D. (1999), ‘The Complexity of Job Mobility among Young Men’, *Journal of Labor Economics*, (17)2: 237-261.

Occari F., and S. Pitingaro (1997) ‘Demografia di impresa e mobilita del lavoro:una stima della componente spuria sulla base degli archivi Inps’, Working Paper n. 7, CNR: Occupazione e livelli di attivita in Italia.

Occari F., G. Tattara, and M. Volpe (2001), ‘Gli archivi anagrafici Inps relativi alle imprese e ai lavoratori dipendenti (Appendice 1)’ in G. Tattara (ed.), *Il piccolo che nasce dal grande. Le molteplici facce dei distretti industriali veneti*, , Milano, Italy: Franco Angeli.

Parent D. (2000), ‘Industry specific capital and the wage profile: evidence from national longitudinal survey of youth and the panel study of income dynamics’, *Journal of Labor Economics* 18 (2): 306– 323.

Parnes H. (1954), *Research on Labor Mobility*, New York: Social Science Research Council 65.

Pissarides C.A. (1994), ‘Search Unemployment with On-the-job Search’, *The Review of Economic Studies*, 61(3): 457-475.

Pitingaro S., M. Volpe, and G. Tattara (2000), ‘Industrializzazione leggera e mobilità del lavoro in una regione industriale’, Dept. of Economics, University of Venice “Ca’ Foscari”, Nota di lavoro 2000/10.

Porro G., A. Vezzulli, and S.M. Iacus (2004), ‘Temporary Agency Workers in Italy: Alternative Techniques of Classification’, *Labour*, 18(4): 699-725.

Reyneri E. (2002), *Sociologia del mercato del lavoro*, Bologna, Italy: Il Mulino.

Rogerson R. (2005). ‘Sectoral Shocks, Human Capital and Displaced Workers’, *Review of Economic Dynamics*, 8: 89-105.

Rogerson R, R. Shimer, and R. Wright (2005), ‘Search-theoretic Models of the Labor Market’, NBER Working Paper n. 10655.

Saavedra S., F. Reed-Tsochas, and B. Uzzi (2008), ‘Asymmetric disassembly and robustness in declining networks’, *PNAS*, 105(43): 16466-16471.

Shettkat R. (ed.) (1996), *The Flow Analysis of Labour Markets*, London, UK: Routledge.

Simon H.A., and C.P. Bonini (1958), ‘The Size Distribution of Business Firms’, *The American Economic Review*, 48(4): 607-617.

Tattara G., and M. Valentini (2003), ‘Un mercato del lavoro molto mobile? Sì, ma con molti se e molti ma’, *Economia e società regionale*, 1/2003: 24-54.

Tattara G., and M. Valentini (2004), ‘Job flows, worker flows in Veneto manufacturing. 1982-1996’, Dept. of Economics, University of Venice “Ca’ Foscari”, Nota di lavoro 2004/7.

Tattara G., and M. Volpe (2001), ‘I distretti industriali: definizioni e storia’, in G. Tattara (ed.), *Il piccolo che nasce dal grande. Le molteplici facce dei distretti industriali veneti*, Milano, Italy: Franco Angeli.

Veneto Lavoro (ed.) (2008a), ‘L’erosione mancata. Il lavoro a tempo determinato cresce… come quello a tempo indeterminato’, Misure: WP n. 14.

Veneto Lavoro (ed.) (2008b), *Il mercato del lavoro nel Veneto. Tendenze e politiche. Rapporto 2007*, Milano, Italy: Franco Angeli.

Vuong Q.H. (1989), ‘Likelihood Ratio Tests for model selection and Non-Nested Hypotheses’, *Econometrica*, 57(2): 307-333.

Watts D.J. (2004), ‘The “New” Science of Networks’, *Annual Review of Sociology*, 30: 243-270.

Watts D.J., and S.H. Strogatz (1998), ‘Collective dynamics of 'small-world' networks’, *Nature*, 393: 440-442.

Weitzman M.L. (1998), ‘Recombinant Growth’, *Quarterly Journal of Economics*, 113(2): 331-360.

White D.R., and M. Houseman (2002), ‘The Navigability of Strong Ties: Small Worlds, Tie Strength and Network Topology’, *Complexity*, 8(1): 72-81.

Work Histories Italian Panel (WHIP), database of work histories developed by the Laboratorio R. Revelli – Centre for Employment Studies: http://www.laboratoriorevelli.it/whip.

Yashiv E. (2007), ‘U.S. Labor Market Dynamics revisited’, *Scandinavian Journal of Economics*, 109(4): 779-806.